26TH Annual SEAAIR Conference 2026

Conference Research Preprint

Reimagining Institutional and Educational Excellence in the Age of AI and Data

19 - 21 October, 2026, Taipei Taiwan



Organizer: Ming Chuan University
Co-organizer: International Education and Management Science Foundation

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Welcome Message
from the Interim President of SEAAIR

Distinguished conference delegates, founding members, colleagues, partners, sponsors, early-career researchers, and friends, welcome to SEAAIR 2026, the 26th Annual Conference. This milestone year marks more than a quarter-century of scholarship, partnership, and practical impact across academic and research systems across ASEAN and Asia. That legacy rests on the foresight of our founders, the dedication of our volunteers and committees, the scholarship of our authors and presenters, and the steady support of institutional partners and sponsors that has made this community possible. Over the coming days, engage broadly, think boldly, question assumptions, and collaborate across disciplines as we turn knowledge into action for a smarter, more inclusive, and more sustainable future.

We thank Ming Chuan University and its Local Organizing Committee for graciously hosting us during this 26th SEAAIR Conference. Ming Chuan University's commitment to global engagement and academic excellence provides an ideal setting for this year's dialogue. The 26th year is both a moment to honor that legacy and a catalyst for renewed ambition. Facing accelerating challenges in the academic and research world, we must move from incremental gains to real breakthroughs in system-level solutions. SEAAIR 2026 is designed to do exactly that: a program that combines rigorous research, high-level policy dialogue, and technical innovation with the 26th Conference Theme, **"Reimagining Institutional and Educational Excellence in the Age of AI and Data."**

This year's conference will focus on five key sub-themes: From Data to Decisions: Leveraging AI in Institutional Planning, University Governance and Strategic Foresight; Data-Driven Quality Assurance: Innovations in Assessment and Accreditation; Building Institutional Readiness and Capabilities of AI in Teaching, Learning & Research; Digital Transformation of Educational Efficiencies and Effectiveness: Roles of IR and IT Integration; and Ethics and Pragmatics of AI in Education and IR. To emerging scholars, bring your ideas and seek mentorship. To established members, continue to guide and open doors. The conference will also feature International Parallel Paper Sessions and a Research Consortium for Graduates and Junior Faculty (RCG-JF), offering a dedicated platform for research presentations towards JIRSEA, professional dialogue, and international exchange. Together, let us honor a proud past and set a decisive course for the next twenty-five years.
Welcome to SEAAIR 2026. Thank you for your paper contribution, your partnership, and your commitment to translating knowledge into action. To everyone who has contributed past, present, and future, we extend our deepest thanks.

Thank you.



Assoc. Prof. Dr. Teay Shawyun
Interim President, SEAAIR

Welcome Message
from the Chancellor of Ming Chuan University

On behalf of Ming Chuan University, it is my honor to welcome all of you to Taipei for the 26th SEAAIR Annual Conference.

This year's conference theme, "Re-imagining Institutional and Educational Excellence in the Age of AI and Data," is especially timely. AI and data are transforming how we teach, conduct research, make decisions, and understand our students. Yet technology cannot replace educational judgment, human understanding, or the values that guide our institutions. A truly excellent university is not defined only by research achievements, teaching quality, or international rankings. It must also understand its students, respond to society, use technology wisely, and remain firmly committed to the human values at the heart of education. This is why international dialogue and collaboration through SEAAIR are so important.

For Ming Chuan University, hosting this conference is especially meaningful as we approach our 70th anniversary. Internationalization has long been one of the defining characteristics of our university. Over the years, Ming Chuan has continued to expand its global presence, including our engagement in higher education in the United States since 2014. This year marked another important milestone as Ming Chuan University expanded to operate at California State University, Long Beach. Building on more than two decades of partnership, we look forward to creating new opportunities in education collaboration and international talent development.

Over the next three days, I hope Ming Chuan University will not just host this conference, but also serve as a bridge connecting countries, universities, scholars, and new ideas. Once again, I warmly welcome all of you to Taiwan and to Taipei. I wish the 26th SEAAIR Annual Conference every success, and I hope you will enjoy meaningful disussions, new friendships, and wonderful memories during your time with us. Thank you very much.

Warm regards,



Professor Dr. Chuan Lee
Chancellor of Ming Chuan University
Host of SEAAIR2026 Annual Conference

Welcome Message
from the President of Ming Chuan University

On behalf of Ming Chuan University, it is my great pleasure to welcome all of you to Taipei for the 26th Annual SEAAIR Conference. Ming Chuan University is truly honored to host this year's conference, joining higher education partners from around the world in this important dialogue.

This year's theme, "Reimagining Institutional and Educational Excellence in the Age of AI and Data," is especially timely. Universities today are not lacking data. The real challenge is how we understand that data, identify the issues behind it, and transform it into better decisions and meaningful action. This is why Institutional Research has become more important than ever in the age of AI.

At Ming Chuan University, we are actively creating an environment where faculty and students can learn, experiment, and innovate with AI. Across our campuses, we have established diverse AI learning environments and innovation hubs, including 49 high-performance workstations equipped with NVIDIA GeForce RTX 5090 GPUs. We are also developing local large language model capabilities to strengthen data security, teaching, research, and institutional innovation. Our goal is not simply for students to know how to use AI, but to understand it, work with it, and apply it responsibly to solve real-world problems.

In the face of rapid technological change, what matters most is our ability to ask sharper questions, use better evidence, exercise sound judgment, and turn new ideas into meaningful action. Through this conference, I hope we can transform data into insight, insight into action, and action into meaningful educational excellence.

I warmly welcome all of you to Taiwan. I wish the 26th Annual SEAAIR Conference every success, and I hope you enjoy fruitful discussions and make wonderful memories during your stay. Thank you very much.

Warm regards,

Hsuan-Shih Lee

Professor Dr. Hsuan-Shih Lee
President of Ming Chuan University
Host of SEAAIR2026 Annual Conference

About SEAAIR

The **South East Asian Association for Institutional Research (SEAAIR)** is a leading regional professional association dedicated to advancing institutional research, higher education management, policy development, quality assurance, and evidence-based decision-making across Southeast Asia and the wider Asia-Pacific region. Established in 2001 following the collaboration of higher education leaders from several countries in the region, SEAAIR provides a vibrant platform for academics, researchers, institutional leaders, planners, and policymakers to share knowledge, research findings, and best practices that support the continuous improvement of post-secondary education institutions.

SEAAIR's mission is to promote research that enhances the understanding, planning, governance, and operation of higher education institutions while fostering professional development, regional cooperation, and scholarly exchange. Through its annual international conference, professional workshops, publications, and collaborative networks, SEAAIR encourages innovative approaches to institutional effectiveness, quality enhancement, strategic planning, assessment, and educational leadership.

Over the past two decades, SEAAIR has evolved into a respected international community connecting scholars and practitioners from Southeast Asia and beyond, including participation from East Asia, Australia, and other regions. Its flagship publications, including the *Journal of Institutional Research in South East Asia (JIRSEA)* and the Annual Conference Proceedings, provide valuable contributions to the global discourse on higher education and institutional research.

As SEAAIR celebrates more than 25 years of impact, it remains committed to fostering excellence in higher education through research, collaboration, innovation, and the sharing of knowledge that informs institutional transformation in an increasingly data-driven and globally connected world.

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Schedule of SEAAIR 2026

Venue: Chientan Youth Activity Center, Taiwan, Taipei

Conference Day 1: October 19, 2026 (Monday)	
09:00 – 09:30	Registration (Cyun Ying Hall)
10:00 – 11:00	**Opening ceremony (Cyun Ying Hall)** ◆ Opening Performance ◆ MCU Opening and VIP Introduction ◆ MCU Chancellor Lee's Remarks ◆ MCU President Lee's Welcome Remarks ◆ SEAAIR Presidential Remarks ◆ TAIR Secretary-General Remarks ◆ MCU Vice President Host Remarks ◆ Gift Presentation Ceremony ◆ Group Photo Session
11:15 – 12:00	**KEYNOTE SPEECH I (Cyun Ying Hall)** Dr. Shyang-Yuh Wang *When Numbers Speak: Transforming Smart Cities Through Data-Driven Aesthetics*
12:00 –14:00	Lunch Time
14:00 –15:30	Parallel Sessions (Teaching Hall-Rooms 312,313,314)
15:30 –16:00	Coffee Break
16:00 –17:30	Parallel Sessions (Teaching Hall-Rooms 312,313,314)
18:00 –21:00	Gala Reception (Banquet Hall)

Schedule of SEAAIR 2026

Venue: Chientan Youth Activity Center, Taiwan, Taipei

Conference Day 2: October 20, 2026 (Tuesday)		
08:00 –08:30	Registration (Teaching Hall-Room 318)	
09:00 –09:45	**KEYNOTE SPEECH II (Teaching Hall-Room 318)** Dr. Teay Shawyun *Living with AI: An Academic Playbook*	
09:45 –10:00	Coffee Break	
10:00 –12:00	Research Consortium for Graduates and Junior Faculty (RCG-JF) Session (Teaching Hall-Room 318)	Parallel Sessions (Teaching Hall-Rooms 312,313,314)
12:00 –14:00	Lunch Time	
14:00 –15:30	Research Consortium for Graduates and Junior Faculty (RCG-JF) Session (Teaching Hall-Room 312)	Parallel Sessions (Teaching Hall-Rooms 313,314)
15:30 –16:00	Coffee Break	
16:00 –17:30	Research Consortium for Graduates and Junior Faculty (RCG-JF) Session (Teaching Hall-Room 312)	Parallel Sessions (Teaching Hall-Rooms 313,314)
18:00 –21:00	Cultural Night (Banquet Hall)	

Conference Day 3: October 21, 2026 (Wednesday)	
08:00 –08:30	Registration (Cyun Ying Hall)
09:00 –10:00	Panel Discussion (Cyun Ying Hall)
10:00 –12:00	Annual General Meeting and Closing Ceremony (Cyun Ying Hall)
12:00	Lunch Time
13:00	City Tour

SEAAIR 2026

Parallel Sessions

Presentation: 20 Minutes, Q & A: 10 Minutes



Day 1: Monday, 19 October 2026

Time: 14:00–15:30 | **Presentation: 20 Minutes, Q & A: 10 Minutes**

Room	Time	No.	Authors	Paper title	Country
312	14:00–14:30	P26009	Nueva D. Salaan	Strengthening Institutional Effectiveness Through Strategic Foresight: A Five-Year Analysis of Internal Quality Audit Findings	Philippines
	14:30–15:00	P26026	Denise O. Orong, Arah C. Jumahali and James A. Almajar	Predicting AI Integration and Strategic Foresight Capacity in Higher Education: A Hierarchical Regression Analysis of Institutional Readiness and AI-Driven Decision Support Systems	Philippines
	15:00–15:30	P26040	Bo-Jui Su, Hsin-Peng Shiahhou and Chin-Lun Tsai	The Underdog's Potential for Retaliation: AI-Enabled Strategic Applications of Strategic Foresight and Competitive Intelligence, the Facilitating Role of Risk Thinking, and the Inhibitory Moderating Role of Organizational Ambition	Taiwan
313	14:00–14:30	P26035	Ya-Wen Hou and Po-Lin Chen	Exploring the Latent Structure of Interdisciplinary Competencies among University Students: An Exploratory Factor Analysis	Taiwan
	14:30–15:00	P26052	Narat Wattanapanit and Krisda Tanchaisak	Institutional Governance and Executive Leadership Efficacy in Higher Education: An Empirical Assessment of An Administrator's Performance in a Thai Public University	Thailand
	15:00–15:30	P26013	Mary Faith G. Magallanes, Akira Everardo E. Napay, Lyn Jill B. Aycardo, Kaycee L. Barajas and Giselle A. Millete	Development of a Parent's Guide for Play-Based Curriculum from Stakeholders' Insights	Philippines
314	14:00–14:30	P26019	Jie-Wen Tsai, Che-Yu Hsu and Feng-Nan Hwang	Early Warning Analysis of Student Performance and Re-Enrollment in Cross-Disciplinary AI Courses	Taiwan
	14:30–15:00	P26020	Familia Novita Simanjuntak, Angelia Patricia Situmorang and Cari Etis	The Role of AI in Implementing Deep Learning to Support Engaging and Enjoyable Learning Experiences	Indonesia
	15:00–15:30	P26030	Arian M. Edullantes and Keth Jerica G. Lim	Artificial Intelligence Literacy and Behavioral Intention of Pre-Service Teachers: Insights from the ABCE Framework and Constructivist Learning Theory	Philippines

Day 1: Monday, 19 October 2026

Time: 16:00–17:30 | **Presentation: 20 Minutes, Q & A: 10 Minutes**

Room	Time	No.	Authors	Paper title	Country
312	16:00–16:30	P26023	Henry Y. Zheng	From Data to Decisions: How University Leaders Connect Analytics and AI to Institutional Strategy	United States
	16:30–17:00	P26042	Jihoe Park and Liu Ting	Institutional Research in Korean Higher Education: Organization and Practice	South Korea
	17:00–17:30	P26043	Jeffrie Atendido, Adlin Mae Dimasuay and Charlie Dujali	AI-Driven Categorical Enrollment Prediction for Strategic Institutional Planning and Governance	Philippines
313	16:00–16:30	P26046	Ma. Judy B. Legaspi and Carlos Eduardo I. Legaspi, Jr.	Operational Risk Management Practices and Resilience of Selected Catholic Higher Educational Institutions in the Philippines	Philippines
	16:30–17:00	P26053	Narat Wattanapanit and Krisda Tanchaisak	Evaluation of Public Relations Channels, Information Awareness, and Applicant Satisfaction in Higher Education Student Recruitment: A Case Study of Ramkhamhaeng University	Thailand
	17:00–17:30	P26058	Narat Wattanapanit, Krisda Tanchaisak and Thayida Lertchanadecha	Administrative Factors Affecting Work Motivation and Organizational Commitment of Personnel in the Faculty of Education, Ramkhamhaeng University	Thailand
314	16:00–16:30	P26002	Charito Garcia Ong	Evaluating the DRIVE Model: A Structured Transfer-and-Implementation Framework for Faculty Technology Integration	Philippines
	16:30–17:00	P26048	Nathee Kerdaroon and Petch Wijitnawin	Exploring Opportunities and Challenges in Collaborating with Parents to Support Children with Special Educational Needs: Reflections From Pre-Service Teachers in Thailand	Thailand
	17:00–17:30	P26012	Lemyr Joshua L. Mimay and Jade M. Balbedina	Faculty Perceptions of AI Use Across ADDIE Instructional Design Phases at DWCL	Philippines

Day 2: Tuesday, 20 October 2026

Time: 10:00–12:00 | **Presentation: 20 Minutes, Q & A: 10 Minutes**

Room	Time	No.	Authors	Paper title	Country
312	10:00–10:30	P26045	Bi-Jen Hsieh, Hsien-Hsiu Chen and Li-Fang Chan	Beyond Campus Facilities: Institutional Identification and the Divergent Pathways to International Students' Further Study and Employment Intentions in Taiwan	Taiwan
	10:30–11:00	P26049	Fr. Jhonatan A. Letada	Mission-Driven Leadership in SVD Higher Education Institutions in the Philippines: Toward an Enhanced Leadership Model	Philippines
	11:00–11:30	P26024	Cherish Delight A. Mahinay-Borres and Jason O. Manaois	Narratives of Filipino Students Navigating Different Learning Modalities in a Pandemic: Insights for Digital Transformation in Higher Education	Philippines
	11:30–12:00	P26032	Junghwa Lee and Baek young Yoo	Beyond AI-Generated Insight: Human-Mediated Critical Reflection Through the Expansion of a GCED Program in Cambodia	South Korea
313	10:00–10:30	P26036	Saruta Ketpradit, Yu-Chuan Chuang and Chin-Lun Tsai	Exploring the Relationships between Sociocultural and Academic Adaptation with Career Decisions among International Students: A Case Study of a Public University of Technology in Taiwan	Taiwan
	10:30–11:00	P26004	Chitraporn Boonthanom and Singthai Suksawangrot	RU: AUN-QA Digital Technology For Internal Quality At Ramkhamhaeng University	Thailand
	11:00–11:30	P26005	Staporn Tavornativat, Pattaraporn Kitchainukoon and Jarunee Wites	Guidelines for Developing Rajabhat Universities toward Excellence Based on the Education Criteria for Performance Excellence (EdPEx)	Thailand
	11:30–12:00	P26050	JP Remar A. Serrano, Rhodora Faye A. Brosas and Christian M. Lana	SentiNet: An AI-Powered Sentiment Analysis and Heat Mapping of Internet Connectivity at Divine Word College of Legazpi	Philippines

Day 2: Tuesday, 20 October 2026

Time: 10:00–12:00 | **Presentation: 20 Minutes, Q & A: 10 Minutes**

(continued)

Room	Time	No.	Authors	Paper title	Country
314	10:00–10:30	P26021	Therese June Aranas and Trisha Mae Bermudez	Enhancing On-Task Academic Engagement of Students with Emotional and Behavioral Disorders through the Good Behavior Game: Implications for AI-Ready Inclusive Classrooms	Philippines
	10:30–11:00	P26022	Sarochar Chaijang, Nampech Tasaboomrung and Thayida Lertchanadecha	The Roles of Special Education Teachers in Promoting the Potential of Students with Special Needs in Inclusive Schools	Thailand
	11:00–11:30	P26034	Sol J. Dalonos, Hannah Vee U. Sabit and Arian M. Edullantes	Navigating the Lived Experiences of Special Education Teachers on the Use of Low-Technology Assistive Tools in Reading Instruction	Philippines
	11:30–12:00	P26017	Rosella O. Ortiz, David S. Almarez Jr., Amelda C. Libres and Dominic T. Polancos	Institutional Drivers of Academic Integrity Readiness in AI-Enabled Higher Education: The Roles of Governance, Culture, Pedagogy, and Operational Support	Philippines

Day 2: Tuesday, 20 October 2026

Time: 14:00–15:30 | **Presentation: 20 Minutes, Q & A: 10 Minutes**

Room	Time	No.	Authors	Paper title	Country
313	14:00–14:30	P26008	Geldolin L. Inte and Evelyn K. Montecalvo	Transforming Tutorial Interventions for Enhanced Interactive Learning in Writing and Speaking English among College Students	Philippines
	14:30–15:00	P26016	Ya-Mei Chiu	A Data-Driven Competency Training Evaluation Framework for the Public Sector: Integrating Learning Analytics, Kirkpatrick Model, IPA, and IR–IT Collaboration	Taiwan
	15:00–15:30	P26031	Yung Yi Chang	Trapped in the Metric Race: A Psychological Decision-Making Mechanism of Post-Loss Perceptions and Behavioral Outcomes under Higher Education IT-IR Frameworks	Taiwan
314	14:00–14:30	P26044	Tai-Wei Sung, Meilun Shih and Ya-Shan Chen	Psychological Readiness for Learning in the AI Era: Academic Risk-Taking, Self-Directed Learning, and Academic Buoyancy Among First-Year University Students	Taiwan
	14:30–15:00	P26018	Marisa B. Petalla and Dennis V. Madrigal	Research Fatigue and Scientific Writing Difficulties Among Thesis and Dissertation Writers in a Catholic University: An Exploratory Sequential Mixed Methods Inquiry	Philippines
	15:00–15:30	P26056	Felsa A. Labis, Dominic T. Polancos, Amelda C. Libres and Ma. Florecilla C. Cinches	Growth Mindset and Techno-Solutionist Thinking among Graduate Students: The Mediating Role of Trust in AI	Philippines

Day 2: Tuesday, 20 October 2026

Time: 16:00–17:30 | **Presentation: 20 Minutes, Q & A: 10 Minutes**

Room	Time	No.	Authors	Paper title	Country
313	16:00–16:30	P26037	Ma. Florecilla C. Cinches, Judith C. Chavez and Ruth Love V. Russell	How Critical Are Students of Technology? Development and Validation of the Critical Technoskepticism Inventory	Philippines
	16:30–17:00	P26033	Mateo R. Borbon, Jr. and Charibeth Cheng	Comparing LDA and NMF for Thematic Analysis of Bilingual Higher-Education Discourse on Reddit	Philippines
	17:00–17:30	P26054	Charlie Dujali, Jeffrie Atendido and Adlin Mae Dimasuay	Faculty Behavioral Intention Toward AI Adoption in Higher Education: A UTAUT-Based PLS-SEM Study in the Philippines	Philippines
314	16:00–16:30	P26028	Mary Louise S. Pimentel	Exposure to Brainrot Content and Its Relationship with Communication and Language Use among Senior High School Learners	Philippines
	16:30–17:00	P26059	Tanutchaporn Namwat, Rungnapha Logatesatian and Siriphan Thongsai	Teacher Non-Verbal Communication and AI Use as Complementary Predictors of Perceived Course Learning Outcomes among Thai Pre-Service Teachers	Thailand
	17:00–17:30	P26027	Grace S. Pimentel and April G. Tondares	Effectiveness of a Communicative-Based Learning Module in Reducing Fear of Negative Evaluation in Speaking Among Freshman College Students	Philippines

SEAAIR 2026

RCG-JF Sessions

Research Consortium for Graduates and Junior Faculty

Presentation: 20 Minutes, Q & A: 10 Minutes



Day 2: Tuesday, 20 October 2026

Time: 10:00–11:30

Presentation: 20 Minutes, Q & A: 10 Minutes

Room	Time	Authors	Paper title	Country
318	10:00–10:30	Sun Dongjun, Chanita Rukspollmuang and Pongsin Viseshsiri	Professional Learning Communities as the Dominant Mediator of Learning-Centred Leadership in Chinese Higher Education	Thailand
	10:30–11:00	Yeji Lim	International Student Recruitment and Retention in South Korean Higher Education: A Comparative IR Analysis of Gachon University and Keimyung University	South Korea
	11:00–11:30	Sophia Shi-Huei Ho, Robin Jung-Cheng Chen and Ying-Yan Lu	Shifting Drivers of Faculty Teaching Engagement and Job Satisfaction in Taiwan: Longitudinal Insights into Policy-Driven Pedagogical Transformations	Taiwan

Day 2: Tuesday, 20 October 2026

Time: 14:00–15:30

Presentation: 20 Minutes, Q & A: 10 Minutes

Room	Time	Authors	Paper title	Country
312	14:00–14:30	Khwanchol Kampan and Anil Kumar Anal	Bridging Digital Capability Gaps: The Role of Higher Education Management in Blockchain Adoption in Thailand's Agri-Food Sector	Thailand
	14:30–15:00	Zhang YingShui, Ren Bingyang, and Ko Jang Wan	A Systematic Review of AI Governance in Higher Education: Current Trends and Future Challenges	South Korea
	15:00–15:30	Daniel Chi-Wang Chiang	Between Excellence and Equity: Public Funding Concentration in Taiwanese Higher Education	Taiwan

Day 2: Tuesday, 20 October 2026

Time: 16:00–17:30 | **Presentation: 20 Minutes, Q & A: 10 Minutes**

Room	Time	Authors	Paper title	Country
312	16:00–16:30	Worapoom Saengkaew, Nongnuch Sriussadaporn, Tanatpan Sukprasert, Ativate Tangamornsuksan, Kanidtha Sungkarat, Kamolwan Punyasuth, Montha Chaihiranwattana, Yanisa Taevajira, Mullika Klongklaew	Documented Alignment, Deferred Evidence: A Single-Case Study of Outcome-Based Education Transition in a Thai Private-University Business English Programme	Thailand
	16:30–17:00	Zhang Yuningjing and Xu Xiwen	Mapping the Evolution of Data-Driven Quality Assurance in Higher Education: A BERTopic Analysis of Assessment and Accreditation Research (2010–2025)	South Korea
	17:00–17:30	Shu-Tzu Wang and Shi-Huei Ho	From Indicators to Data-Informed Governance: A Strategic Framework for University Social Responsibility in Teacher Education Institutions	Taiwan

SEAAIR 2026

Full Article

Sub-Theme I

From Data to Decisions: Leveraging AI in Institutional Planning, University Governance and Strategic Foresight

P26009

Strengthening Institutional Effectiveness Through Strategic Foresight: A Five-Year Analysis of Internal Quality Audit Findings

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ABSTRACT

Higher education institutions require quality assurance systems that support not only compliance but also institutional learning, risk management, and strategic decision-making. This study examines five years of Internal Quality Audit (IQA) findings from 2021 to 2025 across the eight-campus University of Science and Technology of Southern Philippines (USTP) System to explore how longitudinal audit evidence can inform strategic foresight and institutional effectiveness. Using a descriptive-documentary mixed-methods design, the study analyzed 440 process evaluations drawn from IQA registries, audit summary matrices, closing meeting reports, Corrective Action Reports (CARs), and related Quality Management System (QMS) documents. Quantitative analysis examined audit trends and finding classifications, while qualitative content analysis identified recurring patterns and institutional vulnerability domains. Results indicate an improvement in audit conformity, with the annual conformity rate increasing from 65.4% in 2021 to 77.1% in 2025, while recorded non-conformities declined from 17 to 8. Findings were classified as Conformance (C), Observations(Opportunity for Improvement (OFI) Possible Non-Conformity in the Future, Minor Non-Conformance (NC-Mi), Major Non-Conformance (NC-Ma), and Unspecified Non-Conformance (NC-Un). Despite improved conformity, recurring vulnerabilities were identified in human resources, version control, process sequencing, policy implementation, archival and physical resources, and organizational guidance. A 3×3 Risk Priority Matrix based on recurrence and severity was applied to identify vulnerability domains requiring institutional attention.The study proposes a Strategic Foresight-Informed Quality Governance Framework that uses IQA findings to identify recurring and emerging issues and guide institutional planning, resource allocation, policy action, and continuous improvement. Rather than predicting future audit results statistically, the framework uses audit patterns as early signals of potential institutional risks. It provides a practical approach for using quality audit evidence to support more proactive and informed decision-making in a multi-campus higher education system.

Keywords: Internal Quality Audit; Strategic Foresight; Quality Governance; Risk-Based Thinking; Institutional Effectiveness; Higher Education

1. Introduction

Higher education institutions (HEIs) operate in increasingly complex environments characterized by evolving regulatory requirements, changing stakeholder expectations, technological developments, and growing demands for institutional accountability. In this context, quality assurance systems are essential for ensuring that academic and administrative

processes are consistently implemented, monitored, and improved. Quality management in higher education extends beyond compliance and includes institutional learning, evidence-based decision-making, risk management, and continuous improvement (Harvey & Williams, 2010; Srikanthan & Dalrymple, 2007).

The Quality Management System (QMS) provides a structured framework for managing and continually improving organizational processes. ISO 9001:2015 emphasizes the process approach, evidence-based decision-making, risk-based thinking, and continual improvement as foundations of an effective QMS (International Organization for Standardization [ISO], 2015). These principles are particularly relevant to multi-campus universities, where differences in human resources, infrastructure, document control, and local operational practices may affect the consistency of process implementation.

The University of Science and Technology of Southern Philippines (USTP) has implemented an ISO 9001:2015-aligned QMS across its multi-campus structure. Within this system, Internal Quality Audits (IQAs) provide systematic and objective assessments of process conformity and generate evidence for identifying weaknesses and supporting corrective action. However, the value of IQA findings extends beyond addressing individual non-conformities within a single audit cycle. When examined longitudinally, recurring findings may reveal persistent institutional vulnerabilities involving staffing, document control, policy implementation, infrastructure, and organizational governance.

This perspective is consistent with the risk-based thinking emphasized in ISO 9001:2015, which encourages organizations to identify factors that may affect intended outcomes and take appropriate action to address potential risks. In a multi-campus university, recurring audit findings may therefore provide useful signals for identifying areas requiring sustained monitoring, resource allocation, and institutional intervention.

The longitudinal analysis of audit evidence also provides an opportunity to apply strategic foresight to quality governance. Strategic foresight examines emerging trends, signals, uncertainties, and alternative future developments to support informed decision-making in the present (Organisation for Economic Co-operation and Development [OECD], 2019). In this study, recurring IQA findings are not treated as statistical predictions of future audit outcomes but as potential signals of institutional vulnerability that may inform more proactive quality governance.

Despite the established role of internal audits in quality management, limited attention has been given to how accumulated audit evidence can be systematically analyzed to identify recurring vulnerabilities and inform forward-looking institutional planning. This study addresses this gap by examining five years of IQA findings from 2021 to 2025 across the USTP System. Using a descriptive-documentary mixed-methods approach, the study analyzes conformity trends, finding classifications, and recurring institutional vulnerabilities and applies risk-based analysis to prioritize these vulnerabilities according to recurrence and severity.

The study further interprets the findings through a strategic foresight perspective to explore how longitudinal IQA evidence can support institutional planning, resource allocation, risk management, and continuous quality improvement. It ultimately proposes a Strategic Foresight-Informed Quality Governance Framework for the USTP System.

The study aims to achieve the following objectives:

1. To determine the multi-year trajectory of institutional process conformity within the USTP System across the five-year IQA period from 2021 to 2025.
2. To analyze the distribution of IQA findings across Conformance (C), Opportunity for Improvement (OFI), Minor Non-Conformance (NC-Mi), Major Non-Conformance (NC-Ma), and Unspecified Non-Conformance (NC-Un) across successive audit cycles
3. To identify and analyze recurring institutional vulnerability domains emerging across the five-year audit period.
4. To prioritize recurring vulnerability domains using risk-based analysis of recurrence and severity and examine their implications for institutional quality governance.
5. To propose a Strategic Foresight-Informed Quality Governance Framework that uses longitudinal IQA evidence to support proactive institutional

2. Review of Related Literature

2.1 Quality Management and ISO 9001:2015 in Higher Education

Quality management in higher education extends beyond compliance and emphasizes process consistency, evidence-based decision-making, risk-based thinking, and continual improvement. ISO 9001:2015 provides a framework for organizations to establish, implement, monitor, and improve quality management systems (International Organization for Standardization [ISO], 2015). In higher education, these principles are particularly relevant because academic and administrative processes are complex, interconnected, and implemented across diverse organizational units. Effective quality systems can therefore support institutional accountability, process improvement, and organizational learning (Harvey & Williams, 2010; Srikanthan & Dalrymple, 2007).

2.2 Internal Quality Audits and Institutional Improvement

Internal Quality Audits (IQAs) provide systematic and objective assessments of whether organizational processes conform to established requirements and are effectively implemented. ISO 19011:2018 emphasizes systematic audit planning, objective evidence, consistent evaluation, and effective audit-program management (ISO, 2018). In higher education, audit findings can provide valuable evidence for identifying process weaknesses and supporting corrective action and continuous improvement. Longitudinal analysis can reveal persistent patterns involving staffing, document control, policy implementation, infrastructure, and organizational responsibilities that may require system-level interventions.

2.3 Risk-Based Thinking and Strategic Foresight

Risk-based thinking encourages organizations to identify factors that may affect intended outcomes and to take appropriate action to prevent or reduce undesirable effects. Applied to internal audit evidence, recurring findings may serve as indicators of institutional vulnerabilities that warrant closer monitoring and strategic intervention. Although recurrence does not necessarily predict future failure, it can provide evidence for prioritizing risks and allocating institutional resources.

Strategic foresight complements this approach by examining trends, emerging signals,

uncertainties, and possible future developments to inform present decision-making (Organization for Economic Co-operation and Development [OECD], 2019). In higher education, a foresight perspective can help institutions move beyond reactive corrective action toward more proactive planning and governance. Longitudinal IQA findings may therefore function as early signals that inform institutional planning, resource allocation, risk management, and quality improvement.

2.4 Research Gap and Conceptual Synthesis

Existing literature establishes the importance of quality management, internal auditing, risk-based thinking, and strategic foresight in organizational improvement. However, limited attention has been given to how longitudinal internal audit evidence can be systematically analyzed and transformed into forward-looking quality governance insights in multi-campus higher education institutions. This study addresses this gap by integrating five years of IQA evidence with risk-based analysis and a strategic foresight perspective. The study examines recurring institutional vulnerabilities and their implications for proactive planning, resource allocation, and continuous quality improvement within the USTP System**.**

3. METHODOLOGY

3.1 Research Design

The study employed a descriptive-documentary mixed-methods design to analyze five years of Internal Quality Audit (IQA) findings across the University of Science and Technology of Southern Philippines (USTP). Quantitative descriptive analysis examined audit coverage, conformity trends, and finding classifications, while qualitative content analysis identified recurring issues and institutional vulnerabilities (Creswell & Plano Clark, 2018). Risk-based thinking guided the prioritization of recurring vulnerabilities (International Organization for Standardization [ISO], 2015).

3.2 Research Locale and Data Sources

The study covered the eight-campus USTP System in Northern Mindanao. Data were obtained from official IQA registries, audit summary matrices, closing meeting reports, and Quality Management System (QMS) documents maintained by the USTP Quality Management System Office. Records covered five audit cycles from 2021 to 2025 and included academic and administrative processes. The study relied exclusively on institutional documentary records.

3.3 Sampling Strategy

Total enumeration was used, covering all available IQA process evaluations from 2021 to 2025 (**N = 440**). This enabled the analysis of longitudinal trends, recurring findings, and institutional vulnerability patterns across the USTP System.

3.4 Data Extraction, Coding and Classification Procedure

The documentary data were analyzed using a systematic seven-stage coding procedure. First, relevant information was extracted from the Internal Quality Audit (IQA) records using a standardized data extraction template. Second, each audit finding was assigned an initial code based on its classification as Conformance (C), Observation/ Opportunity for Improvement

(OFI), Minor Non-Conformance (NC-Mi), Major Non-Conformance (NC-Ma), or Unspecified Non-Conformance (NC-Un). Third, each coded finding was mapped to the corresponding ISO 9001:2015 clause. Fourth, the coded findings were compared across the five audit cycles (2021–2025) to identify recurring patterns and institutional trends. Fifth, recurring findings were grouped through thematic content analysis into broader institutional vulnerability domains. Sixth, the identified vulnerability domains were prioritized using a 3 × 3 Risk Priority Matrix based on their recurrence and severity to determine their institutional risk levels. Finally, the coded findings, thematic domains, and risk priorities were synthesized to develop the proposed **Strategic Foresight-Informed Quality Governance Framework**, illustrating how longitudinal IQA evidence can support proactive governance, strategic planning, and continuous quality improvement. To ensure analytical consistency, standardized coding criteria were applied throughout the analysis, and all coded findings were verified against the original audit records.

Table 1.1 *Operational Matrix for Risk Priority Evaluation (3 × 3 Matrix)*

3.5 Ethical Considerations

Variable	Scale Level	Value	Operational Definition / Audit Criteria
Recurrence Index (RI)	Low	1	Isolated observation occurring in a single audit cycle.
	Moderate	2	Recurring finding occurring across 2 to 3 audit cycles.
	High	3	Systemic issue persisting across 4 or more audit cycles.
Severity Impact Score (S)	Minor	1	Localized operational discrepancy with minimal impact on overall compliance.
	Moderate	2	Process sequence breakdown or document control failure affecting data integrity.
	Critical	3	Significant regulatory non-compliance, critical resource deficit, or policy deviation requiring executive action.
Risk Priority Score (RPS=RI×S)	Low Risk	1–2	Managed at the local operational unit level through standard corrective actions.
	Medium Risk	3–4	Requires cross-campus administrative monitoring and targeted process intervention.
	High Risk	6–9	Mandates executive escalation, policy review, and strategic resource allocation

Institutional clearance and appropriate ethical approval were secured before data extraction. Institutional records were treated as confidential, and personally identifying information was excluded from the analysis. Data were securely stored and used solely for academic research and quality management purposes.

4. RESULTS AND DISCUSSION

This section presents the multi-year trajectory of internal quality audit findings across the USTP System from 2021 to 2025. Findings are analyzed across operational conformity trends, finding classifications, risk-based vulnerability mapping, and strategic action operationalization.

This section presents the findings of the study based on the analysis of Internal Quality Audit (IQA) reports from 2021 to 2025, along with their interpretation in relation to ISO 9001:2015 principles and risk-based thinking.

4.1 Distribution of Internal Quality Audit Findings (2021-2025)

Table 1. Five-Year IQA Performance and Conformity Trends, 2021–2025

Audit Year	Total Processes Evaluated (N)	Conforming Processes (n)	Non-Conformities (n)	Opportunities for Improvement (n)	Operational Conformity Rate (%)
2021	***78***	***51***	***17***	***10***	***65.4%***
2022	***85***	***61***	***14***	***10***	***71.8%***
2023	***92***	***70***	***11***	***11***	***76.1%***
2024	***89***	***70***	***8***	***11***	***78.7%***
2025	***96***	***74***	***9***	***13***	***77.1%***
5-Year Total (∑)	***440***	***326***	***59***	***55***	***74.1 (Aggregate)***
Annual Mean ($\bar{X}$)	***88.0***	***65.2***	***11.8***	***11.0***	***73.8%***

Note. *Operational Conformity Rate (%) = (Conforming Processes/ Total Processes Evaluated) × 100. The 5-Year Mean Conformity Rate (73.8%) represents the arithmetic mean of the five annual conformity percentages. Non-conformities aggregate both Major (NC-Ma) and Minor (NC-Mi) classifications.*

Table 1 shows an overall increase in conformity from **65.4% in 2021 to 77.1% in 2025**, with the highest rate of **78.6% in 2024** and a five-year mean of **73.8%**. The trend indicates improved process conformity across the audit cycles, consistent with the principles of continual improvement under ISO 9001:2015 (International Organization for Standardization [ISO], 2015). implementations light decline in 2025 and the continued recurrence of concerns in document control, human resources, and policy implementation indicate that improvements in overall conformity coexist with persistent institutional vulnerabilities. Longitudinal analysis of IQA findings is therefore useful for identifying recurring issues and prioritizing areas needing quality improvement (ISO, 2015).

4.2 Distribution of IQA Findings

Table 2.1 Distribution and Classification of Internal Quality Audit Findings, 2025 Audit Cycle (N = 96)

Category Code	Finding Classification	Primary ISO 9001:2015 Clause	Frequency (n)		Percentage (%)

		Alignment			
C	**Conformance**	**Clauses 4, 7, and 8**	**74**		**77.1**
OFI	**Opportunity for Improvement**	**Clauses 9 and 10**	**13**		**13.5**
NC-Mi	**Minor Non-Conformance**	**Clauses 7.5 and 8.5.1**	**7**		**7.3**
NC-Ma	**Major Non-Conformance**	**Clause 7.1.2**	**1**		**1.0**
NC-Un	**Unspecified Non-Conformance**	**Clause 5.3**	**1**		**1.0**
Total			**96**		**100.0**

Note: *Non-conformities for the 2025 cycle total 9 findings (7 NC-Mi + 1 NC-Ma + 1 NC-Un), accounting for 9.3% of evaluated processes*.

The 2025 audit cycle recorded a **77.1% conformity rate**, with 13.5% classified as Opportunities for Improvement and 9.3% as non-conformities. The findings indicate generally strong process conformity, but the presence of minor, major, and unspecified non-conformities highlights persistent areas requiring management attention. In particular, the Major Non-Conformance involving the availability of required licensed personnel represents a significant resource and compliance concern. Overall, the findings support the use of risk-based thinking and continual improvement to address vulnerabilities that may affect QMS effectiveness (International Organization for Standardization [ISO], 2015).

Table 2.2 *Cumulative Distribution of Internal Quality Audit Findings Across Five Cycles (2021–2025, $N = 440$)*

Category Code	**Finding Classification**	**Primary ISO 9001:2015 Clause Alignment**	**Total (n)**	**Percentage (%)**
C	Conforming Processes	Clause 4, Clause 7, Clause 8	336	76.4%
NC	Non-Conformities (Major & Minor)	Clause 5.3, Clause 7.1.2, Clause 7.5, Clause 8.5.1	59	13.4%
OFI	Opportunities for Improvement	Clause 9, Clause 10	45	10.2%
Total			**440**	**100.0%**

Table 2.2 shows that conforming processes comprised the majority of audited processes (76.4%), followed by non-conformities (13.4%) and Opportunities for Improvement (10.2%). The overall decline in annual non-conformities from 17 in 2021 to 9 in 2025 demonstrates systemic progress in process execution. However, the persistence of 59 non-conformities and 45 OFIs across the five cycles underlines the need for sustained monitoring, targeted resource

allocation, and continuous quality improvement aligned with ISO 9001:2015 principles

Table 3 *Risk-Mapping of Recurring Institutional Vulnerabilities and ISO 9001:2015 Alignment*

Institutional Vulnerability	**Recurring Audit**	**Affected Campuses / Operational Units**	**Applicable ISO 9001:2015 Clause**	**Strategic Impact & Risk Level**
Human Resource Deficits	Shortage of licensed guidance counselors and psychometricians due to recruitment and localized budget limitations. Moreover, there is a dearth of guidance counselors as evidenced by the lack of qualified applicants.	Panaon, Oroquieta, Balubal, Claveria	**Clause 7.1.2** *(People / Resource Allocation)*	**High Risk** (Regulatory non-compliance with CHED mandates)
Version Control Non-alignment	Field-level usage of obsolete form revisions; mismatched operational dates across digital portals.	Panaon, Jasaan, Academic Departments	**Clause 7.5** *(Documented Information)*	**Medium Risk** (Traceability gaps and data fragmentation)
Chronological Violations	Syllabus review forms and instructional validations signed weeks after class commencement.	Cagayan de Oro (CDO), Academic Units	**Clause 8.5.1** *(Control of Production & Service Provision)*	**Medium Risk** (Process sequence breakdown)
Policy Slippage	Passing grades issued to students exceeding the maximum 17% allowable unexcused absence threshold.	System-wide Academic Colleges	**Clause 9.1** *(Monitoring, Measurement, Analysis & Evaluation)*	**High Risk** (Academic integrity and handbook deviation)
Archival & Physical Risk	Inadequate workspace and poor ventilation endangering the physical preservation of student records.	Balubal, Jasaan, Claveria (Registrars)	**Clause 7.1.3** *(Infrastructure & Work Environment)*	**Medium Risk** (Physical record degradation and loss)

Structural Guidance Lack	Complete absence of approved operational manuals or defined roles/qualifications for specialized unit staff.	MJST Unit	**Clause 5.3** *(Organizational Roles, Responsibilities & Authorities)*	**High Risk** (Systemic operational ambiguity)

Table 3 identifies six recurring institutional vulnerability domains across the 2021–2025 IQA cycles. **High-risk concerns** include human resource shortages, policy implementation gaps, and unclear organizational roles, while **medium-risk areas** involve document control, process sequencing, and records preservation. The findings indicate that recurring vulnerabilities extend beyond isolated process deviations and may require system-wide interventions in staffing, policy enforcement, document management, infrastructure, and governance. These results support the use of risk-based thinking and continual improvement in strengthening institutional quality governance (ISO, 2015; Fonseca, 2015).

Table 4 ***Summary of Key Audit Problems, Root Causes, Institutional Implications, and Recommended Strategic Actions***

Identified Problem Area	**Observed Issue from IQA Findings**	**Likely Root Cause(s)**	**Institutional Implication**	**Recommended Action**
Document Control Weakness	Field-level usage of obsolete or un updated form revisions.	Delayed document dissemination ; weak version tracking mechanisms.	Inconsistent implementation of procedures; compromised data integrity across campuses.	Strengthen centralized digital document control system and enforce real-time version updates across all campuses.
Process Timing Non-Compliance	Late submission and approval of syllabus review forms and academic documents.	Weak enforcement of academic timelines; lack of automated monitoring mechanisms.	Reduced effectiveness of pre-semester quality assurance processes.	Implement strict academic calendar compliance monitoring and automated submission tracking.
Policy Implementation Gap	Passing grades issued to students despite unexcused absences exceeding the maximum	Inconsistent policy enforcement at the classroom level; weak academic	Threat to academic integrity, handbook compliance, and institutional	Reinforce policy compliance through regular audits, faculty reorientation,

	allowable 17% threshold.	monitoring.	credibility.	and automated attendance tools.
Human Resource Constraints	Absence of licensed guidance counselors and psychometricians in some satellite campuses.	Budgetary limitations; localized workforce allocation gaps.	Non-compliance with CHED regulatory requirements and reduced student support services.	Conduct system-wide manpower planning and prioritize hiring/allocation of required licensed personnel per campus.
Infrastructure Limitations	Poor ventilation and restricted office space in registrar units affecting record storage.	Inadequate facility planning and delays in capital infrastructure funding.	Risk to long-term preservation, physical security, and integrity of academic records.	Upgrade registrar facilities, improve archival storage systems, and accelerate record digitalization.
Governance and Role Ambiguity	Absence of clear operational manuals and defined roles/qualifications in specialized units.	Lack of formalized internal unit documentation and role classification.	Operational inefficiency, process ambiguity, and unclear accountability structures.	Develop, formally approve, and enforce standardized operational manuals and role frameworks per unit.

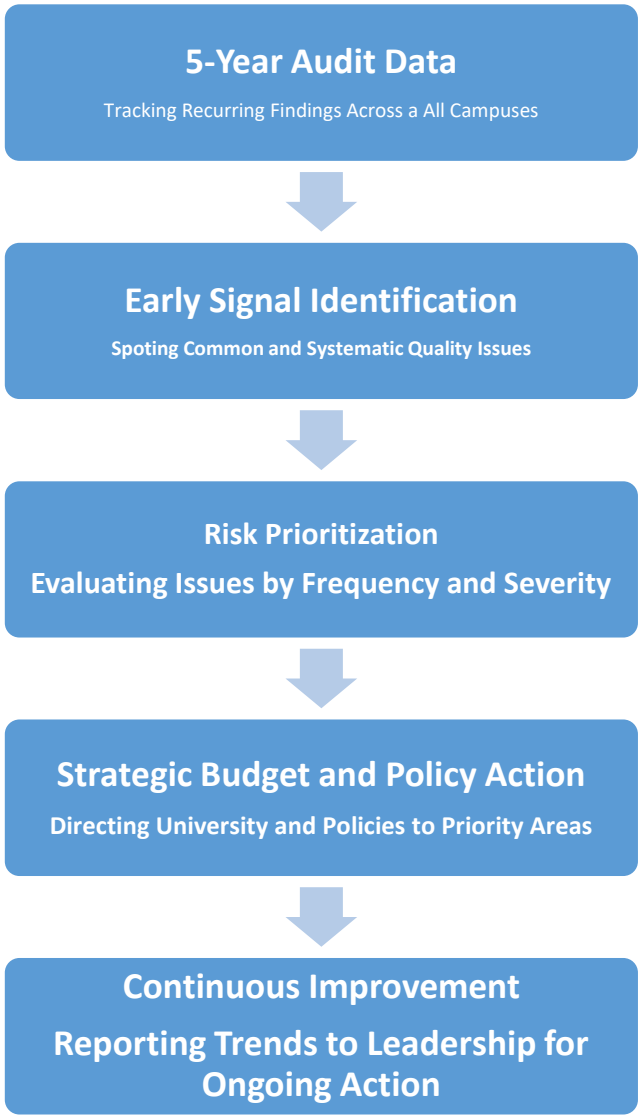
Table 4 consolidates the recurring institutional issues identified through IQA findings, highlighting persistent concerns in document control, process timing, policy implementation, human resources, infrastructure, and governance. These recurring issues suggest systemic gaps in the consistent implementation of the quality management system rather than isolated incidents. The decline in non-conformities from 17 in 2021 to 8 in 2025 indicates progress in corrective action, but continued weaknesses in resource-dependent and operational areas show the need for stronger executive support, resource allocation, and monitoring. Overall, the findings emphasize the importance of strengthening document control, enforcing institutional policies, ensuring adequate staffing and infrastructure, and clarifying organizational roles to support risk-based thinking and continual improvement in accordance with ISO 9001:2015 (ISO, 2015; Fonseca, 2015; Psomas & Antony, 2017).

4.3 Strategic Foresight-Informed Quality Governance Framework

To transition internal quality assurance from a reactive compliance activity to a proactive decision-support tool, this study proposes the Strategic Foresight-Informed Quality

Governance Framework (Figure 1). Rather than evaluating audit records in isolation to confirm past performance, the framework uses multi-year audit trends as early warning signals. This enables university leadership to anticipate potential risks, allocate annual budgets effectively, and update operational policies across all campuses.

Figure 1. Strategic Foresight-Informed Quality Governance Framework.



Through four primary components:

- **Early Signal Detection:** Multi-year audit data are systematically analyzed to differentiate between isolated operational errors and recurring systemic vulnerabilities across satellite campuses.
- **Risk Prioritization:** Identified vulnerability domains are mapped using a 3×3 Risk Priority Matrix, evaluating recurrence frequency against severity impact to escalate critical risks for executive review.

- **Strategic Budget Alignment:** Longitudinal trends directly inform institutional resource allocation, directing capital expenditures toward root-cause solutions such as centralized digital management systems and physical infrastructure upgrades.

- **Continuous Reporting Loop:** A dedicated quality governance unit generates strategic foresight briefs for executive decision-makers, embedding audit evidence into long-term policy development and university planning

5.CONCLUSION

This study examined five years of Internal Quality Audit (IQA) findings of the USTP System to assess compliance trends, categorize audit results, and identify recurring institutional risks using risk-based thinking under ISO 9001:2015. The findings indicate a generally high level of compliance across audit cycles, suggesting that the Quality Management System (QMS) is established and effectively implemented in most operational areas.

However, recurring non-conformities and audit observations reveal persistent systemic issues involving human resource limitations, document control, policy implementation, infrastructure, and organizational role clarity. Their recurrence across multiple campuses indicates that these concerns require sustained, system-wide, and strategic interventions rather than isolated corrective actions.

The study further demonstrates that IQA findings can serve not only as compliance records but also as valuable inputs for risk identification, institutional planning, and decision-making. Through risk-based analysis, recurring vulnerabilities can be prioritized for appropriate management intervention and resource allocation.

Overall, while the university has made substantial progress in developing an effective quality management system, continued efforts are needed to strengthen system integration, communication, policy enforcement, and cross-campus consistency. Strategic use of Internal Quality Audits can therefore contribute significantly to compliance assurance, institutional resilience, and continuous quality improvement.

RECOMMENDATIONS

Based on the findings of the study, the following recommendations are proposed to strengthen the effectiveness of the Internal Quality Audit (IQA) system and enhance the implementation of the ISO 9001:2015 Quality Management System across the USTP System.

First, **it is recommended that the university strengthen human resource planning and allocation**, particularly in campuses with identified shortages of licensed personnel, such as guidance counselors and psychometricians. A long-term staffing plan aligned with regulatory requirements may be developed to ensure adequate personnel support for academic and student services across campuses.

Second, **the university may enhance its document control and dissemination system** through a centralized digital platform with real-time updates and stricter version control mechanisms. This may ensure the consistent use of current approved documents, improve traceability, and minimize process deviations across campuses and operational units.

Third, **the institution is encouraged to strengthen policy implementation and monitoring mechanisms**, particularly in academic processes involving attendance requirements, grading standards, and syllabus compliance. Regular faculty orientation, systematic audit follow-ups, and appropriate digital monitoring mechanisms may be utilized to promote consistent adherence to institutional policies.

Fourth, **priority may be given to infrastructure improvements** in offices responsible for critical institutional records, particularly registrar unit(in some satellite campuses). Adequate workspace, proper ventilation, secure archival facilities, and continued digitalization of records may be pursued to protect the long-term preservation, integrity, and accessibility of academic documents.

Fifth, **the university may establish and enforce clear organizational roles, responsibilities, and operational guidelines** across specialized units. Standardized operational manuals, defined role descriptions, and qualification requirements may be developed and formally approved to strengthen accountability, reduce role ambiguity, and improve operational efficiency.

Finally, **it is recommended that the Internal Quality Audit function be institutionalized as a dedicated IQA unit with an appropriate office, adequate staffing, and sufficient resources**. A formal IQA unit may enhance the independence, continuity, and coordination of audit activities across the USTP System. The unit could oversee audit planning and implementation, maintain institutional audit records, monitor corrective actions, analyze recurring findings and emerging risks, and provide executive leadership with data-driven strategic foresight to inform annual operational planning and resource allocation.

REFERENCES

Fahey, G., & Köster, F. (2019). *Means, ends and meaning in accountability for strategic education governance* (OECD Education Working Papers No. 204). OECD Publishing. https://doi.org/10.1787/1d516b5c-en

Fonseca, L. M. C. M. (2015). From quality gurus and TQM to ISO 9001:2015: A review of several quality paths. *International Journal for Quality Research, 9*(1), 167–180.

Harvey, L., & Williams, J. (2010). Fifteen years of quality in higher education. *Quality in Higher Education, 16*(1), 3–36. https://doi.org/10.1080/13538321003679457

International Organization for Standardization. (2015). *Quality management systems—Requirements (ISO 9001:2015).* International Organization for Standardization.

International Organization for Standardization. (2018). *Guidelines for auditing management systems (ISO 19011:2018).* International Organization for Standardization.

Organisation for Economic Co-operation and Development. (2019). *Strategic foresight for better policies: Building effective governance in the 21st century.* OECD Publishing.

Psomas, E., & Antony, J. (2017). Total quality management elements and results from the implementation of ISO 9001 in the Greek manufacturing sector. *The TQM Journal, 29*(1), 76–96.

Srikanthan, G., & Dalrymple, J. F. (2007). A conceptual overview of a holistic model for quality in higher education. *International Journal of Educational Management, 21*(3), 173–193. https://doi.org/10.1108/09513540710738647

UNESCO. (n.d.). *Quality assurance in higher education.* UNESCO.

University of Science and Technology of Southern Philippines. (2021–2025). *Internal quality*

audit consolidated registries, summary reports, closing meeting presentations, and quality management system documents [Unpublished institutional records]. USTP Quality Management System Office.

Wilkinson, G., & Dale, B. G. (2002). An examination of the ISO 9001:2000 standard and its influence on the integration of management systems. *Production Planning & Control, 13*(3), 284–297. https://doi.org/10.1080/09537280110086383

P26023

From Data to Decisions: How University Leaders Connect Analytics and AI to Institutional Strategy

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ABSTRACT

Higher education institutions have invested heavily in data analytics as an organizational capability and will likely do the same in artificial intelligence (AI). Yet many institutional efforts in data analytics stall at reports and dashboards, never maturing into predictive or prescriptive stages. Whether analytics truly changes strategic decisions depends on organizational conditions that are under-studied, especially as seen by those who make the highest-stake decisions. Using a convergent mixed-methods design pairing semi-structured elite interviews with 12 university presidents, provosts, and a trustee in the US and East Asia with a secondary synthesis of national leadership surveys. This study reports how these leaders account for that gap: (1) leadership demand and focused attention are the driving force of data culture; (2) infrastructure integration, not analytics sophistication, is the binding constraint; (3) the organizational placement of analytics talent determines its strategic influence; (4) effective leaders practice data-informed, not data-driven, decision-making; and (5) AI readiness is testing the same organizational muscles institutions built for analytics. These are accounts of how senior decision-makers understand the conditions for analytics use, not estimates of how widely those conditions obtain. Note: The full study appears in the author's forthcoming MIT Press book, *The Analytics Advantage: A Data-informed Approach to Strategy Development in Higher Education*.

Keywords: data-informed decision-making, institutional planning, university governance, AI readiness, digital transformation, institutional research

INTRODUCTION

Modern higher education institutions are swamped with data. Every system application, from admissions to learning-management platforms, leaves a digital trace, and institutions have invested heavily in enterprise systems, dashboards, and, increasingly, artificial intelligence (AI) tools to capture it. Yet the distance between possessing data and making strategic decisions with it remains stubbornly wide. Dashboards proliferate while decision cultures lag: strategic choices about programs, budgets, and institutional direction are too often made the way they always have been. Borgman and Brand (2022) described this situation as "data rich, data poor, and, sometimes, intentionally data blind" (p. 1278), a paradox in which universities generate enormous quantities of data while lacking infrastructure, coordination, and deliberate efforts to convert those assets into strategic insight.

The rise of AI has shined a new spotlight on this long-standing gap. Generative AI and increasingly agentic AI systems do not merely summarize and visualize data; they act on data assets, performing multi-step analytical and administrative workflows across institutional systems, and are only as useful and trustworthy as the data foundations beneath them. Fragmented records, inconsistent definitions, and siloed systems become active points of

failure when autonomous systems must navigate away from them.

Understanding why some institutions convert analytics investments into genuine strategic decisions while most stall at reports and dashboards is therefore a pressing question, and one the existing literature is poorly positioned to answer. However, if data-informed decision-making ultimately lives or dies in the executive cabinet and the boardroom, then what these leaders demand, believe, and advocate about data evidence is decisive.

This paper addresses the gap through four research questions:

- RQ1. What is the current national landscape of analytics and AI adoption, governance, and readiness among senior academic leaders?
- RQ2. How do senior institutional leaders describe the conditions under which data and analytics genuinely shape strategic decisions?
- RQ3. What organizational capabilities do these leaders identify as enabling or constraining data-informed decision-making?
- RQ4. How are these leaders preparing their institutions for AI as the next stage of this evolution?

To answer them, the study pairs a secondary synthesis of recent national surveys of senior academic leaders in the US with original semi-structured interviews with presidents, provosts, and a governing-board leader at 12 institutions in the United States and East Asia, spanning research universities to 2-year colleges. Five organizational conditions emerged that these leaders attribute with converting data into strategic decisions.

LITERATURE REVIEW

Data-Informed Decision-Making and Analytics Maturity

Higher education's investment in analytics has been framed as a progression through maturity stages, from descriptive reporting through predictive analytics toward prescriptive decision support (Webber & Zheng, 2020; Gaftandzhieva et al., 2023). Yet across two decades of scholarship, most institutions stall at the lower and middle levels of this hierarchy: decision support tools remain underutilized despite demonstrated benefits (Gasevic et al., 2019; Gaftandzhieva et al., 2023), and adoption remains uneven and fragile even as studies identify analytics as pivotal to strategy (EDUCAUSE, 2025b). The gap is not primarily technical: scholars describe a condition of "data poverty" in which institutions possess data but lack the pipelines, quality controls, and skilled staff to render it decision-grade (Prinsloo et al., 2023). Data abundance does not convert to insight without organizational capability.

Leadership and Decision Culture

A smaller literature addresses the executive side. Studies of performance data in university governance show that the mere availability of performance indicators does not change decisions; what matters is how leaders demand, interpret, and bound evidence within existing governance norms (Beerkens, 2021). Within this literature, the distinction between data-driven and data-informed decision-making has become consequential: the former implies that data determines choices, while the latter positions evidence as one input alongside mission, values, and professional judgment (Webber & Zheng, 2020). Practitioner research reports that active and visible executive sponsorship has ranked as the top contributor to technology project success every year since 1998 (Prosci, 2025), yet this evidence base rests on surveys of

analytics and change professionals rather than the testimony of executives themselves, a gap this study addresses.

Governance, Infrastructure, and the "Data Blind" University

Borgman and Brand (2022) attribute the "data blind" condition to decentralized stewardship, siloed systems, vendor dependence, and a pervasive absence of infrastructure thinking. Most institutions lack the coordination, common definitions, and stewardship structures needed to treat data as an enterprise asset (Jim & Chang, 2018); educators experience datafication as fragmented and contested (Stewart et al., 2023); platform and policy pressures have outpaced institutions' capacity to govern their data infrastructure (Williamson, 2019); and realizing value from linked data depends on formal governance, not data volume (Zanti et al., 2022). These dynamics are not exclusively American. In the Asia-Pacific region, quality assurance regimes and government steering mechanisms function as data-culture forcing mechanisms: institutional research in Southeast Asia has long been organized around evidence requirements for accreditation, planning alignment, and performance reporting (AlKhatnai & Shawyun, 2022), and institutions have worked to transform compliance-oriented quality assurance into data-driven strategic management (Shawyun et al., 2025).

AI in Institutional Planning

Artificial intelligence has entered the analytics discussion as both an opportunity and a stress test. Emerging scholarship argues that generative AI can extend analytics capacity while raising new governance demands (Zheng & Webber, 2023; Webber & Zheng, 2024). National surveys confirm this stress: most institutions are working on AI-related strategy in some areas, but few have an institution-wide approach (EDUCAUSE, 2025a), and substantial gaps separate leadership engagement with AI from institutional readiness to act on it (Inside Higher Ed & Hanover Research, 2025). Agentic AI systems, which execute multi-step workflows across institutional systems, sharpen the need for integrated, trusted data: autonomous systems cannot reconcile the conflicting definitions and fragmented records that human analysts routinely work around. AI readiness is thus less a new capability than a higher-stakes test of existing data governance and infrastructure.

The Gap This Study Addresses

Across these literatures, the perspective of senior university decision-makers is under-developed. This study contributes by adding the voice of the senior leaders and joining the strands usually treated separately. Maturity models describe the capabilities marking each stage; governance research describes how data is stewarded; AI-readiness studies describe what has been adopted. None accounts for the executive demand that determines whether any of them reaches a decision. The five conditions below are therefore offered not as a further maturity stage but as an account of movement between stages, specifying what stage models presuppose rather than explaining. They emerged from the analysis rather than preceding it.

METHODOLOGY

Research Design

This study employs a convergent mixed-methods design (Creswell & Plano Clark, 2018) in which quantitative and qualitative strands were developed concurrently, analyzed independently, and merged at interpretation. A structured synthesis of published national surveys establishes the macro-level landscape of analytics and AI adoption in US higher education, while original elite interviews explain how and why leaders make the decisions the

survey data describe in aggregate. The convergent logic is complementarity (Greene et al., 1989): survey indicators supply breadth and national representativeness that a purposive interview sample cannot, while the interviews supply the decision-level mechanisms that aggregate percentages cannot. Using secondary data as a quantitative strand is an accepted variant of mixed-methods practice where primary survey administration is infeasible or duplicative (Creswell & Plano Clark, 2018).

Quantitative Strand: Secondary Survey Synthesis

Indicators were extracted from three recent national surveys of US higher education leaders: the 2025 Survey of College and University Chief Academic Officers (Inside Higher Ed & Hanover Research, 2025; 478 provosts and chief academic officers), the 2024 EDUCAUSE Analytics Landscape Study (514 academic IT leaders), and the 2026 Survey of College and University Presidents (Inside Higher Ed & Hanover Research, 2026; 430 presidents). From each source, indicators were extracted in four domains aligned with the research questions: (a) institutional adoption of analytics and AI strategy and governance; (b) leadership engagement and organizational readiness; (c) investment in talent and professional development; and (d) reported institutional barriers. Indicators were compiled into a comparison matrix and reported descriptively; no inferential analysis was performed, and original response data were not re-analyzed.

Qualitative Strand: Elite Interviews

The qualitative strand comprises semi-structured interviews with 12 senior institutional leaders: 9 presidents, 2 provosts, and 1 trustee across US research, master/bachelor, and 2-year institutions and one Asian institution (Table 1). Fifty invitations were issued with balanced representation across institutional types; the final participant set skewed toward research universities and presidents, a limitation inherent to elite interviewing, offset in part by the secondary survey strand, where participation is more balanced across institutional types.

Table 1: Sector and Region Representation of Elite Interviews

	Presidents	Provosts	Trustees	Total
US Research Universities	4	1	1	6
US 4-Year Master and Bachelor Colleges	2	1		3
Asian 4-Year Master and Bachelor Colleges	1			1
US 2-Year Colleges	2			2
Total	9	2	1	12

Interviews were conducted between June 2025 and March 2026, in person or by video conference, lasting approximately 45-60 minutes, and captured through recording-assisted transcription where participants consented. Participants were interviewed on condition of anonymity; quotations are attributed by role and institutional type, with identifying details generalized or omitted. Transcripts were analyzed thematically following Braun and Clarke (2006). A first pass generated descriptive codes close to participants' own language; a second grouped them into candidate themes recorded in a working codebook, each with a definition, inclusion criteria, and anchor extracts. Codes were applied comparatively, with each new transcript checked against established codes and the codebook revised where material did not

fit. Themes were then tested against the full coded set for coherence and distinctness, and transcripts re-read for disconfirming instances, which are reported below where they qualify a theme. A retention rule required each theme to appear across at least three institutions and at least two institutional types. Five themes met this threshold; three candidates did not and are not reported.

Integration, Positionality, and Limitations

The strands were merged through side-by-side comparison at interpretation (Fetters et al., 2013): each qualitative theme was examined against the survey findings for convergence, complementarity, or divergence, with divergent points, where the interview sample's practices run ahead of nationally reported adoption, treated as leading-edge cases rather than contradictions. Three limitations are of note: the quantitative strand is secondary and descriptive, so integration operates at the level of aggregated survey data points; the interview sample is purposive, modest in size, skewed toward US institutions and presidential views, and based on self-reports rather than observed behaviors; and the survey populations and interview sample overlap imperfectly. These limitations are consistent with the study's aim of analytic rather than statistical generalization (Yin, 2018).

The author's experience and positions influence the interpretation. The author works in institutional research and analytics in higher education, has published analytics and AI in the sector, and is completing a book on the subject; several cited works are the author's own. This background enabled access to senior leaders who rarely participate in research but carries a prior commitment to the value of analytics that could favor confirming views. The disconfirming-case search and the requirement that each theme survive comparison with survey data were adopted partly as counterweights. However, findings are transferable to institutions resembling those in Table 1. Future research should test the five conditions with larger, more geographically diverse leader samples, including Southeast Asian institutions, and with instruments designed to measure them directly.

FINDINGS AND DISCUSSION

Five themes met the retention rule, each appearing across at least four institutions and three institutional types. Each is presented in the same order: interview evidence, then the national survey indicators against which it is read, then interpretation.

Leadership Demand and Focused Attention Are the Driving Force of Data Culture

Across every institutional type, leaders located the origin of data-informed decision-making not in technology acquisition but in executive demand for and focused attention on data evidence. The president of a private research university called his institution's earlier state "data blind": resources moved through "handshake deals," budgets were incremental by default, and there was no common vocabulary for the institution's own data. The turning point was not system implementation but a leadership decision that major processes, including a budget transformation and the university’s strategic plan, must be made "with the help of data and analytics insights." The same causal arrow appeared in the East Asian case, where the president drives the demand for data and a government funding formula tied to assessment results make data "front and center”. A board chair echoed the pattern from the governance side: trustees champion a data-informed culture principally "by consistently asking the right questions." The president of a master/bachelor university ran a program prioritization openly, releasing the full dataset before owning the final decision, so that budget allocation would not default to a

"peanut butter spread".

The national survey data show a sector sharing this stated commitment while falling measurably short in practice: 79% of EDUCAUSE (2024) respondents characterized their leaders as interested in or fully committed to analytics, 69% said analytics is treated as a strategic priority, and 66% said leaders regularly ask for data when making decisions; just 47% said analytics is viewed as an investment rather than a cost. Chief academic officers (CAOs) likewise reported effectiveness in using data for campus decision-making (87%) and fostering a data-driven culture (86%), yet only 29% reported sufficient resources for new initiatives (Inside Higher Ed & Hanover Research, 2025).

The survey evidence qualifies these accounts. The respondents best positioned to observe analytics practice were the least persuaded by it: only 38% of those working primarily in data and analytics agreed their leaders are fully committed and actively investing, compared with 57% of executives (EDUCAUSE, 2024), a caution against reading executive conviction and willingness as accomplished organizational fact. On this reading, leadership demand may be necessary but is not self-fulfilling: the interview cases that went furthest backed the mandate with structure, investment, and sustained attention.

Infrastructure Integration, Not Analytics Sophistication, Is the Binding Constraint

Asked what limits their analytical capability, leaders rarely named tools or modelling sophistication; they pointed to the lack of infrastructure integration. The president of a 4-year college was explicit: the systemic issue is "a lot of ad hoc and Band-Aid approaches" atop systems that "don't talk to each other," compounded by budget limits. His prescription was proportionate: a small college needs not "a Mercedes, but a solid Toyota" in analytical capabilities. A 2-year college president's team built manual "crosswalks" simply to move data from the ERP into the reporting platform. The boldest move came from a master/bachelor university president who arrived to find no data warehouse: reporting was manual and of uncertain validity, and she wondered whether the same question asked of three offices would yield "three different answers." She built an integrated warehouse as a single trusted source, reducing the number of data "gatekeepers". In these examples, institutions do not fail at analytics for lack of algorithms; they fail upstream, at integration, access, and trust.

The survey evidence corroborates this ordering of constraints. Fewer than 40% of EDUCAUSE (2024) respondents agreed that their data infrastructure is well standardized, that data are well defined and understood, or that governance is applied institution-wide, making the "three different answers" worry closer to institutional norm than to an anecdote. Implemented policy follows the same contour: data security (69%) and privacy (65%) are widely governed, while data integration (35%) and data quality (34%) trail badly. The constraint shows equally in use: analytics usage declines monotonically from descriptive (peaking at 59%) to predictive (34%) to prescriptive (24%) (EDUCAUSE, 2024). A sector mainly describing what has already happened lacks the analytical sophistication it needs to innovate and act strategically.

The survey data shows that resource asymmetry is real but not a decisive factor. Smaller institutions reported less access to every category of analytics support yet reported comparable levels of analytics usage, suggesting they extract greater value from thinner resources (EDUCAUSE, 2024). This supports the "solid Toyota" prescription: limited budget can be mitigated through integration, collaboration, and trust. Asked what their institutions could do immediately, survey respondents echoed the interviewees: secure executive buy-in, integrate and centralize data, invest in tools, and hire dedicated staff (EDUCAUSE, 2024).

Where Analytics Sits Determines What It Influences

Leaders framed the placement of analytics talent as a strategic decision in its own right, a signal of whether data work is consequential. At one private research university, institutional research had been undersized and buried within enrollment services; elevating it to a vice-provost-level signaled the importance of data institution-wide. A master/bachelor college president made the same point: having data, or even a data person, is not enough, "the data person must be part of the university's strategy team," not merely a filler of reporting requests. The need for a single version of truth drove one research university president to radical centralization: no unit may run its own data operation ("I need one source of truth"), and assessment, enrollment, student success, and data science all report through a single Chief Academic Effectiveness Officer. Asked about resource constraints, he rejected the premise: "It's not a resource constraint; it's a courage constraint." Two-thirds of CAOs (66 percent) reported that most new funds for academic programs would come from reallocation rather than new revenues (Inside Higher Ed & Hanover Research, 2025), making internal redeployment the sector's normal fiscal mechanism.

Survey data shows that a majority of institutions have neither a chief analytics officer (69% do not) nor a chief data officer (57% do not), and only 27% say designated analytics leadership roles are addressed anywhere in their analytics strategy (EDUCAUSE, 2024). Analytics leadership appears, more often than not, simply undervalued. The lack of institutional level leadership in data analytics may create downstream issues as more institutions are developing and deploying AI strategies, an increase from 18 percent of presidents in 2024 to 71 percent in 2026 (Inside Higher Ed & Hanover Research, 2026). Whether those bodies sit at the strategy table or are appended to it may make a difference.

Data-Informed, Not Data-Driven: The Leadership Philosophy

Strikingly, the leaders most committed to analytics were the most deliberate about bounding its authority. A provost preferred "data-informed" to "data-driven" because the former weighs data alongside other contextual factors rather than letting it dictate decisions. Another president reserved a domain for intuition in critical strategic decisions, where a choice "just has to feel right from the gut as well"; striking that balance is "the essence of executive leadership." The board chair emeritus drew the same boundary at board level: analytics frames the conversation while governance "ensures decisions align with mission and values", science and art as complements, not competitors. The boundary also protects data's credibility: one president cautioned that "numbers are not insights" and that data must serve as an honest broker rather than an instrument for bringing people into line with a predetermined view.

The danger of over-reliance on data to make decisions that these leaders guard against remains more prospective than actual. Prescriptive analytics is the least-used type in every functional area EDUCAUSE (2024) measured. This has implications for AI adoption, where agentic systems require trust and the relinquishing of direct human control. Nationally, while 55 percent of presidents say their own institution is responding adeptly to AI, only 19 percent say the same of higher education as a whole (Inside Higher Ed & Hanover Research, 2026), reflecting a gap between confidence in their own institution's progress and doubt about the sector's.

The surveys expose a parallel gap in practice: only 28% report implemented policies for data ethics, against 69% for data security, and faculty (17%) and students (6%) are only rarely involved in strategic analytics efforts (EDUCAUSE, 2024). The confidentiality of data is governed but its fairness and interpretation are not. An individual president's disposition in influencing data-informed decisions is only as durable as that president's tenure. Against that backdrop, the college president's release of the full program-prioritization dataset

operationalizes the "honest broker" standard: it makes interpretive restraint visible, and therefore accountable, rather than merely asserted.

AI Readiness Is Testing the Same Organizational Muscles

Leaders described artificial intelligence not as a new problem but as a higher-stakes test of the same capabilities, demand, infrastructure, talent, and philosophy. The most advanced posture came from the East Asian university, where AI literacy is mandated for students and faculty, supported by high-performance computing, and the challenge is framed as converting "the mentality of fear to adaptation and advanced use." US leaders navigate a wider gap: only 14 percent of chief academic officers report comprehensive AI governance policies or an institutional AI strategy, even as 65 percent pursue faculty development and AI literacy (Inside Higher Ed & Hanover Research, 2025). A research university president modeled AI use personally: "we should talk about it so we are at the table of helping to steer," treating engagement itself as a leadership obligation. A master/bachelor college president insisted AI must not supplant the human connection that defines residential education, consonant with the 38 percent of provosts reporting significant faculty resistance to AI, rising to 49 percent at community colleges (Inside Higher Ed & Hanover Research, 2025).

The survey data renders the "same muscles" claim quantitatively. The presidents' data show posture outrunning foundations, 71 percent report an AI task force or strategy, but only 41 percent claim strong data governance for AI and only 31 percent report widespread AI literacy (Inside Higher Ed & Hanover Research, 2026). Fewer than a quarter of institutions use AI tools to support analytics at all, with just 10% having implemented policies governing AI in analytics, the lowest figure of any policy domain EDUCAUSE (2024) measured. This is not surprising at all given Borgman and Brand's (2022) observation of "intentional data poor" in many institutions. A decade before generative AI arrived on campus, chief academic officers already rated data-informed decision-making their weakest institutional competency (Jaschik & Lederman, 2015). The institutional muscles AI now tests were reported as underdeveloped well before the technology that exposes them existed, and the interviews suggest why the deficit persisted: none of these capacities can be purchased, and each requires a leader to want it and has the courage and willingness to enforce it.

Where AI is arriving, it is arriving first at the enterprise layer: AI use for scheduling and resource allocation rose from 28 to 47 percent year over year, and for institutional planning from 18 to 32 percent (Inside Higher Ed & Hanover Research, 2026). Yet adopted AI capabilities attach to the analytical surface, big data platforms (34%), machine learning tools (33%), rather than the data foundation beneath, where adoption ranges from 6% to 16% (EDUCAUSE, 2024). A plurality (41%) expects AI to exacerbate rather than alleviate their current data challenges: institutions with unintegrated data do not expect AI to rescue them; they expect it to expose them. Against that revealed preference, the community college president's sequencing, data lake first, agentic-AI ambitions second, looks less like caution than foresight.

CONCLUSION

This study asked why some institutions convert analytics investments into strategic decisions while most stall at dashboards and sought the answer from decision-makers themselves. The five conditions that emerged held across the sample's full resource range, from a 2-year college with a three-person institutional research office to research universities with established data-science teams, suggesting origins that are organizational rather than budgetary. The survey

synthesis situates these leaders as leading-edge rather than typical: sector-wide, declared commitment to analytics is nearly universal while the disciplined practice of asking for evidence, the integration of underlying systems, and the assignment of analytics leadership are not.

The implications follow the audiences of this research. For institutional researchers, influence depends on position: analytics functions shape strategy when seated at the strategy table, not when structured as report-fulfillment operations. For senior leaders, the findings relocate the work of digital transformation from procurement to demand, asking the right questions consistently and building the integrated infrastructure that makes trustworthy answers possible. For governing boards, the data-informed philosophy these leaders articulate rests on individual disposition rather than institutional policy, and codifying it is a governance task boards are positioned to require. AI raises the stakes on all three fronts. These implications rest on the accounts of twelve leaders together with readings from national survey data and are offered as propositions for wider testing. Where the environment institutionalizes data demand, the leadership burden shifts; where it does not, leaders must generate that demand themselves. In either setting, strategic foresight in the AI era is less a planning document than an organizational capability.

References

AlKhatnai, M., & Shawyun, T. (2022). Institutional, Collegial & Programmatic Strategic & Operational Action Plans Analysis, Development & Alignment. Journal of Institutional Research South East Asia, 20(1), 23-54.

Beerkens, M. (2021). An evolution of performance data in higher education governance: A path towards a 'big data' era? Quality in Higher Education, 28(1), 29–49. https://doi.org/10.1080/13538322.2021.1951451

Borgman, C. L., & Brand, A. (2022). Data blind: Universities lag in capturing and exploiting data. Science, 378(6626), 1278–1281. https://doi.org/10.1126/science.add2734

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101.

Creswell, J. W., & Plano Clark, V. L. (2018). Designing and conducting mixed methods research (3rd ed.). SAGE.

EDUCAUSE. (2024). 2024 EDUCAUSE Analytics Landscape Study. Research report. Boulder, CO: ECAR, September 2024. https://www.educause.edu/content/2024/2024-educause-analytics-landscape-study/introduction-and-key-findings

EDUCAUSE. (2025a). 2025 EDUCAUSE AI landscape study: Into the digital AI divide. https://library.educause.edu/resources/2025/2/2025-educause-ai-landscape-study

EDUCAUSE. (2025b). 2025 EDUCAUSE Horizon report: Data and analytics edition. https://library.educause.edu/resources/2025/10/educause-horizon-report-data-and-analytics-edition

Fetters, M. D., Curry, L. A., & Creswell, J. W. (2013). Achieving integration in mixed methods designs. Health Services Research, 48(2), 2134–2156. https://pubmed.ncbi.nlm.nih.gov/24279835/

Gaftandzhieva, S., Hussain, S., Hilcenko, S., Doneva, R., & Boykova, K. (2023). Data-driven decision making in higher education institutions: State-of-play. International Journal

of Advanced Computer Science and Applications, 14(6), 358–367. https://doi.org/10.14569/IJACSA.2023.0140642

Gasevic, D., Tsai, Y. H., Dawson, S., & Pardo, A. (2019). How do we start? An approach to learning analytics adoption in higher education. International Journal of Information and Learning Technology, 36(4), 342-353. https://doi.org/10.1108/IJILT-02-2019-0024

Greene, J. C., Caracelli, V. J., & Graham, W. F. (1989). Toward a conceptual framework for mixed-method evaluation designs. Educational Evaluation and Policy Analysis, 11(3), 255–274. https://doi.org/10.3102/01623737011003255

Inside Higher Ed, & Hanover Research. (2025). 2025 Survey of College and University Chief Academic Officers. Inside Higher Ed. https://www.insidehighered.com/reports/2025/09/12/2025-survey-college-and-university-chief-academic-officers

Inside Higher Ed, & Hanover Research. (2026). 2026 Survey of College and University Presidents. Inside Higher Ed. https://www.insidehighered.com/reports/2026/03/09/2026-survey-college-and-university-presidents

Jaschik, S., & Lederman, D. (2015). The 2015 Inside Higher Ed survey of college and university chief academic officers. Inside Higher Ed & Gallup.

Jim, C. K., & Chang, H.-C. (2018). The current state of data governance in higher education. Proceedings of the Association for Information Science and Technology, 55(1), 198–206. https://doi.org/10.1002/pra2.2018.14505501022

Prinsloo, P., Slade, S., & Khalil, M. (2023). Yes we can (but maybe not yet): The impact of data poverty on realising the potential of learning analytics. Ubiquity Proceedings. https://doi.org/10.5334/uproc.75

Prosci (Singapore). (2025). How Is Effective Change Sponsorship Different to Leadership? Web blog post, Prosci Singapore, Oct. 31, 2025. https://www.prosci.com/blog/how-is-effective-change-sponsorship-different-to-leadership

Shawyun, T., AlKhatnai, M., & Wattanasap, S. (2025). King Saud University's Integrated Quality Assurance: A Longitudinal Mixed-Methods Study of Framework Evolution, Outcomes, and Sustainability in Higher Education Management. Journal of Institutional Research South East Asia, Sept/Oct, 23(3), 261-288.

Stewart, B., Miklas, E., Szcyrek, S., & Le, T. (2023). Barriers and beliefs: A comparative case study of how university educators understand the datafication of higher education systems. International Journal of Educational Technology in Higher Education, 20(1), 1–21. https://doi.org/10.1186/s41239-023-00402-9

Webber, K. L., & Zheng, H. Y. (Eds.). (2020). Big data on campus: Data analytics and decision making in higher education. Johns Hopkins University Press.

Webber, K. L., & Zheng, H. Y. (2024). Artificial intelligence and advanced data analytics: Implications for higher education. New Directions for Higher Education, 2024, 5–13. https://doi.org/10.1002/he.20508

Williamson, B. (2019). Policy networks, performance metrics and platform markets: Charting the expanding data infrastructure of higher education. British Journal of Educational Technology, 50(6), 2794–2809. https://doi.org/10.1111/bjet.12849

Yin, R. K. (2018). Case study research and applications (6th ed.). SAGE.

Zanti, S., Berkowitz, E., Katz, M., Nelson, A. H., Burnett, T. C., Culhane, D., & Zhou, Y. (2022). Leveraging integrated data for program evaluation: Recommendations from the field. Evaluation and program planning, 95, 102093. https://doi.org/10.1016/j.evalprogplan.2022.102093

Zheng, H. Y., & Webber, K. L. (Eds.). (2023). Artificial intelligence and advanced analytics [Special issue]. The AIR Professional File, 2023(Fall). https://www.airweb.org/docs/default-source/documents-for-pages/reports-and-publications/professional-file/apf-2023-fall.pdf

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Predicting AI Integration and Strategic Foresight Capacity in Higher Education: A Hierarchical Regression Analysis of Institutional Readiness and AI-Driven Decision Support Systems

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ABSTRACT

Artificial intelligence (AI) has become an important driver of digital transformation in higher education, extending its applications beyond teaching and learning to institutional governance, strategic planning, and organizational decision-making. This study developed an explanatory model of AI Integration and Strategic Foresight Capacity by examining the contributions of institutional readiness, adoption and utilization of AI tools, and AI-driven decision support systems in higher education institutions. A descriptive-correlational research design employing predictive analysis was utilized. Data were collected from 103 university administrators and academic leaders through a researcher-developed questionnaire with established reliability and construct validity. Descriptive statistics, Pearson product-moment correlation, and hierarchical multiple regression analyses were performed using IBM SPSS Statistics. The findings revealed high to very high levels of institutional readiness, AI-driven decision support systems, and AI Integration and Strategic Foresight Capacity. Ethical and Governance Safeguards obtained the highest mean score, while Adoption and Utilization of AI Tools received the lowest, though it remained high. Correlation analysis showed that all study variables were significantly and positively associated with AI Integration and Strategic Foresight Capacity ($p < .01$). Hierarchical regression analysis indicated that the final model explained 88.7% of the variance in AI Integration and Strategic Foresight Capacity. Quality of Instructional Decision-Making, Ethical and Governance Safeguards, Organizational Readiness, and Resource Allocation and Organizational Responsiveness emerged as significant predictors. In contrast, Technical and Data Readiness, Adoption and Utilization of AI Tools, and Strategic Planning and Policy Quality did not independently predict the outcome. The findings suggest that successful AI integration in higher education depends primarily on effective governance, organizational readiness, evidence-informed decision-making, and institutional responsiveness rather than technological capability alone. The proposed explanatory model provides empirical evidence to guide universities in designing governance frameworks and strategic initiatives for responsible and sustainable AI transformation.

Keywords: Artificial Intelligence, Strategic Foresight Capacity, AI Institutional Readiness, Adoption and Utilization of AI, AI-Driven Decision Support Systems

Introduction

Artificial intelligence (AI) has become a key driver of digital transformation in higher education, extending its applications beyond teaching and learning to institutional governance, strategic planning, quality assurance, and organizational decision-making. Universities are increasingly adopting AI to analyze institutional data, optimize resource allocation, improve administrative efficiency, and support evidence-based policy formulation in response to rapidly evolving educational environments (Organisation for Economic Co-operation and Development [OECD], 2023). Consequently, AI is increasingly recognized not merely as an instructional technology but as a strategic organizational capability that enhances institutional resilience, innovation, and strategic foresight (Miao & Holmes, 2023).

The growing integration of AI in higher education has demonstrated considerable potential to improve institutional effectiveness. Recent studies indicate that AI can strengthen academic planning, administrative decision-making, student support services, and institutional performance through predictive analytics, intelligent decision-support systems, and data-driven governance (Kasneci et al., 2023; Tlili et al., 2023). However, successful AI implementation extends beyond technological acquisition. Institutions must establish organizational readiness, ethical governance, effective leadership, and supportive institutional policies to ensure that AI technologies contribute meaningfully to sustainable institutional transformation (UNESCO, 2021; OECD, 2023).

Recent literature further emphasizes that responsible AI adoption requires comprehensive governance frameworks that promote transparency, accountability, fairness, privacy, and human oversight. The UNESCO Recommendation on the Ethics of Artificial Intelligence (2021) identifies these principles as essential foundations for trustworthy AI implementation, while the OECD Digital Education Outlook 2023 underscores that organizational readiness and governance capacity are critical determinants of institutional AI maturity. Similarly, Dwivedi et al. (2023) argued that organizational culture, leadership commitment, governance, and strategic management play more significant roles in AI adoption than technological capability alone.

Although research on AI in higher education has expanded rapidly, much of the existing literature continues to focus on instructional applications, generative AI, student learning, assessment, and academic integrity (Kasneci et al., 2023; Tlili et al., 2023). Comparatively fewer empirical studies have examined AI from an institutional perspective, particularly its relationship with organizational readiness, governance, AI-driven decision support systems, and strategic foresight. This gap is even more evident in developing countries, where empirical evidence regarding the organizational determinants of institutional AI integration remains limited.

In the Philippine higher education context, universities continue to accelerate digital transformation initiatives while responding to increasing demands for quality assurance, institutional accountability, and global competitiveness. Despite these developments, higher education institutions differ considerably in their levels of organizational readiness, governance capability, technological preparedness, and AI-supported decision-making. These variations suggest that successful institutional AI integration depends not only on technology adoption but also on the alignment of governance structures, organizational readiness, and strategic leadership.

To address these gaps, this study develops and tests an explanatory model of AI Integration and Strategic Foresight Capacity by examining the contributions of institutional readiness, adoption and utilization of AI tools, and AI-driven decision support systems in higher education

institutions. Specifically, the study (1) assesses the levels of institutional readiness, adoption and utilization of AI tools, AI-driven decision support systems, and AI Integration and Strategic Foresight Capacity; (2) examines the relationships among these organizational variables; and (3) determines their incremental predictive effects on AI Integration and Strategic Foresight Capacity using hierarchical multiple regression analysis. By identifying the organizational capabilities that most strongly explain AI strategic capacity, the study contributes to the growing literature on AI governance and digital transformation in higher education and provides evidence that can guide institutional leaders and policymakers in designing governance frameworks and strategic initiatives for responsible, evidence-informed, and sustainable AI implementation.

Theoretical Framework and Related Literature

This study is anchored in an integrative theoretical framework that explains how institutional readiness and AI-driven decision support systems influence AI Integration and Strategic Foresight Capacity in higher education institutions (HEIs). The framework integrates four complementary perspectives: the Technology-Organization-Environment (TOE) Theory, Socio-Technical Systems (STS) Theory, the AI Governance Perspective, and the Strategic Foresight Perspective. Collectively, these perspectives explain that successful AI integration extends beyond technological capability and depends on organizational readiness, responsible governance, evidence-informed decision-making, and institutional responsiveness.

Technology-Organization-Environment (TOE) Theory

This theory, developed by Tornatzky and Fleischer (1990), explains that organizational adoption of technological innovations is influenced by three interrelated contexts: technological capability, organizational readiness, and the external environment. The framework posits that successful technology adoption depends not only on technological resources but also on organizational capability and governance (Baker, 2012). Recent studies likewise affirm that AI implementation requires leadership commitment, organizational readiness, and effective governance in addition to technological infrastructure (Dwivedi et al., 2023).

The technological context refers to Technical and Data Readiness, the organizational context encompasses Organizational Readiness, and the environmental context includes Ethical and Governance Safeguards, which ensure responsible AI implementation. These dimensions are likewise emphasized in the UNESCO Recommendation on the Ethics of Artificial Intelligence (2021) and the OECD Digital Education Outlook 2023, both of which identify governance, transparency, accountability, and institutional readiness as essential conditions for sustainable AI adoption. Accordingly, the TOE theory provides the theoretical foundation for the study's Institutional Readiness construct, consisting of Organizational Readiness, Technical and Data Readiness, and Ethical and Governance Safeguards.

Socio-Technical Systems Theory

This theory explains how AI creates organizational value. Originally proposed by Trist and Bamforth (1951), STS theory argues that organizational performance results from the interaction between technological systems and social systems. Recent AI literature similarly emphasizes that technological capability alone does not improve organizational performance

unless it is integrated with leadership, governance, and institutional decision-making processes (Dwivedi et al., 2023; UNESCO, 2021).

AI-driven decision support systems within higher education constitute the technological subsystem, whereas institutional leaders, academic managers, faculty, and governance structures comprise the social subsystem. Through this interaction, AI-generated insights support strategic planning, instructional decision-making, and resource allocation. Consequently, the STS theory provides the theoretical basis for the study's AI-Driven Decision Support Systems, represented by Strategic Planning and Policy Quality, Quality of Instructional Decision-Making, and Resource Allocation and Organizational Responsiveness (Crompton & Burke, 2023; OECD, 2023).

AI Governance Perspective

Building on institutional readiness and socio-technical integration, the AI Governance Perspective emphasizes that successful AI implementation requires institutional policies and governance mechanisms that ensure transparency, accountability, fairness, explainability, privacy, and human oversight (UNESCO, 2021; OECD, 2023). Rather than viewing AI solely as a technological innovation, this perspective highlights governance as the mechanism that aligns AI applications with institutional goals, ethical principles, and stakeholder interests.

Recent studies indicate that universities are increasingly establishing AI governance frameworks to guide institutional decision-making, safeguard academic integrity, and promote responsible AI innovation (Chan, 2023; An et al., 2025). Consequently, this perspective reinforces the inclusion of Ethical and Governance Safeguards as a critical dimension of institutional readiness.

Strategic Foresight Perspective

The Strategic Foresight Perspective extends the previous theories by explaining how AI contributes to long-term institutional resilience and sustainability. Strategic foresight enables organizations to anticipate emerging trends, interpret environmental changes, and formulate adaptive strategies through evidence-informed decision-making (OECD, 2023). Artificial intelligence enhances this capability by enabling institutions to analyze complex organizational data, identify emerging patterns, and support long-term institutional planning (Dwivedi et al., 2023; UNESCO, 2023).

AI strengthens strategic foresight in higher education only when its analytical capabilities are integrated with effective governance, organizational readiness, and evidence-based leadership (Crompton & Burke, 2023). Thus, AI Integration and Strategic Foresight Capacity is viewed as an organizational capability that emerges from the combined effects of institutional readiness and AI-driven decision support systems.

Methodology

This study employed a descriptive-correlational research design to examine the contributions of institutional readiness, adoption and utilization of AI tools, and AI-driven decision support systems to AI integration and strategic foresight capacity in a higher education institution. Specifically, a predictive correlational approach was adopted to determine the incremental

effects of these organizational variables through hierarchical multiple regression analysis, thereby developing an explanatory model of AI integration and strategic foresight capacity.

The study was conducted in one of the leading private universities in Northern Mindanao, Philippines. The respondents consisted of 103 university leaders, including vice presidents, deans, principals, heads of support service offices, chairpersons, and coordinators from various academic and administrative units. These individuals were directly involved in institutional planning, quality assurance, academic management, digital transformation, and strategic decision-making. Participants were selected through purposive sampling because of their leadership roles and involvement in institutional AI-related initiatives.

Data were collected using a researcher-developed questionnaire designed to measure the organizational dimensions of AI integration in higher education. The instrument comprised 34 items organized into eight constructs: Organizational Readiness (4 items), Technical and Data Readiness (4 items), Ethical and Governance Safeguards (4 items), Adoption and Utilization of AI Tools (6 items), Strategic Planning and Policy Quality (4 items), Quality of Instructional Decision-Making (4 items), Resource Allocation and Organizational Responsiveness (4 items), and AI Integration and Strategic Foresight Capacity (4 items). Responses were measured using a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Prior to data collection, the instrument underwent expert validation to establish content validity. The research instrument was then pilot tested to determine the internal consistency reliability using Cronbach's Alpha. Results indicated excellent reliability across all constructs, with alpha coefficients ranging from 0.901 to 0.990, exceeding the recommended threshold of 0.70 (Hair et al., 2022). The overall questionnaire obtained a Cronbach's Alpha coefficient of 0.984, demonstrating excellent internal consistency.

After obtaining the necessary institutional approval, the questionnaires were administered to the identified respondents through either printed questionnaires or an online survey using Google Forms. Participation was entirely voluntary, and respondents were informed of the study's objectives, the confidentiality and anonymity of their responses, and their right to decline or withdraw from participation at any time. Completed questionnaires were reviewed for completeness and consistency before data coding, encoding, and statistical analysis.

Data were analyzed using SPSS Statistics. Descriptive statistics, specifically means and standard deviations, were used to determine the levels of institutional readiness, adoption and utilization of AI tools, AI-driven decision support systems, and AI integration and strategic foresight capacity.

Pearson product-moment correlation analysis was employed to examine the relationships among the study variables. To determine their incremental predictive effects, hierarchical multiple regression analysis was conducted using three successive models. Model 1 included the institutional readiness variables (Organizational Readiness, Technical and Data Readiness, and Ethical and Governance Safeguards). Model 2 introduced Adoption and Utilization of AI Tools to determine its additional explanatory contribution. Model 3 incorporated the AI-driven decision support system variables—Strategic Planning and Policy Quality, Quality of Instructional Decision-Making, and Resource Allocation and Organizational Responsiveness—to establish the final explanatory model of AI Integration and Strategic Foresight Capacity. Model adequacy was evaluated using R^2, Adjusted R^2, ΔR^2, F-change,

standardized beta coefficients (β), and significance tests. Statistical significance was established at α = .05.

The study adhered to established ethical standards for educational research. Participation was voluntary, informed consent was obtained from all respondents, and confidentiality and anonymity were strictly maintained. Data were used exclusively for research purposes, and the identities of the participants and the institution were protected throughout the conduct of the study.

Results and Discussion

The results of the reliability and construct validity assessment of the research instrument (Table 1) demonstrated that the instrument possesses excellent psychometric properties. Cronbach's alpha coefficients ranged from .910 to .979, exceeding the recommended threshold of .70 and indicating excellent internal consistency across all constructs (Hair et al., 2022). Furthermore, the Kaiser–Meyer–Olkin (KMO) measures of sampling adequacy ranged from .779 to .896, while Bartlett's Tests of Sphericity were statistically significant ($p < .001$) for all constructs, confirming that the data were suitable for factor analysis. The extracted factors accounted for 72.18% to 92.52% of the total variance, surpassing the recommended criterion for construct validity and demonstrating that the retained indicators adequately represented their respective latent constructs (Hair et al., 2022). Collectively, these findings provide strong evidence of the instrument's reliability and construct validity, supporting its suitability for examining organizational readiness, AI adoption, AI-driven decision support systems, and strategic AI integration in higher education institutions. These results are consistent with recent studies highlighting the importance of employing psychometrically sound measurement instruments in investigating artificial intelligence adoption and digital transformation within higher education (Adams et al., 2023; Holmes et al., 2022).

Table 1
Summary of the Confidence and Construct Validity Results of the Instruments

Scales	Explained Variance	Cronbach's Alpha	KMO Measure of Sampling Adequacy	Bartlett's Test of Sphericity
AI Integration and Strategic Foresight Capacity	90.64%	.979	.896	1039.126***
Organizational Readiness	79.02%	.910	.807	.294.370***
Technical and Data Readiness	80.08%	.915	.779	324.018***
Ethical and Governance Safeguards	92.52%	.973	.844	598.913***
Adoption and Utilization of AI Tools	72.18%	.922	.882	72.183***
Strategic Planning and Policy Quality	88.37%	.955	.860	450.891***
Quality of Instructional Decision-Making	89.53%	.961	.832	482.525***
Resource Allocation and Organizational Responsiveness	89.71%	.961	.799	495.921***

Note: *** significant at *P* <.001

The descriptive findings presented in Table 2 indicate that higher education institutions exhibited high to very high levels of institutional readiness, AI-driven decision support systems, and AI Integration and Strategic Foresight Capacity. Among the variables, Ethical and

Governance Safeguards obtained the highest mean score (M = 4.34, SD = 0.81), indicating that institutions place strong emphasis on responsible AI governance, transparency, accountability, and ethical implementation. This finding aligns with the UNESCO Recommendation on the Ethics of Artificial Intelligence, which identifies ethical governance, human oversight, transparency, and accountability as fundamental prerequisites for trustworthy AI adoption in education. It is likewise consistent with the OECD Digital Education Outlook 2023, which recognizes governance frameworks and institutional policies as key indicators of AI maturity in educational institutions.

Table 2

Results of Descriptive Statistics on the Levels of AI Integration and Strategic Foresight, Institutional Readiness, Adoption and Utilization of AI Tools, and AI-Driven Decision Support Systems, and (N = 103)

Variables	Mean	SD	Verbal Interpretation
AI Integration and Strategic Foresight Capacity	4.23	0.77	Very High
Institutional Readiness			
Organizational Readiness	3.93	0.72	High
Technical and Data Readiness	3.89	0.75	High
Ethical and Governance Safeguards	4.34	0.81	Very High
Adoption and Utilization of AI Tools	3.76	0.76	High
AI-Driven Decision Support Systems			
Strategic Planning and Policy Quality	4.08	0.79	High
Quality of Instructional Decision-Making	4.17	0.78	High
Resource Allocation and Organizational Responsiveness	4.12	0.77	High

The very high level of AI Integration and Strategic Foresight Capacity (M = 4.23, SD = 0.77) suggests that participating institutions are increasingly integrating AI into strategic planning and organizational decision-making. Similarly, the high ratings for Quality of Instructional Decision-Making and Resource Allocation and Organizational Responsiveness indicate that AI is increasingly viewed as a strategic enabler of evidence-based governance rather than merely an instructional technology. Miao and Holmes (2023) in education emphasize that AI can strengthen institutional planning, decision-making, and organizational effectiveness when supported by sound governance and leadership.

Although Adoption and Utilization of AI Tools recorded the lowest mean score (M = 3.76, SD = 0.76), it remained within the high category. This suggests that while institutions have established governance structures and organizational readiness, the practical integration of AI technologies is still developing. The OECD (2023) notes that many education systems continue to face challenges in translating AI policies into institutional practice because of capacity-building needs, infrastructure limitations, and organizational readiness. Likewise, Miao & Holmes (2023) in UNESCO's Guidance for Generative AI in Education and Research highlight that successful AI implementation requires continuous institutional support, faculty development, and clear governance mechanisms beyond simply acquiring AI technologies.

Pearson correlation analysis (Table 3) revealed that all dimensions of institutional readiness, adoption and utilization of AI tools, and AI-driven decision support systems were positively and significantly associated with AI Integration and Strategic Foresight Capacity ($p < .01$). These findings indicate that institutions with stronger organizational readiness, governance

mechanisms, and decision-support capabilities are more likely to achieve higher levels of AI integration and strategic preparedness.

Table 3

Pearson Correlations Among Institutional Readiness, Adoption and Utilization of AI Tools, AI-Driven Decision Support Systems and Strategic Foresight Capacity (N = 103)

Variable	1	2	3	4	5	6	7	8
AI Integration and Strategic Foresight Capacity	—							
Institutional Readiness								
Organizational Readiness	.732**	—						
Technical and Data Readiness	.613**	.808**	—					
Ethical and Governance Safeguards	.868**	.617**	.558**	—				
Adoption and Utilization of AI Tools	.501**	.732**	.670**	.376**	—			
AI-Driven Decision Support Systems								
Strategic Planning and Policy Quality	.816**	.725**	.637**	.711**	.567**	—		
Quality of Instructional Decision-Making	.868**	.684**	.613**	.766**	.623**	.858**	—	
Resource Allocation and Organizational Responsiveness	.854**	.755**	.601**	.754**	.539**	.842**	.811**	—

Among the predictors, Ethical and Governance Safeguards ($r = .868$, $p < .01$) and Quality of Instructional Decision-Making ($r = .868$, $p < .01$) demonstrated the strongest relationships with AI Integration and Strategic Foresight Capacity. This finding supports the UNESCO (2021) Recommendation on the Ethics of Artificial Intelligence, which emphasizes that transparency, accountability, fairness, and human oversight are fundamental requirements for responsible AI implementation in educational institutions. Likewise, the OECD (2023) emphasizes that effective AI adoption depends on governance systems that support evidence-based institutional decision-making and long-term organizational development.

Similarly, Resource Allocation and Organizational Responsiveness ($r = .854$, $p < .01$) and Strategic Planning and Policy Quality ($r = .816$, $p < .01$) showed strong positive relationships with AI Integration and Strategic Foresight Capacity. These findings suggest that institutions with responsive leadership, sound policies, and efficient resource management are better positioned to integrate AI into institutional planning and governance. Dwivedi et al. (2023) likewise argued that successful organizational AI adoption depends on leadership, governance, organizational culture, and strategic management rather than technological capability alone. Consistent with the STS theory, the findings revealed that Quality of Instructional Decision-Making and Resource Allocation and Organizational Responsiveness significantly predicted AI Integration and Strategic Foresight Capacity, whereas Strategic Planning and Policy Quality did not demonstrate an independent effect. These findings indicate that AI strengthens institutional strategic capability when embedded in organizational decision-making and resource management processes, supporting the central proposition of the STS theory that organizational performance arises from the effective integration of technological and social systems.

The significant associations of Organizational Readiness ($r = .732$, $p < .01$) and Technical and Data Readiness ($r = .613$, $p < .01$) further indicate that institutional preparedness and digital infrastructure provide important foundations for AI transformation. Similar findings were reported by Kasneci et al. (2023), who emphasized that while technological infrastructure is essential, effective AI implementation in education requires organizational readiness, institutional policies, and human expertise.

Although Adoption and Utilization of AI Tools demonstrated the weakest correlation ($r = .501$, $p < .01$), the relationship remained statistically significant. This suggests that AI utilization alone is insufficient to drive strategic institutional capability without complementary governance structures and organizational readiness. This observation is consistent with Tlili et al. (2023), who concluded that higher education institutions derive greater value from AI when technological adoption is accompanied by institutional policies, ethical governance, leadership support, and faculty capacity building.

A hierarchical multiple regression analysis (Table 4) was conducted to determine the incremental contributions of institutional readiness, adoption and utilization of AI tools, and AI-driven decision support systems in predicting AI Integration and Strategic Foresight Capacity.

Table 4

Hierarchical Multiple Regression Analysis on Institutional Readiness, Adoption and Utilization of AI Tools, and AI-Driven Decision Support Systems in Predicting AI Integration and Strategic Foresight Capacity

Predictor	Model 1 β	Model 2 β	Model 3 β
Institutional Readiness			
Organizational Readiness	.357***	.328***	.209**
Technical and Data Readiness	−.053	−.065	−.037
Ethical and Governance Safeguards	.677***	.683***	.362***
Adoption and Utilization of AI Tools	—	.047	−.104
AI-Driven Decision Support Systems			
Strategic Planning and Policy Quality	—	—	.010
Quality of Instructional Decision-Making	—	—	.373***
Resource Allocation and Organizational Responsiveness	—	—	.190*
Model Statistics			
R	.903	.904	.942
R^2	.816	.817	.887
Adjusted R^2	.810	.810	.878
ΔR^2	.816	.001	.070
F Change	146.406***	.514	19.431***
Overall F	146.406***	109.394***	106.108***

In Model 1, institutional readiness variables explained a substantial proportion of the variance in AI Integration and Strategic Foresight Capacity ($R^2 = .816$, Adjusted $R^2 = .810$, $F = 146.406$, $p < .001$). Among the predictors, Ethical and Governance Safeguards emerged as the strongest predictor ($\beta = .677$, $p < .001$), followed by Organizational Readiness ($\beta = .357$, $p < .001$), whereas Technical and Data Readiness did not significantly predict the outcome ($\beta = -.053$, $p > .05$). These findings indicate that governance mechanisms and organizational preparedness contribute more substantially to institutional AI capability than technological infrastructure alone.

The findings support the Technology-Organization-Environment (TOE) Theory, which posits that organizational capability and governance are critical determinants of successful technology adoption beyond technological resources (Tornatzky & Fleischer, 1990; Baker, 2012). They are likewise consistent with the UNESCO Recommendation on the Ethics of Artificial Intelligence (2021), which emphasizes that transparency, accountability, human oversight, and ethical governance are fundamental prerequisites for responsible AI implementation. Similarly, the OECD Digital Education Outlook 2023 highlights that institutional AI maturity depends not only on digital infrastructure but also on governance capacity, organizational leadership, and institutional readiness (OECD, 2023).

In Model 2, the addition of Adoption and Utilization of AI Tools produced only a negligible increase in explained variance ($\Delta R^2 = .001$, $\Delta F = .514$, $p > .05$), and the variable did not significantly predict AI Integration and Strategic Foresight Capacity ($\beta = .047$, $p > .05$). This finding suggests that the mere use of AI applications does not necessarily translate into stronger institutional strategic capability. Instead, AI tools appear to generate value only when embedded within organizational processes and supported by effective governance. This observation aligns with recent reviews indicating that many higher education institutions are rapidly adopting generative AI technologies; however, institutional benefits remain limited when adoption is not accompanied by governance frameworks, leadership support, and organizational change strategies (Crompton & Burke, 2024; UNESCO, 2023).

The final model demonstrated the highest explanatory power, accounting for 88.7% of the variance in AI Integration and Strategic Foresight Capacity ($R^2 = .887$, Adjusted $R^2 = .878$, $F = 106.108$, $p < .001$). The inclusion of AI-driven decision support system variables significantly improved model prediction ($\Delta R^2 = .070$, $\Delta F = 19.431$, $p < .001$). Quality of Instructional Decision-Making emerged as the strongest predictor ($\beta = .373$, $p < .001$), followed by Ethical and Governance Safeguards ($\beta = .362$, $p < .001$), Organizational Readiness ($\beta = .209$, $p < .01$), and Resource Allocation and Organizational Responsiveness ($\beta = .190$, $p < .05$). Conversely, Technical and Data Readiness, Adoption and Utilization of AI Tools, and Strategic Planning and Policy Quality did not demonstrate significant independent effects.

These findings are consistent with the Socio-Technical Systems Theory, which argues that organizational performance is achieved through the effective interaction between technological systems and human decision-making processes rather than technology alone (Trist & Bamforth, 1951). Recent literature similarly suggests that AI creates institutional value when its analytical outputs inform leadership decisions, improve resource allocation, and strengthen evidence-based governance (Crompton & Burke, 2024; OECD, 2023). In higher education, AI should therefore be viewed as a strategic decision-support capability rather than merely a technological innovation.

Conclusion and Implications

This study developed and tested an explanatory model of AI Integration and Strategic Foresight Capacity by examining the contributions of institutional readiness, adoption and utilization of AI tools, and AI-driven decision support systems in higher education institutions. The findings revealed that the participating institutions generally demonstrated high to very high levels of institutional readiness, AI-driven decision support systems, and AI integration and strategic foresight capacity, indicating that higher education institutions are progressively positioning themselves to leverage artificial intelligence in institutional governance and strategic management.

The study further established that all dimensions of institutional readiness, AI tool utilization, and AI-driven decision support systems were significantly and positively associated with AI Integration and Strategic Foresight Capacity. However, hierarchical regression analysis showed that not all variables contributed equally to explaining AI strategic capability. Ethical and Governance Safeguards, Organizational Readiness, Quality of Instructional Decision-Making, and Resource Allocation and Organizational Responsiveness emerged as significant predictors, whereas Technical and Data Readiness, Adoption and Utilization of AI Tools, and Strategic Planning and Policy Quality did not demonstrate significant independent predictive effects after controlling for other organizational variables.

These findings indicate that successful AI integration in higher education depends primarily on organizational capability, ethical governance, and evidence-informed decision-making rather than the mere availability or use of AI technologies. The explanatory model accounted for 88.7% of the variance in AI Integration and Strategic Foresight Capacity, demonstrating that institutional governance and organizational systems are critical drivers of sustainable AI transformation. Overall, the study supports the proposition that AI becomes a strategic institutional capability only when embedded within robust governance structures, responsive organizational processes, and effective decision-support mechanisms.

The findings have important implications for higher education institutions, policymakers, and university leaders pursuing digital transformation. First, universities should prioritize the development of ethical AI governance frameworks, organizational readiness, and institutional accountability, as these were found to exert stronger influences on AI integration than technological readiness alone. Investments in AI infrastructure should therefore be complemented by policies that promote transparency, responsible AI use, and effective institutional governance.

Second, the significant contributions of Quality of Instructional Decision-Making and Resource Allocation and Organizational Responsiveness suggest that AI initiatives should be integrated into institutional decision-making processes rather than implemented solely as technological innovations. Universities should strengthen leadership capacity, data-informed decision-making, and organizational responsiveness to maximize the strategic value of AI.

Third, the non-significant effects of Technical and Data Readiness and Adoption and Utilization of AI Tools indicate that technological resources alone are insufficient to achieve meaningful AI transformation. Institutions should therefore invest in leadership development, governance capacity, organizational culture, and faculty capability to ensure that AI technologies are translated into sustainable institutional improvements.

Finally, the explanatory model generated by this study provides an empirical framework that may guide higher education institutions in assessing their AI readiness and designing evidence-based strategies for AI implementation. The model may also serve as a useful reference for policymakers in developing institutional AI governance standards and digital transformation initiatives that strengthen strategic foresight and long-term organizational resilience. Future studies may validate the model across diverse higher education contexts and employ

longitudinal or structural equation modeling approaches to further examine the causal pathways among institutional readiness, AI governance, decision-support systems, and AI integration.

References:

Adams, C., Pente, P., Lemermeyer, G., and Rockwell, G. (2023). Ethical principles for artificial intelligence in K-12 education, Elsevier https://doi.org/10.1016/j.caeai.2023.100131

Alshamaila, Y., Papagiannidis, S., & Li, F. (2013). Cloud computing adoption by SMEs in the north east of England: A multi-perspective framework. *Journal of Enterprise Information Management, 26*(3), 250–275. https://doi.org/10.1108/17410391311325225

An, Y., et al. (2025). *Investigating the higher education institutions' guidelines and policies for generative artificial intelligence*. *International Journal of Educational Technology in Higher Education, 22*.

Baker, J. (2012). The technology–organization–environment framework. In Y. K. Dwivedi, M. R. Wade, & S. L. Schneberger (Eds.), *Information systems theory: Explaining and predicting our digital society* (Vol. 1, pp. 231–245). Springer. https://doi.org/10.1007/978-1-4419-6108-2_12

Baxter, G., & Sommerville, I. (2011). Socio-technical systems: From design methods to systems engineering. *Interacting with Computers, 23*(1), 4–17. https://doi.org/10.1016/j.intcom.2010.07.003

Bovens, M. (2007). Analysing and assessing accountability: A conceptual framework. *European Law Journal, 13*(4), 447–468. https://doi.org/10.1111/j.1468-0386.2007.00378.x

Burrell, J. (2016). How the machine "thinks": Understanding opacity in machine learning algorithms. *Big Data & Society, 3*(1), 1–12. https://doi.org/10.1177/2053951715622512

Chan, C. K. Y. (2023). *A comprehensive AI policy education framework for university teaching and learning*. arXiv. https://arxiv.org/abs/2305.00280

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education, 20*(1), 22. https://doi.org/10.1186/s41239-023-00392-8

Daniel, B. K. (2015). Big data and analytics in higher education: Opportunities and challenges. *British Journal of Educational Technology, 46*(5), 904–920. https://doi.org/10.1111/bjet.12230

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2019). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management, 57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., et al. (2023). So what if ChatGPT wrote it? Multidisciplinary perspectives on opportunities, challenges, and implications of generative conversational AI for research, practice, and policy. *International Journal of Information Management, 71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Floridi, L., Cowls, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2018). AI4People—An ethical framework for a good AI society. *Minds and Machines, 28*(4), 689–707. https://doi.org/10.1007/s11023-018-9482-5

Graham, C. R., Woodfield, W., & Harrison, J. B. (2013). A framework for institutional adoption and implementation of blended learning in higher education. *The Internet and Higher Education, 18*, 4–14. https://doi.org/10.1016/j.iheduc.2012.09.003

Greller, W., & Drachsler, H. (2012). Translating learning into numbers: A generic framework for learning analytics. *Educational Technology & Society, 15*(3), 42–57.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2022). *Multivariate data analysis* (8th ed.). Cengage Learning, 2022

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial Intelligence in Education: Promise and Implications for Teaching and Learning*.

Holmes, W., Persson, J., Chounta, I.-A., Wasson, B., & Dimitrova, V. (2022). *Artificial intelligence and education: A critical view through the lens of human rights, democracy and the rule of law*. Council of Europe. https://rm.coe.int/artificial-intelligence-and-education-a-critical-view-through-the-l/1680a886bd

Kasneci, E., Sessler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeiffer, F., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., ... Kasneci, G. (2023). *ChatGPT for good? On opportunities and challenges of large language models for education*. *Learning and Individual Differences, 103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). Statistical and machine learning forecasting methods: Concerns and ways forward. *PLoS ONE, 13*(3), e0194889. https://doi.org/10.1371/journal.pone.0194889

Miao, F., & Holmes, W. (2023). *Guidance for generative AI in education and research*. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000386693

Mintzberg, H. (1994). *The rise and fall of strategic planning*. Free Press.

Nguyen, A., et al. (2022). Ethical principles for artificial intelligence in education. *Computers and Education: Artificial Intelligence*.

Organisation for Economic Co-operation and Development. (2023). *OECD digital education outlook 2023: Towards an effective digital education ecosystem*. OECD Publishing. https://doi.org/10.1787/c74f03de-en

Porter, W. W., & Graham, C. R. (2016). Institutional drivers and barriers to faculty adoption of blended learning in higher education. *British Journal of Educational Technology, 47*(4), 748–762. https://doi.org/10.1111/bjet.12269

Rohrbeck, R., & Kum, M. E. (2018). Corporate foresight and its impact on firm performance: A longitudinal analysis. *Technological Forecasting and Social Change, 129*, 105–116. https://doi.org/10.1016/j.techfore.2017.12.013

Sánchez-Torres, J. A., Canada, F. J. A., Sandoval, A. V., & Alzate, J. A. S. (2018). E-government and organizational readiness: The mediating role of institutional capability. *Government Information Quarterly, 35*(4), S82–S90.

Selwyn, N. (2019). *Should robots replace teachers? AI and the future of education*. Polity Press.

Shattock, M. (2013). *University governance, leadership and management in a decade of diversification and uncertainty*. Higher Education Academy.

Siemens, G., & Long, P. (2011). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review, 46*(5), 30–40.

Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). *What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education*. *Smart Learning Environments, 10*(1), 15. https://doi.org/10.1186/s40561-023-00237-x

Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.

Trist, E. L., & Bamforth, K. W. (1951). Some social and psychological consequences of the longwall method of coal-getting. *Human Relations, 4*(1), 3–38. https://doi.org/10.1177/001872675100400101

UNESCO. (2021). *Recommendation on the Ethics of Artificial Intelligence*. UNESCO Recommendation on the Ethics of Artificial Intelligence

United Nations Educational, Scientific and Cultural Organization. (2021). *Recommendation on the ethics of artificial intelligence*. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000381137

United Nations Educational, Scientific and Cultural Organization. (2025). *AI and education: Guidance for policy-makers*. UNESCO. https://www.unesco.org/en/articles/ai-and-education-guidance-policy-makers

United Nations Educational, Scientific and Cultural Organization. (2023). *Guidance for generative AI in education and research*. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000386693

Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. *Learning, Media and Technology, 45*(3), 223–235. https://doi.org/10.1080/17439884.2020.1798995

Wu, C., Zhang, H., & Carroll, J. M. (2024). *AI governance in higher education: Case studies of guidance at Big Ten universities*. arXiv. https://arxiv.org/abs/2409.02017

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The Underdog's Potential for Retaliation: AI-Enabled Strategic Applications of Strategic Foresight and Competitive Intelligence, the Facilitating Role of Risk Thinking, and the Inhibitory Moderating Role of Organizational Ambition

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ABSTRACT

This study adopts a strategy formation process perspective to examine how Strategic Foresight Capability and Competitive Intelligence Capability influence organizational competitive outcomes through Organizational Power-Inversing Capability, while investigating the moderating effects of Strategic Risk Thinking and Organizational Ambition. Strategic Foresight Capability is conceptualized as an information acquisition mechanism incorporating Generative AI for real-time information processing and cross-domain weak-signal detection, whereas Competitive Intelligence Capability serves as a competitive interpretation mechanism integrating Generative AI for competitive scenario and competitor-response simulation and Causal AI for causal and counterfactual analysis. Data were collected from 265 organizational members in Taiwan with strategic participation and decision-making experience. The results show that both Strategic Foresight Capability and Competitive Intelligence Capability significantly and positively affect Organizational Power-Inversing Capability, with Organizational Power-Inversing Capability exhibiting significant partial mediation. Risk transformation thinking positively moderates the relationship between Competitive Intelligence Capability and Organizational Power-Inversing Capability. whereas Organizational Ambition shows only a marginally significant negative moderating effect on organizational learning. Accordingly, this study develops a strategy formation process model linking information sensing, competitive interpretation, power-inversing action, and competitive outcomes and identifies the instrumental roles of Generative AI and Causal AI in information acquisition, competitive scenario simulation, and causal analysis. The findings address theoretical gaps in front-end strategic cognition, AI-assisted analysis, and cognition-to-action transformation while offering strategic implications for underdog firms seeking to overcome resource constraints and competitive adversity.

Keywords: Generative AI and Causal AI, Strategic Foresight and Competitive Intelligence, Organizational Power-Inversing Capability, Strategic Risk Thinking; Organizational Ambition

I. Problem Awareness

1. An Unequal Competition Perspective on Organizational Power-Inversing

In an era of global competition, rapid technological change, and heightened uncertainty, disadvantaged organizations face more severe resource constraints and less room for trial and error than powerful organizations endowed with superior capital, technology, and market positions. As markets become increasingly concentrated and competitive advantages continue to accumulate, powerful organizations are able to consolidate their established positions, making it increasingly difficult for disadvantaged organizations to break through existing competitive structures. Accordingly, this study adopts an unequal competition perspective and draws on the theory of Power-Inversing proposed by Hsiao et al. (2017) to examine how disadvantaged organizations overcome existing competitive constraints through opportunity awareness, power transformation, and innovative reconstruction, while investigating the strategic antecedents and outcomes of Organizational Power-Inversing Capability.

Regarding strategic antecedents, this study draws on information processing and competitive analysis perspectives to develop two cognitive capabilities: Strategic Foresight Capability and Competitive Intelligence Capability. Strategic Foresight Capability serves as an information acquisition mechanism through which organizations perceive future changes (Rohrbeck & Kum, 2018; Gordon et al., 2020). This study further incorporates a social network perspective by distinguishing the information agility provided by strong ties from the scarce information obtained through weak ties that span heterogeneous networks and structural holes. Generative AI is further introduced as an instrumental extension to enhance the efficient processing of large volumes of real-time information and the detection of cross-domain weak signals (Granovetter, 1973; Burt, 1992; Fitkov-Norris & Kocheva, 2024). Competitive Intelligence Capability emphasizes the interpretation of competitors' relative positions and actions (Bose, 2008). Beyond comparing relative strengths and weaknesses, it incorporates competitive interaction and competitive dynamics simulation (Chen & Miller, 1994), as well as strategic thinking concerning affordable loss, leverage, and potential release. It further integrates Generative AI to construct multiple competitive scenarios and simulate competitor responses,

and Causal AI to conduct causal analysis, counterfactual simulation, and strategic consequence assessment, thereby strengthening competitive interpretation and action design (Sarasvathy, 2001; Taleb, 2012; Miller, 2003; Fitkov-Norris & Kocheva, 2024).

Furthermore, because competitive engagement inherently involves market risk, this study incorporates Strategic Risk Thinking as a front-end moderating mechanism to examine how risk transformation thinking and holistic thinking influence the extent to which strategic cognition is translated into power-inversing action (Miller, 2003; Zhai, 2018). Organizational Ambition is introduced as a back-end moderating mechanism to examine whether collective achievement striving and competitive aspirations influence the extent to which Organizational Power-Inversing Capability is translated into organizational outcomes (Judge & Kammeyer-Mueller, 2012; Hirschi & Spurk, 2021).

II. Antecedents and Outcomes of Organizational Power-Inversing Capability: Strategic Foresight Capability and Competitive Intelligence Capability

1. Organizational Power-Inversing Capability

Power-Inversing theory is grounded in the perspectives of asymmetric competition and structural constraints. It suggests that when disadvantaged organizations face resource scarcity, suppression by powerful competitors, and institutional constraints, they can identify institutional blind spots and latent weaknesses embedded within the advantage structures of dominant organizations through “seeking weakness within strength.” By recombining resources and transforming power relations, disadvantaged organizations can recreate competitive space, demonstrating that competitive advantages and disadvantages are not fixed conditions but can be transformed through strategic action (Hsiao et al., 2017). Huang (2021) further conceptualized Power-Inversing as a capability comprising three dimensions: opportunity awareness, power transformation, and innovative reconstruction. These dimensions respectively emphasize identifying reverse opportunities, leveraging unique advantages and alliances to reshape power structures, and recombining existing resources under resource constraints to create new competitive conditions.

2. Antecedents of Power-Inversing: Strategic Foresight Capability and Competitive Intelligence Capability

Strategic Foresight Capability comprises two factors. “Strong Ties–Agility” refers to an organization's reliance on frequent interactions, stable relationships, and high-trust network connections. Through Generative AI-enabled large-scale text processing, organizations can simultaneously retrieve, filter, summarize, and connect large volumes of real-time information, thereby rapidly receiving and integrating mainstream and timely information from industries and markets to establish an initial basis for foresight interpretation and response (Freeman, 1979; Borgatti & Halgin, 2011; Fitkov-Norris & Kocheva, 2024).

“Weak Ties–Scarcity” refers to an organization's ability to access cross-community, cross-domain, and cross-market network connections and leverage Generative AI to transcend existing disciplinary and knowledge boundaries. By identifying nonlinear trends, cross-domain relationships, and weak signals from large volumes of heterogeneous and unstructured information, organizations can access non-redundant information and early signals that have not yet been absorbed into mainstream networks. This enhances their ability to anticipate potential changes in industry and market structures and develop an initial understanding before emerging trends become fully apparent (Granovetter, 1973; Burt, 1992; Fitkov-Norris & Kocheva, 2024). Accordingly, this study conceptualizes these two factors as complementary information acquisition mechanisms that enable organizations to both capture real-time market changes and identify emerging opportunities, potential threats, and weak signals in advance, thereby providing an informational foundation for subsequent power-inversing actions and increasing the possibility of overcoming existing competitive constraints.

Competitive Intelligence Capability also comprises two factors. “Strength–Weakness Comparison–Leverage and Potential Realization” refers to an organization's use of competitors as reference points to compare relative differences in resources, capabilities, and competitive positions. By applying Causal AI for causal discovery, causal graph modeling, and counterfactual simulation, organizations can identify causal pathways among resources, actions, and competitive outcomes, thereby reducing observational bias and assessing the

potential cascading effects of alternative strategic choices. This process enables organizations to identify their structural disadvantages and latent advantages, define affordable losses and introduce complementary external advantages through leverage, and realize existing capabilities and select favorable competitive positions through potential realization. Consequently, limited resources and latent capabilities can be transformed into competitively valuable asymmetric advantages (Sarasvathy, 2001; Taleb, 2012; Miller, 2003; Ndofor et al., 2011; Fitkov-Norris & Kocheva, 2024).

“Dynamic Interaction–Leverage and Potential Realization” refers to an organization's view of competition as a dynamic process consisting of continuous actions and responses. Through Generative AI, organizations can construct multiple competitive scenarios and simulate potential competitor responses and the resulting evolution of competitive dynamics. Causal AI can further support counterfactual simulations and strategic intervention tests to assess the cascading consequences of alternative competitive actions. These analyses enable organizations to define affordable losses and exit boundaries across different competitive scenarios in advance, thereby controlling downside risks arising from competitor retaliation. At the same time, organizations can introduce complementary external advantages in response to evolving competitive dynamics and continuously identify how existing capabilities can be deployed across different market positions and competitive contexts. This enables them to dynamically adjust risk exposure, sources of advantage, and strategic leverage points as competitive interactions unfold (Sarasvathy, 2001; Chen & Miller, 1994; Chen, 1996; Miller, 2003; Ndofor et al., 2011; Fitkov-Norris & Kocheva, 2024). This study therefore conceptualizes these two factors as complementary competitive interpretation mechanisms that enable organizations to identify structural disadvantages and latent advantages from their current competitive positions while dynamically adjusting affordable losses, introducing external advantages, and realizing internal potential in response to competitor reactions and evolving competitive dynamics. These mechanisms provide an action-oriented basis for subsequent power-inversing actions and increase the possibility of overcoming existing competitive constraints.

Overall, Strategic Foresight Capability and Competitive Intelligence Capability constitute important antecedents of Organizational Power-Inversing Capability. This study proposes that their positive effects on competitive advantage, organizational resilience, organizational learning, and strategy formation process criteria are realized through the mediating role of Organizational Power-Inversing Capability. Accordingly, the following hypotheses are proposed:

H*$_1$: Strategic Foresight Capability and Competitive Intelligence Capability positively affect organizational outcomes, including (a) competitive advantage, (b) organizational learning, (c) organizational resilience, and (d) strategy formation process criteria.*

H*$_2$: Organizational Power-Inversing Capability mediates the positive effects of Strategic Foresight Capability and Competitive Intelligence Capability on organizational outcomes, including (a) competitive advantage, (b) organizational learning, (c) organizational resilience, and (d) strategy formation process criteria.*

3. Strategic Risk Thinking: The Moderating Effects of Risk Transformation Thinking and Holistic Thinking

Strategic Risk Thinking comprises two dimensions. Risk Transformation Thinking refers to decision makers' perception of risk as a strategic condition that can be managed through risk sharing, transfer, and reallocation. It emphasizes redistributing downside risks originally concentrated within a single organization to multiple participants or transferring them to other actors. Decision makers may also deliberately assume specific risks to avoid greater potential losses or increase competitors' action costs, thereby reducing concentrated risk exposure and supporting risk governance and strategic commitment (Miller, 1992; Miller & Reuer, 1996; Wang et al., 2003; Zhai, 2018).

Holistic Thinking refers to evaluating risk from the broader perspectives of industry systems, competitive structures, and stakeholder networks. It involves considering dynamic interactions among multiple actors, their interests, and the cascading consequences of strategic actions to assess the potential impacts of current decisions on future competitive situations and the overall

competitive landscape. This perspective enables decision makers to move beyond isolated risk events and short-term outcomes by evaluating strategic alternatives within a broader contextual and relational framework (Miller, 1992; Teng, 2025; Zhai, 2018).

Overall, although Strategic Foresight Capability and Competitive Intelligence Capability respectively provide the foundations for environmental sensing and competitive interpretation, whether organizations subsequently engage in power-inversing actions depends on how decision makers perceive and manage the risks associated with such actions. The same levels of Strategic Foresight Capability and Competitive Intelligence Capability may therefore lead to different degrees of power-inversing action under different forms of Strategic Risk Thinking. Accordingly, this study proposes that Strategic Risk Thinking moderates the relationship between front-end strategic cognition and Organizational Power-Inversing Capability.

***H3**: Strategic Risk Thinking moderates the positive effects of Strategic Foresight Capability and Competitive Intelligence Capability on Organizational Power-Inversing Capability.*

4. The Moderating Effect of Organizational Ambition

Organizational Ambition is constructed by extending the individual-level perspective of ambition, which represents an important psychological tendency to continuously pursue success, achievement, and value realization. It comprises two dimensions. “Achievement Striving” refers to the persistent pursuit of outstanding performance and long-term goals, reflecting an intrinsic drive to proactively set challenging goals, invest effort, realize self-worth, exceed existing performance levels, achieve higher goals, and fulfill one's potential (Maslow, 1943; McClelland, 1961; Barsukova, 2016; Adeel et al., 2023; Resta et al., 2023). “Enjoyment of Competitive Challenges” refers to a positive attitude toward external competition and challenges, whereby competition is regarded as an opportunity to demonstrate competence, validate self-worth, and pursue superior performance. It reflects an action-oriented drive activated by competitive situations, motivating individuals to actively engage in competition, respond to external challenges, and derive achievement and sustained motivation from surpassing established standards or competitors (Spence & Helmreich, 1983; Hofstede, 2001).

Accordingly, this study proposes that Organizational Ambition does not constitute power-inversing action itself; rather, it represents an important organizational climate condition that influences whether Organizational Power-Inversing Capability can be further translated into competitive advantage, organizational resilience, organizational learning, and strategy formation process criteria. Therefore, the following moderating hypothesis is proposed:

H4: *Organizational Ambition moderates the positive effect of Organizational Power-Inversing Capability on organizational outcomes, including (a) competitive advantage, (b) organizational resilience, (c) organizational learning, and (d) strategy formation process criteria.*

5. Outcomes of Organizational Power-Inversing Capability: Competitive Advantage, Organizational Learning, Organizational Resilience, and Strategy Formation Process Criteria

The outcomes of Organizational Power-Inversing Capability include four dimensions. “Competitive Advantage” refers to an organization's ability to establish a more favorable competitive position relative to competitors through clear strategic positioning and consistent action configuration, while demonstrating differentiated value, strategic precision, and stability of competitive position in market competition. It reflects the actual effects of organizational strategic actions on competitive position and performance outcomes (Porter, 1985, 1996; Bhatt et al., 2010).

“Organizational Learning” refers to an organization's ability to transform experience accumulated through strategic actions and competitive interactions into knowledge and action foundations for subsequent strategy formation and capability renewal through knowledge absorption, reflection, sharing, and institutionalization. It reflects the extent to which an organization continuously revises existing cognition and evolves its competitive capabilities through competitive experience (Alegre & Chiva, 2008).

“Organizational Resilience” refers to an organization's ability to absorb shocks, adjust its structure, and maintain core operations when facing external disruptions, uncertain events, and

competitive retaliation. It enables the organization to maintain stable operations, adapt rapidly, and continue advancing strategic actions under highly dynamic conditions, reflecting its capacity to withstand, adapt to, and recover from uncertainty and external disruptions (Bruneau et al., 2003; Chang, 2023).

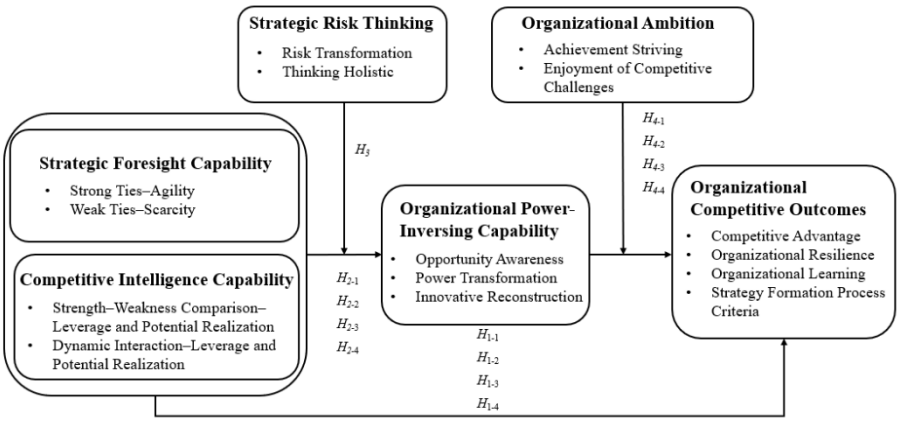
"Strategy Formation Process Criteria" refers to the extent to which an organization establishes a shared direction through strategic planning activities, integrates cognition and resources across organizational levels, and effectively translates strategic ideas into concrete actions and competitive outcomes. It reflects the overall effectiveness of the strategy formation process, from planning and coordination to implementation and execution (Schaefer & Guenther, 2016).

II. Research Framework and Methodology

This study examines Strategic Foresight Capability and Competitive Intelligence Capability as antecedents of Organizational Power-Inversing Capability. Strategic Foresight integrates information agility, information scarcity, and Generative AI to enhance real-time information processing and weak-signal detection, whereas Competitive Intelligence combines competitive analysis with Generative AI for dynamic simulation and Causal AI for causal interpretation (Granovetter, 1973; Burt, 1992; Chen & Miller, 1994; Fitkov-Norris & Kocheva, 2024).

Organizational Power-Inversing Capability serves as the mediating mechanism that transforms information sensing and competitive interpretation into opportunity awareness, power transformation, and innovative reconstruction (Hsiao et al., 2017; Huang, 2021). Strategic Risk Thinking moderates the formation of power-inversing capability, while Organizational Ambition moderates its effects on organizational outcomes. The outcomes include Competitive Advantage, Organizational Resilience, Organizational Learning, and Strategy Formation Process Criteria. Accordingly, Figure 1 presents the proposed research framework linking strategic cognition, power-inversing capability, and organizational outcomes.

Figure 1. Research Framework



Source: Compiled by the authors.

III. Research Sample, Instruments, and Variables

This study surveyed organizational members in Taiwan with strategy formation and decision-making experience, yielding 265 valid responses. Manufacturing accounted for 33.9% of the sample, and 70.2% of respondents held managerial positions or above.

All constructs were measured using a five-point Likert scale. Strategic Foresight Capability comprises Strong Ties–Agility and Weak Ties–Scarcity; Competitive Intelligence Capability comprises Strength–Weakness Comparison and Dynamic Interaction, both incorporating Leverage and Potential Realization; Organizational Power-Inversing Capability comprises Opportunity Awareness, Power Transformation, and Innovative Reconstruction. Strategic Risk Thinking comprises Risk Transformation Thinking and Holistic Thinking, while Organizational Ambition comprises Achievement Striving and Enjoyment of Competitive Challenges. The outcomes include Competitive Advantage, Organizational Resilience, Organizational Learning, and Strategy Formation Process Criteria. As shown in Table 1, all constructs demonstrated satisfactory reliability and factorability.

Table 1. Reliability and Factor Analysis of Research Variables

Construct	Items	α	KMO	Bartlett's χ^2	p	Eigenvalue	%Variance
Strategic Foresight Capability	4	.87	.78	578.32	< .05	2.93	73.12
Competitive Intelligence Capability	4	.87	.77	564.57	< .05	2.89	72.47
Organizational Power-Inversing Capability	18	.89	.96	4,005.422	< .05	11.031	61.282

Risk Decision-Making Mindset	8	.88	.908	1,400.374	< .001	4.800	59.999
Organizational Ambition	6	.92	.900	1,429.805	< .001	4.389	73.158
Competitive Advantage	5	.94	.879	1,112.992	< .001	3.722	74.448
Organizational Resilience	5	.93	.888	1,078.050	< .001	3.654	73.079
Organizational Learning	7	.92	.912	1,179.892	< .001	4.292	61.321
Strategy Formation Process Criteria	6	.95	.916	1,459.021	< .001	4.478	74.633

Source: Compiled by the authors.

III. Research Results

1. Correlation Analysis

All major variables were significantly and positively correlated in the expected directions, providing preliminary support for subsequent analyses.

2. Main and Mediation Effects

As shown in Table 2, Strategic Foresight Capability and Competitive Intelligence Capability significantly and positively predicted all four organizational outcomes, supporting ***H1(a)–H1(d)***. Organizational Power-Inversing Capability significantly mediated these relationships and positively predicted Competitive Advantage (β = .432***), Organizational Learning (β= .473***), Organizational Resilience (β = .389***), and Strategy Formation Process Criteria (β= .438***). Full mediation was found for the effect of Strategic Foresight Capability on Competitive Advantage and for the effect of Competitive Intelligence Capability on Organizational Learning, whereas the remaining relationships showed partial mediation. Accordingly, ***H2(a)–H2(d)*** were supported, with full mediation identified in specific paths and partial mediation in the remaining paths.

3. Moderating Effects

(1) Moderating Effect of Strategic Risk Thinking

Strategic Risk Thinking had a significant positive effect on Organizational Power-Inversing Capability (β = .25***, ΔR^2 = .04, p < .001). The interaction between Competitive

Intelligence Capability and Risk Transformation Thinking was significantly positive (β = .24*), whereas the interaction between Competitive Intelligence Capability and Holistic Thinking was marginally negative (β = −.19+). The interactions between Strategic Foresight Capability and both dimensions of Strategic Risk Thinking were not significant. These findings reveal differentiated moderating effects: Risk Transformation Thinking strengthens the translation of competitive intelligence into power-inversing action, whereas Holistic Thinking may inhibit this process. Thus, ***H3*** was partially supported.

(2) Moderating Effect of Organizational Ambition

Organizational Power-Inversing Capability significantly and positively affected Competitive Advantage (β = .43***), Organizational Learning (β = .47***), Organizational Resilience (β= .39***), and Strategy Formation Process Criteria (β = .44***). Organizational Ambition also had significant positive direct effects on all four outcomes. However, its interaction with Organizational Power-Inversing Capability was marginally negative only for Organizational Learning (β = −.22+), while all other moderating effects were nonsignificant. This suggests that although Organizational Ambition directly enhances organizational outcomes, excessive competitive and achievement orientation may constrain exploration, experimentation, and reflective learning. Thus, ***H4(c)*** was partially supported.

IV. Conclusions and Recommendations

1. Research Conclusions

(1) From Dual Cognition to Power-Inversing Action

Strategic Foresight Capability and Competitive Intelligence Capability jointly form the cognitive foundations of power-inversing action. Strategic Foresight leverages Generative AI to enhance information agility and scarcity, while Competitive Intelligence integrates Generative AI and Causal AI to support competitive analysis, dynamic simulation, and strategic leverage. These findings identify both capabilities as critical antecedents of Organizational Power-Inversing Capability.

(2) Differentiated Dynamics of Strategic Risk Thinking

Competitive Intelligence interacted positively with Risk Transformation Thinking (β = .238*) but negatively with Holistic Thinking (β = −.188*), whereas the interactions involving Strategic Foresight were nonsignificant. These findings indicate that different risk-thinking patterns can either facilitate or inhibit the translation of strategic cognition into power-inversing action.

(3) Organizational Ambition: Drive and Learning Tension

Organizational Ambition positively contributes to organizational outcomes, but shows a marginally negative moderating effect on Organizational Learning. This suggests that excessive outcome orientation may constrain exploration, reflection, and experimentation, creating tension between competitive drive and organizational learning.

2. Theoretical and Practical Implications

(1) A Dual-Cognitive Framework for Strategy Formation

Building on the cognitive school of strategy (Mintzberg et al., 1998), this study develops a dual-cognitive framework comprising Strategic Foresight Capability and Competitive Intelligence Capability. Whereas the cognitive school conceptualizes strategy formation as a process involving attention, encoding, storage and retrieval, decision, and action (Corner et al., 1994), this study extends this perspective by explaining how organizations acquire diverse information, construct competitive interpretations, and translate cognition into concrete power-inversing actions. Strategic Foresight expands organizational attention through strong- and weak-tie information networks, while Competitive Intelligence provides competitive meaning through strength–weakness comparison, dynamic interaction, leverage, and potential realization. The findings thus extend the cognitive process of strategy formation into a sequence of information source expansion, competitive meaning construction, and power-inversing action transformation.

(2) A Matrix of Power-Inversing Dynamics: The Differentiated Role of Strategic Risk Thinking

Strategic Risk Thinking does not uniformly facilitate or inhibit power-inversing action but forms four differentiated dynamics depending on its interaction with Strategic Foresight and Competitive Intelligence. The Competitive–Risk type produces the strongest positive effect (β= .238, p < .05), as competitive interpretation provides an action path and Risk Transformation Thinking provides a risk-utilization logic. In contrast, the Competitive–Holistic type shows the strongest negative effect ($\beta = -.188$, $p < .05$), as excessive consideration of stakeholders and long-term consequences may increase decision complexity and inhibit action. The Foresight–Risk type shows a negative tendency ($\beta = -.100$), reflecting the paradox of "knowing more but becoming less willing to act," whereas the Foresight–Holistic type is nearly neutral (β = .040), as broader information and holistic planning do not necessarily translate into concrete action.

Practically, this matrix provides a diagnostic tool for identifying why power-inversing action stalls. Rather than simply urging managers to be more aggressive or cautious, organizations should determine whether inaction results from insufficient competitive interpretation, risk-information overload, excessive holistic concerns, or failure to translate cognition into action. Disadvantaged firms should therefore identify weaknesses embedded within dominant competitors' advantage structures and create new action spaces through strategic alliances, rule reconfiguration, resource recombination, or competitive repositioning.

Figure 2: Power-Inversing Action Dynamics Matrix of Strategic Risk Thinking

		Level of Power-Inversing Action	
		Power-Inversing Action Inhibited	Power-Inversing Action Facilitated
Strategic Decision	Risk Transformation Thinking	Conflict Type: Excessive Trade-Offs / Foresight–Risk β= -.100	Facilitating Type: Active Engagement / Competitive–Risk **β= .238****
	Holistic Thinking	Inhibitory Type: Conservative Hesitation / Competitive–Holistic **β= -.188**$^{+}$	Conflict Type: Excessive Information Gathering / Foresight–Holistic β= .040

Source: Compiled by the authors.

(3) Reconsidering Organizational Ambition: Potential Nonlinear Effects

Although Organizational Ambition directly improves organizational outcomes, its moderating effects are largely nonsignificant and even marginally negative for Organizational Learning, suggesting diminishing returns or a potential inverted U-shaped relationship. The Too-Much-of-a-Good-Thing effect explains how initially beneficial organizational attributes may become detrimental beyond an inflection point (Pierce & Aguinis, 2013). Excessive ambition may intensify performance orientation (Ames, 1992), undermine psychological safety and learning (Edmondson, 1999), and foster managerial hubris that leads organizations to overestimate their capabilities and underestimate external risks (Hayward & Hambrick, 1997). Its limited moderating effect may also reflect competitive restraint arising from anticipated retaliation and long-term interdependence (Chen, 1996; Edwards, 1955), potentially reinforced by the relational and harmony-oriented context of East Asian culture.

Practically, managers should not equate greater ambition with superior strategic outcomes. While moderate ambition can drive growth and competition, excessive emphasis on performance, expansion, and competitive victory may constrain exploration, reflection, and long-term capability development. Organizations should therefore balance competitive aspirations with learning capacity, available resources, environmental conditions, and long-term relationships.

References

Adeel, A., Kee, D. M. H., Mubashir, T., Samad, S., & Daghriri, A. A. (2023). Leaders' ambition and followers' cheating behavior: The role of performance pressure and leader identification. *Frontiers in Psychology, 14*, Article 982328. https://doi.org/10.3389/fpsyg.2023.982328

Alegre, J., & Chiva, R. (2008). Assessing the impact of organizational learning capability on product innovation performance: An empirical test. *Technovation, 28*(6), 315–326. https://doi.org/10.1016/j.technovation.2007.09.003

Ames, C. (1992). Classrooms: Goals, structures, and student motivation. *Journal of Educational Psychology, 84*(3), 261–271. https://doi.org/10.1037/0022-0663.84.3.261

Barsukova, O. V. (2016). Psychological characteristics of ambitious person. *Journal of Process Management New Technologies, 4*(2), 79–80.

Bhatt, G. D., Emdad, A. F., Roberts, N., & Grover, V. (2010). Building and leveraging information in dynamic environments: The role of IT infrastructure flexibility as enabler of organizational responsiveness and competitive advantage. *Information & Management, 47*(7–8), 341–349. https://doi.org/10.1016/j.im.2010.08.001

Borgatti, S. P., & Halgin, D. S. (2011). On network theory. *Organization Science, 22*(5), 1168–1181. https://doi.org/10.1287/orsc.1100.0641

Bose, R. (2008). Competitive intelligence process and tools for intelligence analysis. *Industrial Management & Data Systems, 108*(4), 510–528. https://doi.org/10.1108/02635570810868362

Bruneau, M., Chang, S. E., Eguchi, R. T., Lee, G. C., O'Rourke, T. D., Reinhorn, A. M., Shinozuka, M., Tierney, K., Wallace, W. A., & von Winterfeldt, D. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra, 19*(4), 733–752. https://doi.org/10.1193/1.1623497

Burt, R. S. (1992). *Structural holes: The social structure of competition*. Harvard University Press.

Chen, M.-J. (1996). Competitor analysis and interfirm rivalry: Toward a theoretical integration. *Academy of Management Review, 21*(1), 100–134. https://doi.org/10.5465/amr.1996.9602161567

Chen, M.-J., & Miller, D. (1994). Competitive attack, retaliation and performance: An expectancy-valence framework. *Strategic Management Journal, 15*(2), 85–102. https://doi.org/10.1002/smj.4250150202

Comer, D. R., Kinicki, A. J., & Keats, B. W. (1994). Integrating organizational and individual information processing perspectives on choice. *Organization Science, 5*(3), 294–308. https://doi.org/10.1287/orsc.5.3.294

Edmondson, A. C. (1999). Psychological safety and learning behavior in work teams. *Administrative Science Quarterly, 44*(2), 350–383. https://doi.org/10.2307/2666999

Edwards, W. (1955). The prediction of decisions among bets. *Journal of Experimental Psychology, 50*(3), 201–214. https://doi.org/10.1037/h0040674

Fitkov-Norris, E., & Kocheva, N. (2024, September 3–6). *Beyond the crystal ball: Unveiling the power of causal and generative AI for strategic foresight* [Paper presentation]. OR 2024: Data, Learning, and Optimization, Munich, Germany.

Freeman, L. C. (1979). Centrality in social networks: Conceptual clarification. *Social Networks, 1*(3), 215–239. https://doi.org/10.1016/0378-8733(78)90021-7

Gordon, A. V., Ramic, M., Rohrbeck, R., & Spaniol, M. J. (2020). 50 years of corporate and organizational foresight: Looking back and going forward. *Technological Forecasting and Social Change, 154*, Article 119966. https://doi.org/10.1016/j.techfore.2020.119966

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology, 78*(6), 1360–1380. https://doi.org/10.1086/225469

Hayward, M. L. A., & Hambrick, D. C. (1997). Explaining the premiums paid for large acquisitions: Evidence of CEO hubris. *Administrative Science Quarterly, 42*(1), 103–127. https://doi.org/10.2307/2393810

Hirschi, A., & Spurk, D. (2021). Ambitious employees: Why and when ambition relates to performance and organizational commitment. *Journal of Vocational Behavior, 127*, Article 103576. https://doi.org/10.1016/j.jvb.2021.103576

Hofstede, G. (2001). *Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations* (2nd ed.). Sage Publications.

Judge, T. A., & Kammeyer-Mueller, J. D. (2012). On the value of aiming high: The causes and consequences of ambition. *Journal of Applied Psychology, 97*(4), 758–775. https://doi.org/10.1037/a0028084

Maslow, A. H. (1943). A theory of human motivation. *Psychological Review, 50*(4), 370–396. https://doi.org/10.1037/h0054346

McClelland, D. C. (1961). *The achieving society*. Van Nostrand.

Miller, D. (2003). An asymmetry-based view of advantage: Toward an attainable sustainability. *Strategic Management Journal, 24*(10), 961–976. https://doi.org/10.1002/smj.316

Miller, K. D. (1992). A framework for integrated risk management: Toward the strategic management of uncertainty. *Academy of Management Review, 17*(4), 556–579. https://doi.org/10.5465/amr.1992.4279065

Miller, K. D., & Reuer, J. J. (1996). Measuring organizational downside risk. *Strategic Management Journal, 17*(9), 671–691. https://doi.org/10.1002/(SICI)1097-0266(199611)17:9%3C671::AID-SMJ838%3E3.0.CO;2-1

Mintzberg, H., Ahlstrand, B., & Lampel, J. (1998). *Strategy safari: A guided tour through the wilds of strategic management*. Free Press.

Ndofor, H. A., Sirmon, D. G., & He, X. (2011). Firm resources, competitive actions and performance: Investigating a mediated model with evidence from the in vitro diagnostics industry. *Strategic Management Journal, 32*(6), 640–657. https://doi.org/10.1002/smj.901

Pierce, J. R., & Aguinis, H. (2013). The too-much-of-a-good-thing effect in management. *Journal of Management, 39*(2), 313–338. https://doi.org/10.1177/0149206311410060

Porter, M. E. (1985). *Competitive advantage: Creating and sustaining superior performance*. Free Press.

Porter, M. E. (1996). What is strategy? *Harvard Business Review, 74*(6), 61–78.

Resta, E., Kruglanski, A. W., Ellenberg, M., & Pierro, A. (2023). Ambition-driven aggression in response to significance-threatening frustration. *European Journal of Social Psychology, 53*(7), 1458–1474. https://doi.org/10.1002/ejsp.2988

Rohrbeck, R., & Kum, M. E. (2018). Corporate foresight and its impact on firm performance: A longitudinal analysis. *Technological Forecasting and Social Change, 129*, 105–116. https://doi.org/10.1016/j.techfore.2017.12.013

Sarasvathy, S. D. (2001). Causation and effectuation: Toward a theoretical shift from economic inevitability to entrepreneurial contingency. *Academy of Management Review, 26*(2), 243–263. https://doi.org/10.5465/amr.2001.4378020

Schaefer, T., & Guenther, T. (2016). Exploring strategic planning outcomes: The influential role of top versus middle management participation. *Journal of Management Control, 27*(2–3), 205–249. https://doi.org/10.1007/s00187-016-0227-1

Spence, J. T., & Helmreich, R. L. (1983). Achievement-related motives and behavior. In J. T. Spence (Ed.), *Achievement and achievement motives: Psychological and sociological approaches* (pp. 10–74). W. H. Freeman.

Taleb, N. N. (2012). *Antifragile: Things that gain from disorder*. Random House.

Wang, H., Barney, J. B., & Reuer, J. J. (2003). Stimulating firm-specific investment through risk management. *Long Range Planning, 36*(1), 49–59. https://doi.org/10.1016/S0024-6301(02)00203-7

Chang, J.-Y. (2023). *The effects of resilient organizational strategies on survivability and competitiveness: A loss-process perspective* [Unpublished master's thesis]. Fu Jen Catholic University.

Hsiao, R.-L., Ou, S.-H., & Su, Y. (2017). Power-inversing theory: The process of resource construction through bricolage. *NTU Management Review, 27*(4), 1–32.

Huang, T.-Y. (2021). *The way of managing to overcome the strong with the weak: Validation of power-inversing management factors* [Unpublished master's thesis]. Fu Jen Catholic University.

Teng, S.-T. (2025). *The effects of successors' risk decision-making on performance: Managerial implications of the mediating mechanism of ambition and the moderating effects of developmental trajectories* [Unpublished master's thesis]. Fu Jen Catholic University.

Zhai, W.-M. (2018). *Game theory*. China Overseas Chinese Publishing House.

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Institutional Research in Korean Higher Education: Organization and Practice

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ABSTRACT

Institutional research (IR) has attracted growing attention as higher education institutions seek to use institutional data for quality assurance, performance assessment, planning, and decision-making. In South Korea, IR-related functions are performed through diverse organizational arrangements, including dedicated IR units, performance-management organizations, educational innovation centers, and planning-related departments. This study examines the organization and current practice of IR through an online survey of 177 managers and practitioners affiliated with 104 Korean higher education institutions. The respondents comprised 46 managers and 131 practitioners. Descriptive statistics and content analysis of open-ended responses were used to examine organizational and staffing patterns, the functional scope of IR practice, and priorities for further development. Managers reported an average IR-related unit size of 4.76 staff members, with reported sizes ranging from 2 to 11. Among practitioners, 71.7% had fewer than three years of IR-related experience, and the proportion of their work devoted to IR varied considerably. Data and information management, together with analysis and evaluation, were the most frequently reported areas of IR practice, whereas planning and decision support, although included in reported activity portfolios, was less frequently identified as the main focus of IR. Regarding further development, managers most frequently emphasized data governance, dedicated personnel, and information systems, while practitioners highlighted feedback and the use of analytical results, integrated systems, professional capacity, organizational awareness, and data access. The findings provide empirical evidence on the organization and current practice of IR in Korean universities.

Keywords: Institutional Research, Higher Education, University Organization, Data-informed Decision-making, South Korea

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AI-Driven Categorical Enrollment Prediction for Strategic Institutional Planning and Governance

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ABSTRACT

Enrollment volatility remains a central challenge for strategic enrollment management in higher education because it affects faculty deployment, classroom use, budgeting and institutional planning. Most prior studies have focused on numeric enrollment forecasts or student-level outcomes such as performance and dropout. Fewer studies have examined interpretable categorical prediction designed for institutional governance. This study proposes an eXplainable Artificial Intelligence framework that classifies program-level enrollment into Low, Medium and High enrollment capacity tiers. The analysis uses 775,376 longitudinal enrollment records from 2000 to 2025 aggregated into 3,188 program-term macro cohorts from a private Philippine higher education institution. Seven supervised algorithms were evaluated under a leakage-free expanding window walk-forward design in which tertile thresholds were recomputed inside each training fold. LightGBM achieved the highest performance with an average accuracy of 98.50% and a Macro F1-score of 0.9849 followed by HistGradientBoosting and XGBoost. SHapley Additive exPlanations showed that recent enrollment momentum, especially the 3-term rolling average, previous year enrollment and previous term enrollment, was the primary driver of classification. Demographic composition and external indicators for COVID-19 and K-12 reform added limited incremental predictive value after these momentum features were included, however, it should not be interpreted as evidence that those events lacked institutional effect. Naive baselines confirmed that LightGBM still improved on a rolling-mean rule. The validated model was deployed in an interactive Power BI dashboard that combines capacity tier forecasts to support faculty loading, resource allocation and program review. The contribution is an integrated governance pipeline rather than machine learning prediction alone.

Keywords: Enrollment Prediction, Explainable Artificial Intelligence, Higher Education Governance, Machine Learning Classification

Introduction

Enrollment stability is a structural determinant of institutional sustainability in higher education institutions (HEIs) shaping faculty deployment, curriculum planning and sustainable competitive positioning (Daniel, 2016; Shattock, 2019). In competitive and responsive market systems, enrollment volatility exposes institutions to operational risk (OECD, 2023) making forecasting capacity an essential component of strategic management (Dela Cruz et al., 2020; Loder, 2025). Predictive analytics converts historical administrative data into proactive decision intelligence (Ifenthaler & Yau, 2020); when paired with clear decision thresholds and interpretability mechanisms, it enables administrators to align staffing, classroom capacity and resource distribution with projected student demand (Ayasi et al., 2023). This positioning aligns with strategic enrollment management and institutional risk governance, where the task is not only to forecast demand but to anticipate resource dependence and operational exposure when enrollment moves across capacity bands. However, Artificial Intelligence (AI) for institutional adoption raises legitimate concerns about interpretability and accountability that must be balanced against computational performance (Zawacki-Richter et al., 2019; Arrieta et al., 2020). This study advances an integrated governance-oriented framework that combines categorical capacity tier classification, leakage-aware validation, eXplainable AI (XAI) specifically, SHapley Additive exPlanations (SHAP) and an interactive dashboard to translate longitudinal enrollment data into actionable institutional intelligence for decision-making.

Categorical forecasting reframes continuous enrollment counts into structured decision levels, Low, Medium and High, facilitating interpretability in governance context (Shao et al., 2022). Tree-based and ensemble classifiers particularly, Decision Tree (DT), Random Forest (RF), HistGradientBoosting (HGB), Light Gradient Boosting Machine (LightGBM) and eXtreme Gradient Boosting (XGBoost), alongside Support Vector Machines (SVM) and Gaussian Naïve Bayes (NB), offer complementary strengths for this task. In the Philippine context, the Universal Access to Quality Tertiary Education Act (UAQTEA) reshaped enrollment dynamics by expanding access to public institutions (Dela Cruz et al., 2020) yet institutional research in many Philippine HEIs remains largely descriptive with limited systematic application of AI-driven categorical forecasting.

Although the literature demonstrates growing adoption of AI in higher education analytics, 3 gaps remain evident. First, prior research has predominantly focused on student-level outcomes, particularly, academic performance and dropout risk, while comparatively less attention has been given to institutional enrollment as a basis for strategic governance, capacity planning and resource allocation (Viberg et al., 2018). Second, numeric regression outputs are rarely translated into decision logic categorical frameworks and lastly, predictive models are rarely

integrated with interactive and operational dashboards that translate analytical outputs into actionable insights for institutional governance.

Research Questions

This study addresses 3 gaps through the following research questions:

RQ1. How accurately can supervised ML models (DT, RF, HGB, LightGBM, XGBoost, SVM, NB) classify program-level enrollment into Low, Medium and High capacity tiers using the 26 years of longitudinal data from XYZ College in the Philippines?

RQ2. Which temporal, structural and demographic features most strongly influence the classification of enrollment capacity tiers according to SHAP analysis?

RQ3. How can the validated classification model combined with SHAP explanations and an interactive Power BI dashboard support institutional planning and governance decisions?

Literature Review

HEIs operate amid demographic transitions, intensified competition and growing accountability demands, making enrollment volatility a critical concern for institutional sustainability, resource allocation and long-term planning (Dela Cruz et al., 2020; Guevara-Reyes et al., 2025). Traditional trend analysis offers useful baseline insight but struggles to capture non-linear patterns and structural breaks in large institutional datasets (Eli et al., 2025), motivating the shift toward machine learning (ML) and AI-based forecasting.

Recent studies show ensemble methods such as RF, Gradient Boosting, SVM and XGBoost outperforming traditional techniques in predicting enrollment demand, retention and dropout risk (Dela Cruz et al., 2020; Al Hashmi et al., 2025), although most remain focused on brief temporal accuracy or student-level prediction rather than institutional governance applications. Concerns about model obscurity have further driven the adoption of XAI, enabling stakeholders to interpret and trust predictions that inform critical decisions such as program continuation (Zawacki-Richter et al., 2019; Arrieta et al., 2020). A further limitation of prior work is its emphasis on numeric forecasting; institutional administrators frequently require categorical and actionable insights such as Low, Medium or High expected enrollment, to support scenario planning (Shao et al., 2022). The integration of categorical predictions with XAI and operational decision-support tools remains largely unexplored, particularly using extensive longitudinal data from emerging higher education systems.

Table 1**:** Comparison of the Present Study with Selected Prior Enrollment Forecasting Studies

Study	Prediction Target	Validation Approach	Explainability	Decision Support Tool	Key Distinction of Present Study
Dela Cruz et al. (2020)	Continuous enrollment counts	Traditional time-series	None	None	Categorical tiers + SHAP + dashboard
Slim et al. (2018)	Semester enrollment yield	Seasonal ARIMA + classification	None	None	Leakage-free walk-forward + institutional governance focus
Loder (2025)	Active student numbers	Hybrid ML + ARIMA	Feature selection (RFE)	None	Full SHAP explanations + Power BI deployment
Ayasi et al. (2023)	Course enrollment	Standard train-test	Limited	None	26-year longitudinal data + fold-specific thresholds
Shao et al. (2022)	Course-level enrollment	Static yearly train-test split	Classification + Regression Trees (CART) + RF	None	26-year longitudinal data + fold-specific thresholds + Interactive dashboard
Present Study	Enrollment capacity tiers (Low/Medium/High)	Expanding walk-forward (leakage-free)	SHAP (global + local)	Interactive Power BI dashboard	Integrated governance framework

Table 1 positions the present study relative to selected prior research. While earlier work has made important contributions using time series models or standard ML approaches, most studies have focused on continuous numeric prediction, lacked rigorous leakage-free temporal validation or did not combine model outputs with XAI and operational decision support tools. The current framework advances the literature by integrating categorical capacity tier classification, target discretization, leakage-aware validation, interpretability and an interactive dashboard into an institutional governance analytical framework.

Background of the Study

The Philippine higher education sector comprises state universities and colleges, local universities and colleges and private institutions regulated by the Commission on Higher Education. The UAQTEA broadened access to public institutions and reshaped enrollment dynamics (Dela Cruz et al., 2020), while regional economic disparities and policy-driven expansions continue to influence enrollment patterns. Despite growing digitalization, institutional research in many Philippine HEIs remains predominantly descriptive rather than predictive and systematic categorical enrollment forecasting frameworks remain limited. For institutional research offices in the Philippines and the wider Southeast Asian region, categorical capacity tiers are often more usable than exact headcount forecasts because staffing, classroom assignment and section opening are already decided in bands rather than in precise counts.

Conceptual Framework

Figure 1 presents the conceptual framework guiding this study (adapted from Guevara-Reyes et al., 2025), linking longitudinal institutional data, feature engineering, walk-forward validation (leakage-aware model), XAI and integrating a dashboard decision support tool into a single institutional governance analytical pipeline.

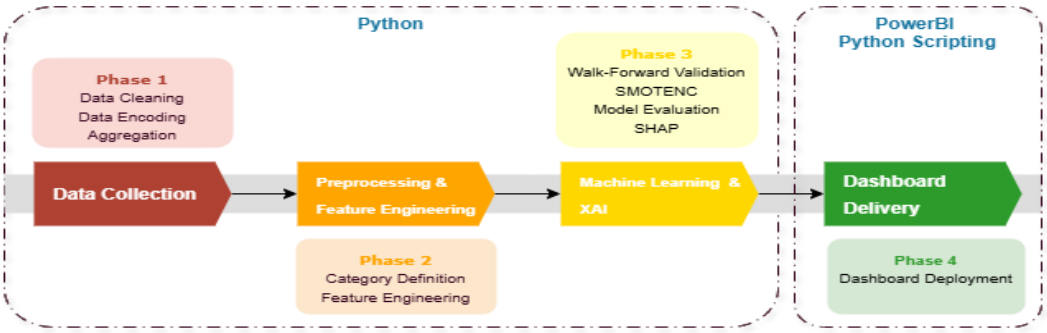


Figure 1**:** Conceptual Framework (Guevara-Reyes et al. 2025)

Methodology

This study adopted a supervised ML framework to develop a multiclass enrollment capacity classification model using longitudinal institutional data following a pipeline of data collection, preprocessing, feature engineering, temporal validation, ML modelling, XAI and dashboard integration.

Data and Cohort Formulation

This study used 775,376 individual student transaction records from the Student Information System of XYZ College in the Philippines covering academic years 2000 to 2025. XYZ College is a private HEI in Metro Manila offering undergraduate and graduate programs across several academic units. The dataset therefore reflects a multi school private HEI rather than a single faculty or a public university. Records were then aggregated into macro cohorts defined by the unique combination of academic year, term, school and program producing 3,188 macro cohort observations. Each observation includes categorical identifiers (school, program), structural indicators (k12_indicator, covid_indicator), demographic proportions (male_perc, female_perc, filipino_perc, dai_perc and ncr_perc), a sequential time index (concatenated year and term) and total enrollment as the continuous outcome variable. All student identifiers were anonymized and obfuscated resulting in a dataset consisting only with structural, numerical

and categorical features prior to analysis with permission obtained from institutional data custodians in accordance with the Philippine Data Privacy Act.

Equal Frequency Discretization

One incomplete observation was removed. To support interpretable governance decisions, total enrollment was discretized into 3 enrollment capacity tiers specifically, Low, Medium and High using equal frequency discretization (tertile cutoffs). To prevent target leakage, the 33.3rd and 66.7th percentile cutoffs were calculated independently within the training portion of each validation fold and applied only to that fold's training and test observations; hence, future observations never contributed to threshold construction. Table 2 reports enrollment capacity tier ranges for the full dataset.

Table 2**:** Enrollment Capacity Ranges Based on the Overall Macro Cohort Distribution

Enrollment Capacity Tiers	Range From	Range To
Low	1	30
Medium	31	172
High	173	Above

Feature Engineering

Feature engineering extracted temporal and structural indicators while reducing statistical redundancy. The academic term was transformed into sine and cosine components to capture seasonal cycles within the academic calendar. Lag features (lag1, lag2, lag3 and lag4) and rolling averages (rolling_mean_3 and rolling_mean_6) were constructed strictly from past observations within each macro cohort to represent enrollment momentum without lookahead. Year was dropped due to near perfect collinearity with the time index.

Walk-Forward Validation

Because enrollment records are sequential, random train-test splitting would introduce lookahead bias. The study instead used a 4-fold expanding window walk-forward design. Table 3 shows that the training set grew chronologically while testing was confined to subsequent unseen terms, with capacity tier thresholds reestimated within each fold as described above. Synthetic Minority Oversampling Technique for Nominal and Continuous features (SMOTENC) oversampling, feature scaling and model fitting were performed exclusively on each fold's training data and test data were held out in original form for evaluation.

Table 3**:** Expanding Window Validation

Fold	Training Period	Training Rows	Testing Period	Testing Rows	Low/Medium Cutoff	Medium/High Cutoff
1	20001 to 20164	2064	20171 to 20183	217	27.00	159.30
2	20001 to 20183	2281	20184 to 20203	244	28.00	166.00
3	20001 to 20203	2525	20211 to 20231	290	29.00	169.00
4	20001 to 20231	2815	20232 to 20252	373	29.00	173.00

Modeling, Explainability and Deployment

Seven classifiers were trained particularly, DT, RF, HGB, LightGBM, XGBoost, SVM and NB were evaluated using accuracy, macro precision, macro recall and macro F1-score all averaged across folds. Explainability analysis was subsequently conducted for the best performing model using TreeExplainer, combining global feature attribution to identify the principal drivers of enrollment tier classification with local beeswarm analysis to examine the direction and magnitude of feature effects for the High capacity tier.. The final model was deployed in an interactive Power BI dashboard combining enrollment trajectories, color coded capacity bands filterable by school and program. Dataset, python scripts, feature dictionary table and Power BI Dashboard are publicly available (github.com/jeffatendido/paper-P26043); the raw dataset is withheld to protect institutional records, consistent with data governance and ethics requirements.

Analysis and Results

Table 4 summarizes cross validation performance across the seven classifiers. LightGBM achieved the strongest average results (accuracy = 98.50%, Macro F1 = 0.9849) closely followed by HGB and XGBoost while distance-based and probabilistic classifiers, SVM and NB performed markedly worse, reflecting limited suitability for the data's temporal structure.

Table 4**:** Cross-Validated Predictive Performance Summary

Model Name	Average Accuracy	Average Macro Precision	Average Macro Recall	Average Macro F1-Score
LightGBM	0.9850	0.9856	0.9844	0.9849
HGB	0.9789	0.9797	0.9781	0.9788
XGBoost	0.9670	0.9679	0.9649	0.9661
RF	0.9591	0.9595	0.9584	0.9585
DT	0.9324	0.9333	0.9325	0.9323
SVM	0.8275	0.8339	0.8212	0.8223
NB	0.5718	0.6128	0.5933	0.5626

To test whether this performance simply reflected historical persistence, three naive baselines were evaluated under an identical protocol using the same fold-specific thresholds (Table 5): previous-term persistence (Macro F1 = 0.6074), a rolling-mean threshold rule (0.8889) and

lag-only logistic regression (0.8686). LightGBM outperformed the strongest baseline by approximately 9.6 percentage points in Macro F1, indicating that the full feature set and gradient boosting architecture add significant value beyond simple rules based on momentum.

Table 5**:** Naive Baseline Performance

Baseline	Average Accuracy	Average Macro F1
Previous-term Persistence	0.6264	0.6074
Rolling-mean Rule	0.8923	0.8889
Lag-only Logistic Regression	0.8690	0.8686

SHAP analysis of the LightGBM model (Figure 2A) identified recent enrollment momentum as the dominant driver of prediction. The rolling_mean_3 or 3-term rolling average, contributed most strongly and more than double the next ranked feature, followed by prev_year_enrollment, prev_term_enrollment, re_enrollment_rate and the rolling_mean_6 or 6-term rolling average. Structural identifiers (program, school), the sequential time index, demographic proportions and the COVID-19 and K-12 reform indicators each registered comparatively low mean SHAP values, indicating limited incremental predictive contribution once historical enrollment momentum was accounted for. This limited incremental contribution inside the model should not be interpreted as evidence that program identity, school context or the pandemic and K-12 transition were without real institutional effect on enrollment outcomes. Their influence is most plausibly already embedded within the momentum features themselves, since rolling averages and lagged enrollment implicitly carry forward any specific program, school or period shifts that occurred in prior terms.

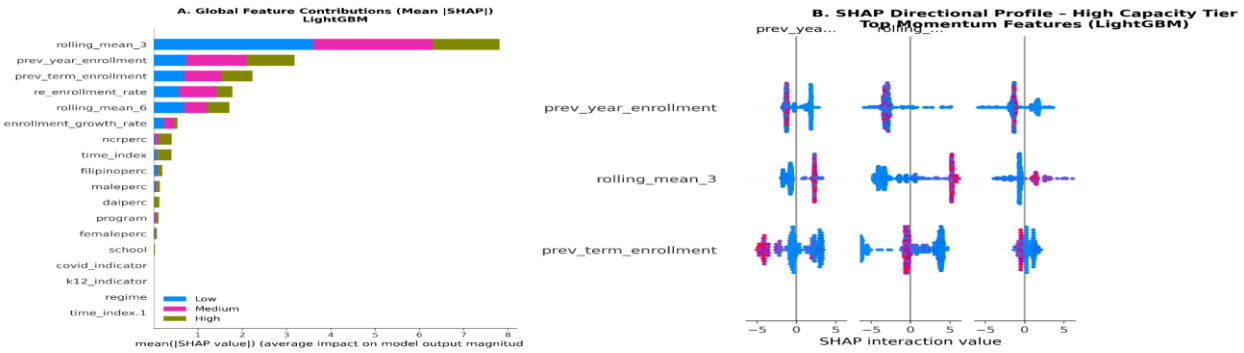


Figure 2: (A) Global Feature Contributions via Mean Absolute SHAP
(B) SHAP Directional Performance Profile for High Capacity Target Tier

The beeswarm profile for the High capacity tier (Figure 2B) shows that higher values of the 3-term rolling average, previous year enrollment and previous term enrollment push predictions

toward the High capacity tier. Lower values of these same features pull predictions away from that tier. Reading together with Table 5, this indicates that LightGBM's advantage over the rolling-mean rule comes from combining the dominant momentum signal with secondary lagged and rate based features, rather than from a different set of drivers. The validated model was embedded in an interactive Power BI dashboard that overlays enrollment trajectories with color coded capacity bands and SHAP explanations, filterable by school or program, functioning as an operational early warning system for faculty loading, section planning and resource allocation.

Discussions and Implications

Theoretical and Substantive Discussion

These results confirm a core assumption in enrollment forecasting. Under a leakage-free design, recent enrollment momentum was the main basis on which capacity tiers could be anticipated. The 3-term rolling average, previous year enrollment, previous term enrollment, reenrollment rate and 6-term rolling average dominated the LightGBM predictions. This replicates the emphasis on lagged information in Dela Cruz et al. (2020), Slim et al. (2018) and Loder (2025) and extends that work by using SHAP to show the size of the imbalance. The 3-term rolling average contributed more than twice the next ranked feature.

This pattern differs from recent SHAP studies of student level outcomes. Al Hashmi et al. (2025) found withdrawn semesters to be the main driver of dropout risk. Guevara Reyes et al. (2025) identified mathematics proficiency and student-teacher ratio as leading predictors of examination performance. Ahmed et al. (2025) reported that previous scores accounted for most of the explained variance in student performance indices. At the institutional capacity tier level examined here, short term enrollment velocity outweighs program and school identities, demographic composition and external disruption indicators.

The low SHAP contribution of program and school identities, the time index and the COVID-19 and K-12 indicators should be read as limited incremental predictive value once momentum features are already in the model. It should not be interpreted as evidence that these factors lack real institutional relevance. Their effects are most plausibly already carried forward inside the momentum features themselves.

From a governance standpoint, categorical capacity classification remains useful. University leaders rarely need an exact headcount. They need a reliable signal that a program is likely to

operate in a Low, Medium or High capacity regime so that faculty loading, classroom allocation and budget decisions can be adjusted in advance.

Because the dominant features are recent rolling averages and lagged enrollment, the model is strongest as a short term capacity tier warning system. It should not be treated as a medium term causal forecast of why demand will rise or fall.

Methodological Implications

The main contribution is not the use of ML itself. It is the assembly of a leakage-aware, interpretable and governance aligned pipeline. The expanding window walk-forward design, with tertile thresholds recomputed inside each training fold, is a more rigorous standard for longitudinal educational data than randomized train-test splits. The comparison of seven algorithms under the same temporal constraints showed a consistent advantage for gradient boosting. SHAP then made the best model auditable by showing that predictions rest primarily on recent enrollment trajectory.

The naive baselines are essential to this claim. Previous-term persistence performed poorly (Macro F1 = 0.6074). The rolling-mean rule was much stronger (Macro F1 = 0.8889), which is expected once SHAP has shown that rolling averages dominate. Even so, LightGBM improved Macro F1 to 0.9849, a gain of about 9.6 percentage points over the strongest baseline. The model therefore adds value beyond a simple historical threshold rule.

Practical and Institutional Implications

Because predictions are anchored in each program's recent enrollment trajectory, the outputs can update each term as new data arrive. Programs whose momentum consistently points toward the High capacity tier can be prioritized for additional sections, classroom reservations and faculty recruitment. Programs trending toward Low capacity can be reviewed for consolidation or targeted recruitment. Embedding SHAP explanations in the Power BI dashboard allows non-technical stakeholders to see that a given forecast is driven by recent enrollment trends rather than an opaque mix of factors. That supports accountability and faster translation of analytics into operational decisions.

Potential Applicability

Although the study was conducted in one private Philippine HEI, the pipeline can be transferred in principle to state universities, local colleges and other private institutions. The same design

can also support related forecasting tasks such as faculty workload planning, program viability review, classroom demand projection and program-level retention risk classification. Successful transfer depends on consistent longitudinal records and local retraining.

Ethical Considerations and Governance Risk

A momentum based model carries a specific governance risk. Because it relies so heavily on a program's own recent history, it may be least reliable where administrators most need foresight on newly launched programs, programs undergoing deliberate strategic change or periods of abrupt external disruption. There is also an equity risk. A model that follows historical momentum may keep directing resources toward already large programs and away from smaller or newer programs that the institution may wish to grow. In those cases, recent momentum is a poor guide to what comes next. SHAP explanations help administrators recognize when a forecast rests almost entirely on historical persistence (Holmes et al., 2022), but transparency alone does not resolve the limitation. Predictions should remain a decision support tool rather than automated decisions. Academic leaders must retain the authority to override model outputs when qualitative information, equity goals or strategic priorities indicate a different course of action.

Conclusion

This study developed and validated an explainable ML framework for categorical enrollment capacity prediction to support institutional planning and governance. Using 775,376 longitudinal student records from 2000 to 2025, aggregated into 3,188 program-term macro cohorts, seven algorithms were compared under a leakage-free expanding window walk-forward design with fold-specific tertile thresholds. LightGBM was the strongest classifier, with an average accuracy of 98.50% and a Macro F1 score of 0.9849.

SHAP analysis showed that recent enrollment momentum drove classification. The 3-term rolling average, previous year enrollment, previous term enrollment, reenrollment rate and 6-term rolling average ranked far above program and school identities, demographic composition and the COVID-19 and K-12 indicators. This should be read as limited incremental predictive value for those secondary features once momentum is already in the model, not as evidence that they lack real institutional effect. Enrollment capacity in this setting is therefore strongly path dependent, a program's recent trajectory is the most useful signal of whether it will fall into a Low, Medium or High capacity tier.

The model still adds value beyond simple persistence. Previous-term persistence performed poorly. The rolling-mean rule was much stronger, as expected given the SHAP ranking, yet LightGBM improved Macro F1 by about 9.6 percentage points over that strongest baseline. The advantage comes from combining the dominant momentum signal with secondary features and non-linear learning, not from an entirely different set of drivers.

By integrating leakage-aware validation, categorical capacity classification, SHAP interpretability and interactive Power BI deployment, the framework moves beyond conventional numeric forecasting. It supplies administrators with transparent, decision ready signals for faculty loading, classroom allocation and program review. The main contribution is this governance aligned pipeline, not the use of ML alone.

Limitations

Several limitations qualify these findings. The analysis draws on a single private HEI in the Philippines. The longitudinal coverage is substantial, but the results may not generalize to state universities, local colleges or institutions operating under different regulatory or market conditions. Aggregation into macro cohorts discards student level heterogeneity. The absence of external validation leaves the observed dominance of momentum features untested in other settings.

Because predictions rely so heavily on recent enrollment history, the framework is most reliable for programs with established trajectories. It may perform less well for newly launched programs, programs undergoing deliberate strategic change or periods of abrupt disruption. The Power BI dashboard has not yet been formally evaluated with institutional administrators. SHAP values indicate association rather than causation. Also, SHAP attributions also assume that features can be examined separately, even though lag and rolling features are correlated. The rankings should therefore be read as a description of model reliance, not as independent causal effects. Concept drift arising from policy, demographic or labor market shifts has also not been systematically monitored.

Future Research

Future research should test the framework across multiple Philippine and Southeast Asian institutions. External data streams, such as senior high school graduation volumes and regional labor market indicators, should be added to improve sensitivity to structural shifts. Sequential deep learning architectures, including Long Short Term Memory networks, Gated Recurrent

Units and Temporal Fusion Transformers, should be compared with LightGBM under the same expanding window design.

A further step is the move from prediction to prescription, using optimization routines to recommend section merging or faculty reallocation under human oversight. Prospective usability studies with registrars, deans and planning officers are needed to assess trust and decision impact. Mechanisms for detecting concept drift and triggering retraining should also be developed. A practical updating rule is to retrain the model when Macro F1 on the most recent terms falls below the rolling-mean baseline or when the SHAP rank of the 3-term rolling average changes substantially. Finally, research should examine the organizational conditions that shape adoption, including data culture, collaboration between institutional research and information technology units, leadership support and change management.

Additional robustness checks, including fold level error analysis, class wise metrics, ablation of lag and rolling features and alternative capacity thresholds, should be reported in a follow up multi institution study. Lastly, future work should also test program-specific capacity thresholds and evaluate the dashboard in a prospective real-time deployment with registrars and deans.

Declaration on the use of AI in the writing process

During the preparation of this study, the authors used ChatGPT to enhance readability and refine the language, as well as other AI tools for data visualization. After using these tools or services, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

References

Ahmed, W., Wani, M. A., Plawiak, P., Meshoul, S., Mahmoud, A., & Hammad, M. (2025). Machine learning-based academic performance prediction with explainability for enhanced decision-making in educational institutions. *Scientific Reports*, *15*(1). https://doi.org/10.1038/s41598-025-12353-4

Al Hashmi, R. A. M., D. Zervopoulos, P., M. Elmehdi, H., & Ozturk, I. (2025). Predicting dropout in MENA STEM higher education using explainable AI: a machine learning approach. *Emerging Science Journal*, *9*, 268–286. https://doi.org/10.28991/esj-2025-sied1-016

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., Garcia, S., Gil-Lopez, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2020). Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI. *Information Fusion*, *58*, 82–115. https://doi.org/10.1016/j.inffus.2019.12.012

Ayasi, B., Saleh, M., Gracia-Vico, Á . M., & Carmona, C. (2023). Predicting Course Enrollment with Machine Learning and Neural Networks: A Comparative Study of Algorithms. *Studies on Social and Education Sciences 2023*, 157–182. ISTES Organization.

Daniel, B. K. (2016). *Big data and learning analytics in higher education*. Springer London, Limited.

Dela Cruz, A. P., Basallo, Ma. L. B., Bere III, B. A., Aguilar, J. B., Calvo, C. K. P., Arroyo, J. C. T., & Delima, A. J. P. (2020). Higher education institution (HEI) enrollment forecasting using data mining technique. *International Journal of Advanced Trends in Computer Science and Engineering*, *9*(2), 2060–2064. https://doi.org/10.30534/ijatcse/2020/179922020

Eli, A. A., Rahman, A., & Kshetri, N. (2025). D3s3real: Enhancing student success and security through real-time data-driven decision systems for educational intelligence. *Digital*, *5*(3), 42. https://doi.org/10.3390/digital5030042

Guevara-Reyes, R., Ortiz-Garcés, I., Andrade, R., Cox-Riquetti, F., & Villegas-Ch, W. (2025). Machine learning models for academic performance prediction: Interpretability and application in educational decision-making. *Frontiers in Education*, *10*. https://doi.org/10.3389/feduc.2025.1632315

Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., Shum, S. B., Santos, O. C., Rodrigo, M. T., Cukurova, M., Bittencourt, I. I., & Koedinger, K. R. (2022). Ethics of AI in education: Towards a community-wide framework. *International Journal of Artificial Intelligence in Education*, *32*(3), 504–526. https://doi.org/10.1007/s40593-021-00239-1

Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development*, *68*(4), 1961–1990. https://doi.org/10.1007/s11423-020-09788-z

Loder, A. K. F. (2025). Machine learning for university management: Micro Cluster Learning

to predict “active” students. *Studies in Educational Evaluation*, *85*, 101463. https://doi.org/10.1016/j.stueduc.2025.101463

OECD. (2023). *Education at a glance 2023: OECD indicators*. OECD Publishing. https://doi.org/10.1787/e13bef63-en

Shao, L., Ieong, M., Levine, R. A., Stronach, J., & Fan, J. (2022). Machine Learning Methods for Course Enrollment Prediction. *Strategic Enrollment Management Quarterly*, *10*(2).

Shattock, M., & Horvath, A. (2019). *The governance of British higher education: The impact of governmental, financial and market pressures*. Bloomsbury Academic.

Slim, A., Hush, D., Ojah, T., & Babbitt, T. (2018). Predicting Student Enrollment Based on Student and College Characteristics. *International Educational Data Mining Society*.

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior*, *89*, 98–110. https://doi.org/10.1016/j.chb.2018.07.027

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1). https://doi.org/10.1186/s41239-019-0171-0

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Beyond Campus Facilities: Institutional Identification and the Divergent Pathways to International Students' Further Study and Employment Intentions in Taiwan

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ABSTRACT

This study examines how international students' campus experiences are associated with institutional identification and their intentions to pursue further study or employment in Taiwan. Drawing on an institutional research perspective, the study uses survey data from 142 international students at a private university in central Taiwan. The questionnaire covered demographic background, learning feedback, teaching quality, language and cultural exchange activities, campus support services and facilities, institutional identification and willingness to recommend the university, and post-graduation intentions. In this study, institutional identification and willingness to recommend the university were treated as a single composite construct rather than as analytically distinct outcomes. Hierarchical multiple regression was first used to identify predictors of institutional identification. Hierarchical binary logistic regression was then applied to examine the factors associated with further study intention and employment intention. Random forest classification was used as an exploratory predictive analysis to supplement the regression models. The results show that institutional identification was associated with multiple dimensions of campus experiences, especially living convenience and safety support, campus integration and administrative support, language and cultural exchange activities, teaching quality, and scholarship support. For further study intention, learning feedback was the most consistent predictor. In contrast, institutional identification emerged as the key predictor of employment intention. The random forest results provided supplementary evidence but also highlighted the limitation of class imbalance. As a single-institution, cross-sectional study, these findings should be interpreted as associational rather than causal, and the random forest results should be read as exploratory rather than confirmatory. The findings suggest that international student support should move beyond isolated facility improvements. Universities should integrate learning, administrative, living,

cultural, and career support to build an inclusive campus environment that supports institutional identification and informs evidence-based recruitment and retention strategies.

Keywords: International Students, Institutional Identification, Further Study Intention, Employment Intention, Institutional Research, Random Forest

Introduction

As higher education becomes increasingly internationalized and cross-border talent mobility intensifies, recruiting and cultivating international students has become more than an indicator of university internationalization. It has also become a pathway through which countries attract, develop, and retain global talent and sustain national competitiveness (Choudaha & de Wit, 2014; OECD, 2025, 2026). For Taiwan, international students are relevant not only to university internationalization but also to long-term issues such as demographic decline, enrollment pressure, labor shortages, and talent development.

International students' decisions to remain in a host country after graduation are not determined solely by recruitment policies or employment opportunities. Prior research indicates that students' intentions are influenced by a combination of personal background, learning experience, host-country adjustment, labor-market expectations, and institutional support (Baruch et al., 2007; Kruanak & Ruangkanjanases, 2014). Campus experience is therefore a critical institutional factor. Positive teaching interactions, academic support, administrative assistance, living support, and intercultural exchange may contribute to students' sense of belonging and institutional identification, which in turn may influence future study or employment decisions.

This study examines international students at a private university in central Taiwan. It asks three questions: (1) Which campus experience factors predict institutional identification and willingness to recommend the university? (2) Which factors are associated with international students' intention to pursue further study in Taiwan? (3) Which factors are associated with their intention to work in Taiwan? By combining hierarchical regression and random forest classification, this study seeks to provide evidence that can support institutional decision-making, international student advising, campus support design, and talent retention strategies.

The main contribution of this study lies in distinguishing between two post-graduation pathways rather than treating retention as a single outcome. Further study intention and employment intention are associated with different dimensions of the student experience, suggesting that "further-study retention" and "employment retention" may require different

institutional strategies. The former appears more closely related to academic feedback and advising, whereas the latter is more strongly associated with institutional identification and broader administrative, living, and cultural support. From an institutional research perspective, this distinction offers a basis for differentiated, evidence-informed retention strategies.

Literature Review

International Student Mobility and Post-Graduation Intentions

International student mobility has become increasingly connected to national talent strategies. Host countries and higher education institutions now compete not only to recruit international students, but also to retain graduates who can contribute professional skills, linguistic competencies, and intercultural knowledge to the host society. The OECD (2026) notes that although many international students intend to remain in the host country after graduation, their actual post-graduation pathways are shaped by factors such as visa and permit arrangements, recognition of qualifications, employment opportunities, and integration into the host society.

Studies on international students' intention to remain in a host country further suggest that post-graduation plans are multidimensional and should be understood within broader processes of brain gain, brain circulation, and talent retention. Baruch et al. (2007) found that international students' inclination to stay abroad after their studies was influenced by perceptions of host-country labor markets, adjustment processes, and family or social ties. Similarly, Kruanak and Ruangkanjanases (2014) showed that foreign students' intention to remain in Thailand after graduation was shaped by life and study adjustment, social support, and career perceptions. Evidence from South Korea also indicates that academic satisfaction, social adjustment, and life satisfaction were positively associated with Global Korea Scholarship students' intention to stay in the host country for work or further study after graduation (Istad et al., 2021). In the Taiwan context, Mntshali et al. (2017) found that international students' intention to work in Taiwan after graduation was shaped by personal factors, university experiences, and labor-market considerations.

Taken together, these studies suggest that universities should not examine international students' post-graduation retention intentions solely from the perspectives of employment opportunities or immigration policies. Instead, greater attention should be paid to how academic experiences, campus support, cultural integration, institutional identification, and perceived career opportunities jointly influence students' future decisions to remain in the host country. This perspective provides the conceptual foundation for the present study, which examines how international students' learning feedback, campus support experiences, and

institutional identification are associated with their intentions to pursue further study or employment in Taiwan. In this study, learning feedback refers to students' perceived learning progress, academic gains, and positive evaluation of learning outcomes.

Campus Experience, Belonging, and Institutional Identification

Student persistence and future engagement are closely linked to academic and social integration. Tinto's (1993) theory of student retention emphasizes that institutional action should create inclusive academic and social communities. For international students, belonging is especially important because they must navigate academic expectations, language barriers, cultural adjustment, and daily-life adaptation simultaneously.

Belonging and cross-cultural interaction have been shown to support international students' academic success and campus engagement (Glass & Westmont, 2014). In this study, institutional identification refers to students' overall sense of trust, belonging, positive evaluation, and willingness to recommend the university. This construct is treated as an attitudinal outcome of campus experience and as a potential predictor of future intention. Willingness to recommend the university was treated as an integral component of this composite construct rather than as an analytically distinct outcome. The two elements were therefore combined into a single mean score, hereafter referred to as institutional identification.

Differentiating Further Study and Employment Intentions

Learning experiences and campus support services are important factors in shaping international students' post-graduation intentions. In this study, learning feedback refers to students' perceived learning progress, academic gains, and positive evaluation of learning outcomes. This is conceptually distinct from teaching quality, which in this study refers to students' evaluation of instructors' teaching effectiveness and classroom delivery; learning feedback captures students' perception of their own academic progress, whereas teaching quality captures their evaluation of the instruction they receive. For students considering further study, learning feedback and teaching quality may be particularly important because continuing education requires students to believe that they are academically progressing and are capable of meeting future academic demands. Positive learning feedback may therefore strengthen students' confidence in their academic development and increase their willingness to pursue further study in the host country.

By contrast, employment intention may depend more strongly on students' overall institutional identification and their perception that the university supports their transition to the host society

and labor market. Campus support services, administrative responsiveness, language and cultural exchange activities, and a welcoming campus environment may help international students develop a stronger sense of belonging and trust in the institution. These experiences may not only improve students' satisfaction during their studies, but also shape whether they view the host country as a viable place for future work and development. Accordingly, this study distinguishes between intention to pursue further study and intention to work in Taiwan, assuming that these two post-graduation pathways may be influenced by different mechanisms. This reasoning extends Tinto's (1993) integration framework beyond academic persistence. In a cross-border context, the belonging and institutional trust associated with continued enrollment may extend to students' broader willingness to remain in the host society, making institutional identification a theoretically plausible antecedent of employment intention.

Regression and Predictive Analytics in Institutional Research

Traditional regression models are well suited to explaining the direction and strength of relationships between predictors and outcomes. In institutional research, such models are useful for identifying whether student background factors, learning experiences, or campus support variables are significantly associated with educational outcomes. However, higher education data may also involve nonlinear relationships, complex interactions among variables, and imbalanced outcome categories. Educational data mining research suggests that machine learning methods can support institutional decision-making by identifying students who may need additional support and by ranking the relative importance of predictors (Beaulac & Rosenthal, 2019; Yadav et al., 2012).

Random forest is a supervised machine learning method that builds and aggregates multiple decision trees and provides both predictive performance indicators and feature-importance estimates (Breiman, 2001). This makes it useful as a supplementary tool for examining whether predictors identified through regression models also appear important in a predictive classification context. Accordingly, this study uses regression models as the primary explanatory approach and random forest classification models as supplementary predictive analyses for students' intentions to pursue further study and employment in Taiwan.

Methodology

Research Design and Participants

This study adopted a quantitative single-case design focused on international students at a private university in central Taiwan. Data were collected through a structured questionnaire

covering demographic background, learning feedback, teaching quality, satisfaction with campus support services and facilities, language and cultural exchange activities, institutional identification and willingness to recommend the university, and post-graduation intentions.

A total of 142 valid responses were collected. The sample included 73 female students (51.41%) and 69 male students (48.59%). Vietnamese students formed the largest group (n = 73, 51.41%), followed by Indonesian students (n = 41, 28.87%). The remaining 28 students (19.72%) came from other countries. In terms of academic program, 84 students (59.15%) were enrolled in the International Foundation Program, 31 students (21.83%) in graduate programs, and 27 students (19.01%) in bachelor's programs.

Ethical Considerations

This research adhered to institutional research ethical guidelines. All participants provided explicit informed consent prior to participating. Participation was entirely voluntary, and survey responses were collected anonymously to protect participants' privacy. No directly identifying information was included in the analytical dataset, and the results are reported only in aggregate form.

Measures and Variable Construction

All multi-item constructs were measured using five-point Likert-type scales, with higher scores indicating more positive evaluations. Table 1 reports the construct definitions, item counts, representative items, and internal-consistency estimates.

The campus-support dimensions were examined using principal axis factoring with Promax rotation and Kaiser normalization. One attention-check item was excluded from construct scoring and factor analysis. Following an initial EFA of 21 substantive items, library resources, accommodation arrangement, and academic or learning support were removed because of low primary loadings, insufficient separation between factor loadings, or limited conceptual consistency. The final 18-item analysis showed satisfactory sampling adequacy, KMO = .887, Bartlett's $\chi^2(153) = 1027.556$, $p < .001$, and yielded three factors accounting for 67.47% of the extracted variance: campus integration and administrative support (9 items), living convenience and safety support (6 items), and learning and career development support (3 items). Items were assigned primarily according to their highest pattern coefficients and conceptual interpretability. The final pattern matrix is presented in Table 2.

Table 1: Construct Definitions, Item Counts, and Reliabilities.

Construct	Items	Cronbach's α	Sample Item
Learning Feedback	5	.79	I can apply what I have learned in class to real-life situations or projects.
Teaching Quality	6	.87	The instructor explained concepts in an easy-to-understand way.
Language & Cultural Exchange	1	—	Language and cultural exchange activities
Campus Integration & Administrative Support	9	.95	Administrative assistance (registration, visa, insurance, systems)
Learning & Career Development Support	3	.89	Career counseling
Living Convenience & Safety Support	6	.88	Campus safety and emergency assistance
Institutional Identification	5	.93	I feel a sense of belonging to the university's campus and learning atmosphere.

The binary outcomes were coded 1 for positive intention and 0 for uncertain, low, or no intention. Further-study intention included 124 positive cases (87.3%) and 18 nonpositive cases (12.7%); employment intention included 121 positive cases (85.2%) and 21 nonpositive cases (14.8%).

Table 2: Pattern Matrix for the Final Exploratory Factor Analysis of Campus-Support Items.

Item	**Factor 1**	**Factor 2**	**Factor 3**
YouTalk Lounge communication space	.965		
Scholarship information	.824		
Muslim prayer room	.675		
Administrative assistance (registration, visa, insurance, systems)	.657		
On-campus job matching	.592		
Student clubs and activities	.590		
Internship matching	.579		
Medical and health care services	.565		
Job fairs	.525		.392
Transportation convenience		.815	
Campus life facilities		.795	
Food quality and dining environment		.522	.380
Campus safety and emergency assistance	.346	.513	
Dormitory self-cooking facilities	.402	.495	

Off-campus housing information	.344	.456	
Career workshops or lectures			.962
Career counseling			.860
Company visits	.558		.583
Initial eigenvalue	10.856	1.120	1.076
Extracted variance, %	58.562	4.657	4.253
Cumulative extracted variance, %	58.562	63.218	67.471

Note. N = 142. Principal axis factoring with Promax rotation and Kaiser normalization was conducted on 18 campus-support items. Pattern coefficients below .30 were suppressed.

Conceptual Model

This study proposes a conceptual model examining how international students' campus experiences are associated with institutional identification and their future intentions in Taiwan. Campus experience variables include learning feedback, teaching quality, language and cultural exchange activities, and three dimensions of campus support: campus integration and administrative support, learning and career development support, and living convenience and safety support.

Institutional identification is treated as an attitudinal outcome of students' campus experiences and as a potential predictor of two post-graduation outcomes: intention to pursue further study in Taiwan and intention to work in Taiwan. Overall, the model reflects a sequential framework linking students' background and campus experiences to institutional identification and, subsequently, to their future study and employment intentions. The study does not estimate or claim a formal mediation effect, the proposed sequence is conceptual, and the empirical analyses test associations only.

Analytical Strategy

Descriptive statistics summarized the sample characteristics, main variables, and outcome distributions. Hierarchical multiple regression examined factors associated with institutional identification. Demographic variables, academic experiences, language and cultural exchange, and the three EFA-derived campus-support dimensions were entered sequentially. Changes in R^2, standardized coefficients, and variance inflation factors were examined.

Separate hierarchical binary logistic regression models were estimated for further-study and employment intentions using the same sequential blocks, followed by institutional identification. Model fit was assessed using omnibus tests, pseudo-R^2, Hosmer–Lemeshow

tests, odds ratios, and 95% confidence intervals. Given the imbalanced outcomes, classification performance was evaluated using accuracy, sensitivity, specificity, balanced accuracy, precision, recall, and F1 at a cutoff of .50.

Random forest was used as a supplementary exploratory analysis and evaluated using out-of-bag accuracy, test accuracy, and AUC. No class weighting or resampling was applied; therefore, minority-class performance and feature-importance results were interpreted cautiously.

Results

Predictors of Institutional Identification

A hierarchical multiple regression analysis was conducted to examine predictors of institutional identification. In this study, institutional identification refers to the composite construct combining institutional identification and willingness to recommend the university.

The final model explained a substantial proportion of variance, $R^2 = .700$, adjusted $R^2 = .669$, $F(13, 128) = 22.964$, $p < .001$. All VIF values were below 3.5, indicating no multicollinearity concerns. Significant positive predictors included living convenience and safety support ($\beta = .284$, $p = .001$), campus integration and administrative support ($\beta = .234$, $p = .008$), language and cultural exchange activities ($\beta = .220$, $p = .002$), teaching quality ($\beta = .194$, $p = .011$), and scholarship support ($\beta = .110$, $p = .033$). Among the control variables, being enrolled in a bachelor's program showed a negative association with institutional identification compared to the International Foundation Program ($\beta = -.124$, $p = .039$), while scholarship support remained a stable positive predictor. Table 3 details the full multiple regression model.

Table 3: Final Hierarchical Multiple Regression Predicting Institutional Identification.

Predictor	B	SE	β	*t*	*p*	95% CI for B	VIF
Constant	0.159	0.339	—	0.469	.640	[-0.512, 0.830]	—
Nationality: Indonesia	-0.065	0.082	-.047	-0.799	.426	[-0.227, 0.096]	1.469
Nationality: Other	-0.001	0.103	.000	-0.005	.996	[-0.204, 0.203]	1.789
Program: Bachelor's	-0.199	0.095	-.124	-2.085	.039	[-0.388, -0.010]	1.503
Program: Graduate	-0.122	0.096	-.080	-1.272	.206	[-0.312, 0.068]	1.689
Study period: 6–24 months	0.029	0.101	.020	0.290	.772	[-0.170, 0.228]	1.932
Study period: 2 years or more	-0.017	0.084	-.012	-0.200	.842	[-0.183, 0.150]	1.584

Scholarship support	0.160	0.074	.110	2.161	.033	[0.013, 0.306]	1.108
Learning feedback	-0.136	0.089	-.113	-1.520	.131	[-0.313, 0.041]	2.349
Teaching quality	0.241	0.093	.194	2.581	.011	[0.056, 0.425]	2.413
Language and cultural exchange	0.186	0.058	.220	3.179	.002	[0.070, 0.301]	2.037
Living convenience and safety support	0.319	0.091	.284	3.490	.001	[0.138, 0.500]	2.819
Learning and career development support	0.089	0.079	.090	1.135	.259	[-0.066, 0.245]	2.695
Campus integration and administrative support	0.280	0.104	.234	2.687	.008	[0.074, 0.486]	3.249

Note. N = 142. The dependent variable was institutional identification. Vietnam, the International Foundation Program, and the shortest study-period category were the reference groups. B = unstandardized coefficient; SE = standard error; CI = confidence interval; VIF = variance inflation factor.

Factors Associated with Intention to Pursue Further Study in Taiwan

The logistic regression results showed that learning feedback was the most consistent factor associated with intention to pursue further study. When only demographic variables were entered, the initial model was not significant, $\chi^2(7) = 4.811$, $p = .683$. However, adding learning feedback and teaching quality significantly improved the model, $\Delta\chi^2(2) = 11.354$, $p = .003$, increasing the Nagelkerke R^2 to .202. Learning feedback was a significant positive predictor, Exp(B) = 6.703, $p = .008$. In the final model (Nagelkerke $R^2 = .256$), learning feedback remained significant, Exp(B) = 8.703, $p = .010$, whereas teaching quality, cultural exchange, campus support, and institutional identification were not significant (see Table 4). Because the confidence interval was wide and the outcome was imbalanced, the magnitude of this association should be interpreted cautiously.

Table 4: Binary Logistic Regression Predicting Intention to Pursue Further Study.

Predictor	***B***	***SE***	**Wald χ^2**	***p***	**OR**	**95% CI for OR**
Nationality: Indonesia	-0.376	0.682	0.304	.581	0.686	[0.180, 2.615]
Nationality: Other	1.150	1.103	1.086	.297	3.157	[0.363, 27.428]
Program: Bachelor's	-0.411	0.859	0.229	.632	0.663	[0.123, 3.571]
Program: Graduate	-0.751	0.911	0.679	.410	0.472	[0.079, 2.814]
Study period: 6–24 months	0.114	0.921	0.015	.902	1.121	[0.184, 6.819]
Study period: 2 years or more	-0.276	0.731	0.143	.706	0.759	[0.181, 3.178]

Scholarship support	-0.272	0.758	0.129	.719	0.762	[0.172, 3.366]
Learning feedback	2.164	0.844	6.572	.010	8.703	[1.664, 45.505]
Teaching quality	-0.716	0.840	0.727	.394	0.489	[0.094, 2.534]
Language and cultural exchange	0.193	0.474	0.166	.684	1.213	[0.479, 3.074]
Living convenience and safety support	-0.614	0.885	0.481	.488	0.541	[0.095, 3.069]
Learning and career development support	-1.156	0.806	2.056	.152	0.315	[0.065, 1.528]
Campus integration and administrative support	1.427	1.021	1.953	.162	4.167	[0.563, 30.837]
Institutional identification	0.870	0.770	1.277	.259	2.387	[0.528, 10.795]
Constant	-6.677	3.303	4.086	.043	0.001	—

Note. N = 142. The dependent variable was further-study intention, coded 1 = positive intention and 0 = uncertain, low, or no intention. Vietnam, the International Foundation Program, and the shortest study-period category were the reference groups. OR = odds ratio; CI = confidence interval.

As a supplementary analysis, the Random Forest model achieved an OOB accuracy of 93.42% and a test accuracy of 88.89%, with an AUC of .5417. Given the class imbalance, the accuracy results should be interpreted cautiously. Learning feedback ranked first in feature importance, followed by teaching quality.

Factors Associated with Intention to Work in Taiwan

The final employment model was significant, $\chi^2(14) = 30.442$, $p = .007$, Nagelkerke $R^2 = .340$; the Hosmer–Lemeshow test indicated no substantial misfit, $\chi^2(8) = 8.206$, $p = .414$. Adding institutional identification improved model fit, $\Delta\chi^2(1) = 6.336$, $p = .012$, and institutional identification was the only significant predictor, OR = 6.813, 95% CI [1.392, 33.335], $p = .018$ (Table 5). Classification performance is summarized in Table 6.

The random forest model achieved a test accuracy of 77.78% and an AUC of .8036. However, it classified all test cases into the majority class, indicating failure to identify minority-class cases. Feature-importance rankings placed language and cultural exchange first, followed by living convenience and safety support, with institutional identification also contributing; these rankings are interpreted as exploratory signals only.

Table 5: Binary Logistic Regression Predicting Intention to Work in Taiwan.

Predictor	*B*	*SE*	Wald χ^2	*p*	OR	95% CI for OR
Nationality: Indonesia	0.311	0.725	0.184	.668	1.364	[0.330, 5.649]
Nationality: Other	0.338	0.847	0.160	.689	1.403	[0.267, 7.376]
Program: Bachelor's	-0.635	0.801	0.627	.428	0.530	[0.110, 2.549]
Program: Graduate	-0.583	0.857	0.463	.496	0.558	[0.104, 2.997]
Study period: 6–24 months	-0.674	0.946	0.507	.477	0.510	[0.080, 3.258]
Study period: 2 years or more	-1.335	0.758	3.105	.078	0.263	[0.060, 1.162]
Scholarship support	-1.413	0.879	2.585	.108	0.243	[0.043, 1.363]
Learning feedback	1.358	0.794	2.920	.087	3.887	[0.819, 18.445]
Teaching quality	-0.868	0.861	1.017	.313	0.420	[0.078, 2.270]
Language and cultural exchange	-0.478	0.521	0.842	.359	0.620	[0.223, 1.722]
Living convenience and safety support	0.547	0.859	0.405	.524	1.728	[0.321, 9.307]
Learning and career development support	-1.335	0.823	2.630	.105	0.263	[0.052, 1.321]
Campus integration and administrative support	0.538	1.007	0.286	.593	1.713	[0.238, 12.324]
Institutional identification	1.919	0.810	5.610	.018	6.813	[1.392, 33.335]
Constant	-3.147	3.073	1.049	.306	0.043	—

Note. N = 142. The dependent variable was employment intention, coded 1 = positive intention and 0 = uncertain, low, or no intention. Vietnam, the International Foundation Program, and the shortest study-period category were the reference groups. OR = odds ratio; CI = confidence interval.

Table 6: Logistic Regression Model Fit and Classification Performance.

Outcome	Model χ^2 (*df*)	*p*	Nagelkerke R^2	Accuracy	Sensitivity	Specificity	Balanced accuracy	Precision	Recall	F1
Further-study intention	20.838 (14)	.106	.256	90.8%	100.0%	27.8%	63.9%	90.5%	100.0%	95.0%
Employment intention	30.442 (14)	.007	.340	88.0%	98.3%	28.6%	63.4%	88.8%	98.3%	93.3%

Discussion

Campus Experiences and Institutional Identification

The results show that institutional identification is shaped by a combination of academic, social, administrative, and daily-life experiences. Living convenience and safety support was the strongest predictor, followed by campus integration and administrative support.

This suggests that international students' identification with the university depends not only on teaching quality, but also on whether they feel safe, supported, and well integrated into campus life. Language and cultural exchange also contributed significantly, indicating that social and cultural integration may strengthen students' connection with the institution.

Scholarship support showed a smaller but still significant effect, suggesting that financial support may contribute to positive institutional evaluations but is unlikely to be sufficient on its own. The high explanatory power of the institutional-identification model should nevertheless be interpreted cautiously. Because predictors and the outcome were collected through the same self-report survey and some concepts may overlap, part of the observed association may reflect shared method variance rather than fully distinct effects. The cross-sectional design also precludes causal inference.

An Academic Pathway to Further Study Intention

Further study intention followed a different pattern. Demographic characteristics were not significant, while learning feedback emerged as the key predictor. This suggests that decisions about further study are closely related to students' perceptions of academic progress and learning outcomes. Students may be more willing to continue their education when they feel that they are learning effectively and are prepared for advanced study.

The Random Forest results were broadly consistent with this pattern, as learning feedback ranked first in feature importance. However, the low AUC indicates that these machine-learning results should be interpreted as supplementary rather than confirmatory.

From an institutional perspective, universities seeking to increase further study intention may therefore need to strengthen academic advising, learning feedback, language support, and access to learning resources.

An Institutional Integration Pathway to Employment Intention

Employment intention was primarily associated with institutional identification. Students with stronger institutional identification were more likely to express an intention to work in Taiwan.

This finding suggests that employment decisions may depend more on students' broader sense of belonging, integration, and connection to the university than on academic performance alone. The Random Forest results also highlighted the importance of language and cultural exchange and living convenience and safety support, indicating that social, cultural, and daily-life experiences may further shape students' employment intentions.

These findings imply that universities seeking to retain international graduates should strengthen not only career services, but also intercultural engagement, living support, and opportunities that foster students' connection to the host environment and their sense of belonging to the institution. Living convenience and safety support predicted institutional identification but did not directly predict either intention outcome. One possible interpretation is "satisfaction without commitment": supportive daily-life conditions may strengthen positive evaluations of the university without, by themselves, overcoming the academic, career, visa, language, or labor-market considerations involved in deciding whether to remain in Taiwan. In this sense, living support may function as an enabling condition for identification rather than as a direct determinant of post-graduation choice.

Two Distinct Pathways for Remaining in Taiwan

Taken together, the findings show two distinct pathways for international students' intention to remain in Taiwan. The further study pathway is primarily associated with academic development: students are more likely to continue studying in Taiwan when they perceive meaningful learning progress and academic support. The employment pathway is more closely associated with institutional identification: students are more likely to consider working in Taiwan when they develop trust, belonging, and a positive evaluation of the university.

This distinction has important implications for institutional management. Improvements in facilities alone are unlikely to address both pathways. Strategies for further study should emphasize academic development and feedback, whereas strategies for employment retention should place greater emphasis on social integration, institutional belonging, cultural engagement, and career connections.

Conclusion

This study contributes to institutional research by showing that international students' intentions to remain in Taiwan may follow two distinct pathways. Further study intention was most consistently associated with learning feedback, suggesting an academic development pathway, whereas employment intention was more strongly associated with institutional

identification, suggesting an institutional integration pathway. Institutional identification itself was associated with multiple dimensions of campus experience, including academic, administrative, cultural, financial, and daily-life support.

These findings have practical implications for international student recruitment and retention. Universities should avoid treating retention as a single outcome or relying primarily on improvements in physical facilities. Students considering further study may benefit more from academic advising, learning feedback, language support, and access to learning resources, whereas those considering employment may require stronger intercultural engagement, living support, career connections, and opportunities to develop a sense of belonging. A differentiated approach may therefore help institutions align student support more closely with different post-graduation pathways.

Several limitations should be acknowledged. First, the study was conducted at a single private university in central Taiwan with a modest sample size, limiting the generalizability of the findings. Second, the binary outcome variables were imbalanced, reducing the ability of both logistic regression and random forest models to identify minority-class cases. Third, the cross-sectional design does not permit causal inference or determine whether stated intentions translate into actual post-graduation behavior. Future research should use larger and more diverse samples, compare different institutional contexts, consider retaining the original ordinal outcome scales, apply methods designed for imbalanced data, and use longitudinal tracking to examine whether students' intentions lead to subsequent study or employment in Taiwan.

References

Baruch, Y., Budhwar, P. S., & Khatri, N. (2007). Brain drain: Inclination to stay abroad after studies. Journal of World Business, 42(1), 99–112. https://doi.org/10.1016/j.jwb.2006.11.004

Beaulac, C., & Rosenthal, J. S. (2019). Predicting university students' academic success and major using random forests. Research in Higher Education, 60, 1048–1064. https://doi.org/10.1007/s11162-019-09546-y

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5–32. https://doi.org/10.1023/A:1010933404324

Choudaha, R., & de Wit, H. (2014). Challenges and opportunities for global student mobility in the future: A comparative and critical analysis. In B. Streitwieser (Ed.),

Internationalisation of higher education and global mobility (pp. 19–34). Symposium Books.

Glass, C. R., & Westmont, C. M. (2014). Comparative effects of belongingness on the academic success and cross-cultural interactions of domestic and international students. International Journal of Intercultural Relations, 38, 106–119. https://doi.org/10.1016/j.ijintrel.2013.04.004

Istad, F., Varpahovskis, E., Miezan, E., & Ayhan, K. J. (2021). Global Korea Scholarship students: Intention to stay in the host country to work or study after graduation. Politics & Policy, 49(6), 1323–1342. https://doi.org/10.1111/polp.12436

Kruanak, K., & Ruangkanjanases, A. (2014). Brain gain for Thailand: The determinants of international students' intention to stay on after graduation. International Journal of Trade, Economics and Finance, 5(4), 337–346.

Mntshali, W. W. (2017). The factors influencing international students' choice of working in Taiwan after graduation [Master's thesis, National Taiwan Normal University]. National Digital Library of Theses and Dissertations in Taiwan.

OECD. (2025). What are the key trends in international student mobility? Education Indicators in Focus, No. 88. OECD Publishing. https://doi.org/10.1787/2a423a76-en

OECD. (2026). International students in higher education. OECD Publishing. https://www.oecd.org/en/publications/international-students-in-higher-education_005ff28d-en.html

Tinto, V. (1993). Leaving college: Rethinking the causes and cures of student attrition (2nd ed.). University of Chicago Press.

Yadav, S. K., Bharadwaj, B., & Pal, S. (2012). Data mining applications: A comparative study for predicting student's performance. International Journal of Innovative Technology and Creative Engineering, 1(12), 13–19.

P26049

Mission-Driven Leadership in SVD Higher Education Institutions in the Philippines: Toward an Enhanced Leadership Model

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ABSTRACT

This study investigates how mission-driven leadership is understood, practiced, and sustained within higher education institutions (HEIs) administered by the Society of the Divine Word (SVD) in the Philippines. Adopting a qualitative, multi-case study design within a human-AI collaborative analytical environment, empirical data were gathered from 69 educational leaders across three SVD institutions. Data collection comprised 15 semi-structured individual interviews with top-level administrators and 8 focus group discussions (FGDs) with 54 middle-level managers, complemented by institutional document analysis. Findings reveal that educational leaders conceptualize mission-driven leadership as an identity-rooted vocation and witness to the Divine Word rather than a mere administrative function. This leadership ethos is operationalized across four distinct dimensions: Service-Oriented, Transformative, Values-Centered, and Purpose-Driven. These dimensions guide institutional practice across academic programs, administrative operations, and community engagement. However, leaders continuously navigate operational tensions, including resource constraints, administrative burdens, market competitiveness, and secularization pressures. To address these realities, the study proposes a research-informed, preliminary framework: the Enhanced Model of Mission-Driven Leadership for SVD HEIs. This model offers actionable pathways for leadership formation, governance review, succession planning, and mission alignment.

Keywords: Mission-driven leadership, SVD educational charism, higher education governance, faith-based HEIs, qualitative research, human-AI collaboration

Introduction

Background of the Study

Mission serves as both a theological imperative and an organizational foundation within faith-based institutions. Honig et al. (2025) frame mission as a strategic commitment to achieving transformative goals that generate enduring public value. Biblically, mission originates in God's covenantal initiative (Genesis 12:1–3), expands through prophetic traditions demanding justice and mercy (Isaiah 49:6), and culminates in the universal mission of Christ. In contemporary higher education discourse, mission-driven leadership has emerged as a distinct

paradigm that transcends transactional management (Colwell, 2018; Saldivar, 2024). Unlike standard educational management models focused primarily on market metrics or operational efficiency, mission-driven leadership intentionally aligns governance, strategic planning, and daily practices with an institution's foundational core purpose (Colwell, 2018).

In higher education, leaders must balance academic rigor and financial viability while actively preserving institutional identity (Davies, 2004). Within the Society of the Divine Word (SVD), education represents a vital expression of the missionary apostolate. Grounded in the conviction that "Mission is life, life is mission" (Pernia, 2019), SVD education views leadership as an active participation in the Missio Dei. SVD-administered higher education institutions (HEIs) are guided by the charism of the Divine Word, characterized by prophetic dialogue with diverse cultures, faith traditions, and marginalized communities.

Despite growing literature on higher education administration, limited empirical research explores how the specific SVD missionary charism is operationalized within academic governance, administrative operations, and community engagement in the Philippines. Frameworks often treat Catholic leadership generically, failing to capture the distinct operational tensions, charism-driven practices, and contextual realities of religious-administered HEIs operating within competitive educational environments.

Differentiating SVD Leadership Charism

While SVD higher education institutions share a common foundation with Catholic higher education generally such as a commitment to truth, the integration of faith and reason, and ethical human formation, the SVD model is distinguished by its missionary charism. SVD leadership is specifically shaped by three foundational pillars:

1. Prophetic Dialogue: A methodology of engagement that enters into respectful, transformative dialogue with seekers of faith, people of diverse cultures, and the poor and marginalized.
2. Interculturality: Moving beyond cross-cultural tolerance to intentionally build inclusive communities where cultural diversity is recognized as a locus for academic and spiritual enrichment.
3. Witness to the Divine Word: Framing academic excellence, research, and governance not merely as professional duties, but as an active incarnation of the Word of God in culture and society.

Theoretical and Conceptual Framework

This study is anchored in a multi-theoretical framework synthesizing established leadership models with SVD theological constructs. Frances Hesselbein’s (1996) assertion that authentic leadership acts as a steward of institutional mission provides the overarching baseline. This

concept converges with four established leadership theories:

1. Servant Leadership (Greenleaf, 1977): Places service, humility, and moral responsibility at the core of authority. In an SVD context, this mirrors Christological diakonia and pastoral accompaniment.
2. Transformational Leadership (Burns, 1978): Emphasizes vision, moral elevation, and intellectual stimulation. Within SVD HEIs, transformational practices drive faculty development, pedagogical renewal, and student character formation.
3. Values-Based Leadership (Kraemer, 2011): Focuses on ethical integrity, self-reflection, and authentic alignment between stated core values and institutional actions.
4. Purpose-Driven Leadership (Lencioni, 2012): Ensures that administrative governance and strategic decisions remain anchored in the institution's primary reason for existence.

To bridge general leadership theory with the specific charism of the Society of the Divine Word, the framework maps leadership theories directly to SVD charism components, theoretical convergences, and expected leadership practices:

Table 1: Theoretical Alignment Matrix: Leadership Theories, SVD Charism Components, Theoretical Convergence, and Expected Leadership Practices

Leadership Theory	SVD Charism Component	Theoretical Convergence	Expected Leadership Practices
Servant Leadership (Greenleaf, 1977)	Witness to the Word & Pastoral Care	Authority as service (diakonia); humble witness.	Spiritual accompaniment, active listening, availability, and advocacy for the marginalized.
Transformational Leadership (Burns, 1978)	Prophetic Dialogue & Integral Formation	Intellectual and moral growth; holistic transformation.	Mentoring faculty, innovative pedagogy, capability building, and student character formation.
Values-Based Leadership (Kraemer, 2011)	Interculturality & Ethical Integrity	Authentic alignment between faith, culture, and ethics.	Transparent decision-making, ethical resource allocation, and intercultural dialogue.
Purpose-Driven Leadership (Lencioni, 2012)	Missionary Mandate (Missio Dei)	Organizational alignment with institutional	Mission-aligned strategic planning, policy integration, and

		purpose.	community extension.

Statement of the Problem

This study explored how mission-driven leadership is understood, practiced, and sustained within SVD-administered higher education institutions in the Philippines. Specifically, it addressed the following research questions:

1. What is the educational leaders' conceptual understanding of mission-driven leadership within the framework of their institutional identity and the SVD educational charism?
2. What specific mission-driven leadership practices do educational leaders employ across academic programs, administrative operations, and community engagement?
3. What structural and contextual challenges do educational leaders encounter in practicing mission-driven leadership across these functional domains?
4. What research-informed model can be developed to enhance mission-driven leadership, formation, and governance in SVD higher education institutions in the Philippines?

Method

Research Design

This study utilized a qualitative multi-case study research design to examine the lived experiences, perspectives, and practices of educational leaders across SVD-administered HEIs. A qualitative inquiry was selected because mission-driven leadership in faith-based institutions is a context-bound, highly interpretive phenomenon that requires detailed exploration of participant narratives, organizational culture, and institutional documents. Primary data collection was conducted through semi-structured individual in-depth interviews and focus group discussions (FGDs), triangulated with documentary analysis of institutional vision-mission statements, university statutes, strategic development plans, and policy manuals.

Institutional Context and Participant Profile

The study was conducted across three SVD higher education institutions in the Philippines, selected through purposeful sampling based on geographic representation (Luzon, Visayas), institutional scale (small, medium, large), and historical development:

School A (Divine Word College of Bangued): Located in Northern Luzon; serves predominantly rural communities and Indigenous populations (Itneg/Tinguian).

School B (Divine Word College of Calapan): Located in Mindoro; medium-scale college serving regional development and local Indigenous communities (Mangyan).

School C (University of San Carlos): Located in Cebu City; large-scale comprehensive university with research-intensive operations and an international student body.

A total of 69 educational leaders participated in the study. The participant group was stratified into top-level administrators (individual in-depth interviews) and middle-level managers (focus group discussions) to capture perspectives across governance tiers:

Table 2: Distribution of Study Participants by Institution, Leadership Role, Data Gathering Source, and Sample Size

Institution	Level / Role Category	Data Gathering Source	Sample Size (n)
School A	Top-Level Administrators (Presidents, Vice Presidents)	In-Depth Individual Interviews	4
	Middle-Level Managers (Deans, Dept. Chairs, Program Heads)	Focus Group Discussions (FGDs)	16
School B	Top-Level Administrators (Presidents, Vice Presidents)	In-Depth Individual Interviews	5
	Middle-Level Managers (Deans, Dept. Chairs, Program Heads)	Focus Group Discussions (FGDs)	18
School C	Top-Level Administrators (Presidents, Vice Presidents)	In-Depth Individual Interviews	6
	Middle-Level Managers (Deans, Dept. Chairs, Program Heads)	Focus Group Discussions (FGDs)	20
Total	Top & Middle-Level Leadership Across 3 HEIs	Interviews (15) & FGDs (54)	69

Instrumentation and Validation

Data collection instruments comprised semi-structured interview guides for individual sessions and protocols for focus group discussions. Key protocol domains included conceptual understandings of SVD charism, domain-specific operational practices, structural challenges, and strategic recommendations.

The instruments underwent content validation by a panel of three experts in educational management, missiology, and qualitative research methodology. Protocols were pilot-tested at the Divine Word College of Legazpi (DWCL) with 5 SVD administrators and 12 middle managers. Feedback from pilot testing refined question wording, ensuring clear differentiation between generic administrative management functions and mission-specific leadership practices.

Ethics, Anonymity, and Human-AI Integration Protocols

Ethical Clearance & Informed Consent: Institutional review board (IRB) approval and

administrative clearances were secured prior to data gathering. Written informed consent was obtained from all 69 participants, outlining voluntary participation, confidentiality, and data usage.

Anonymity & Data Masking: Institutional identities were masked (School A, School B, School C), and individual participants were assigned alphanumeric identifiers (e.g., Respondent A-Top-01, Respondent C-Mid-04).

AI Tool Integration & Data Privacy: Generative AI (Google Gemini) was integrated within a collaborative human-AI qualitative framework to assist with initial thematic processing. To maintain strict ethical compliance:

1. Complete Data Anonymization: Transcripts were stripped of all personally identifiable information (PII), names, specific geographic markers, and institutional titles prior to AI analysis.
2. Explicit Participant Consent: Consent forms explicitly informed participants that anonymized transcripts would undergo AI-assisted qualitative data analysis.
3. Enterprise Privacy Standards: AI tools were operated within enterprise environments configured with zero-data retention, ensuring inputs were neither stored nor used for AI model training.

Human-AI Collaborative Analysis and Audit Trail

Qualitative data were analyzed using inductive thematic analysis, structured through an iterative five-stage Human-AI Collaborative Audit Trail:

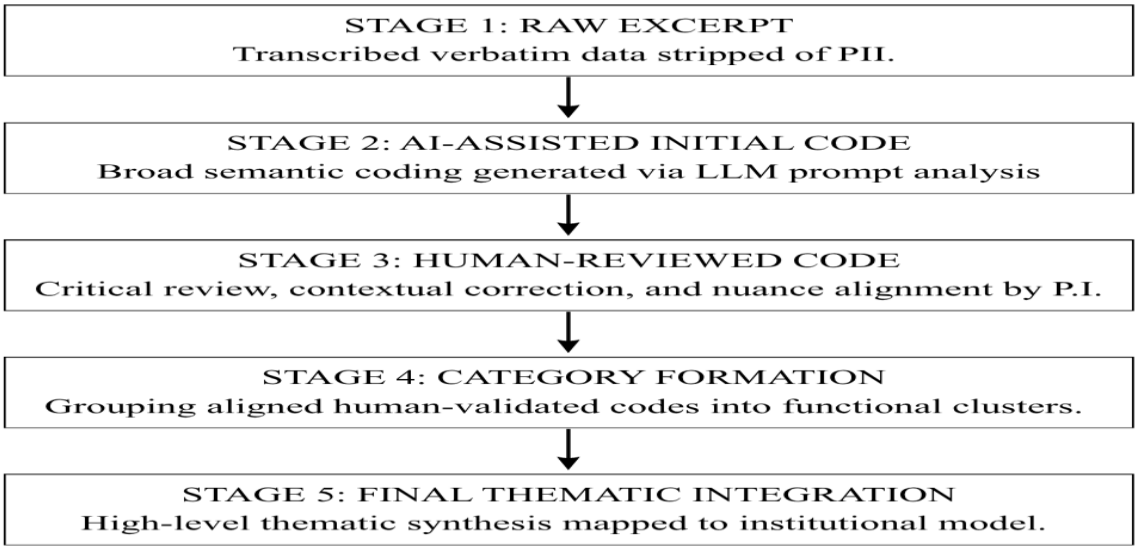


Figure 1: Human-AI Collaborative Audit Trail

The table below illustrates the qualitative audit trail across the five stages of data transformation:

Table 3: Qualitative Data Analysis Progression: From Raw Excerpt to AI-Assisted Code, Human-Reviewed Code, Category, and Final Theme

Stage 1: Raw Excerpt	Stage 2: AI-Assisted Initial Code	Stage 3: Human-Reviewed Code	Stage 4: Category	Stage 5: Final Theme
"Our leadership style must be the first example of the Gospel values we teach. I have to be a witness to the Word."	Exemplary modeling of religious values.	Authentic Gospel witnessing through daily administrative action.	Witnessing and Charism Embodiment.	Witness to the Word (Core Identity)
"To see that the spiritual formations and growth of the people in the community are taken care of."	Spiritual care taking for employees.	Pastoral accompaniment of faculty and staff spiritual growth.	Spiritual Accompaniment and Care.	Service-Oriented Leadership
"We mentor new teachers so they can align with the USC spirit and become leaders themselves."	Mentoring teachers for leadership.	Intentional mentoring for mission alignment and faculty development.	Disciplined Mentorship and Growth.	Transformative Leadership
"Financial stewardship is framed as responsibility... I am the caretaker of the money for the mission."	Money management for school mission.	Ethical resource allocation and mission-driven financial stewardship.	Mission-Driven Resource Management.	Values-Centered Leadership
"Every activity, syllabus, and	Activity alignment	Strategic alignment of	Purpose-Driven Program	Purpose-Driven Leadership

program must align with the institution's goal of evangelization."	with goal.	academic programs with evangelization mandate.	Alignment.	

Documentary Triangulation

To ensure analytical rigor and construct validity, qualitative findings were triangulated against primary institutional artifacts, including:

1. Institutional Vision, Mission, and Core Value statements.
2. University Statutes and Administrative Manuals.
3. Strategic Development Plans (2020–2025).
4. Faculty Evaluation Metrics and Syllabi Frameworks.
5. Community Extension and Social Action Annual Reports.

RESULTS AND DISCUSSION

Educational Leaders' Understanding of Mission-Driven Leadership

Educational leaders across all three institutions conceptualize leadership not as an administrative rank, but as an identity-rooted vocation and living witness to the Divine Word. Seven interrelated conceptual themes emerged from the qualitative analysis:

Table 4: Educational Leaders' Understanding of Mission-Driven Leadership

Theme	Conceptual Focus	Representative Participant Statements
Witness to the Word	Exemplary Gospel-centered living in administrative practice.	"I have to be a witness. It is about being a witness to the Word." "Our leadership style must be the first example of the Gospel values we teach."
Word-Centered & Charism-Anchored Governance	Placing scripture and SVD vision at the center of institutional decisions.	"Leading with a clear sense of purpose, place the Word of God at the center of our service." "Mission-driven leadership would mean making decisions for the students and the employees based on our vision, mission as an institution."

Identity-Rooted Vocation	Leadership grounded in missionary identity rather than career ambition.	"I am a missionary. This is the reason why I'm here... My identity becomes the motivation for service." "It is a leadership where you lead with a heart of an SVD."
Transformative-Holistic Education	Balancing academic excellence with character and spiritual formation.	"Leadership is not just a position. It is a mission-driven service to transform the academic community." "Excellence in our field (Scientia) driven by a heart for the mission (Devotio)."
Community Belonging & Shared Mission	Fostering inclusive fellowship and lay-religious collaboration.	"Leadership is not about power or position but about service and love." "It is about cultivating a sense of belongingness from the cabinet level down to the students, ensuring everyone is moving toward the same SVD mission."
Stewardship & Strategic Discernment	Ethical management of human, financial, and physical assets.	"I am the caretaker of the money of the school, not for me but for the mission." "You set a vision for the school, a direction, guide them toward that goal."
Prophetic & Missionary Engagement	Active outreach, interculturality, and service to the marginalized.	"We are not just for ourselves. We are sent to others. We have to share our knowledge with others, and we also have to share our faith." "We must incorporate prophetic dialogue and a preferential option for the poor and marginalized."

These findings organize into four functional dimensions that define SVD mission-driven leadership:

1. Service-Oriented Leadership: Grounded in Christological diakonia, leaders view authority as pastoral accompaniment, active listening, and availability.
2. Transformative Leadership: Focuses on capability building, faculty mentorship, and empowering leaders to drive social transformation.
3. Values-Centered Leadership: Operates as an internal moral compass, ensuring consistency between core values and institutional decision-making.
4. Purpose-Driven Leadership: Functions as the integrative driver, ensuring that strategic planning and academic policies remain directed toward the institutional mission.

Mission-Driven Leadership Practices Across Institutional Functional Domains

Grounded in SVD charism, mission-driven practices were mapped across three core operational domains:

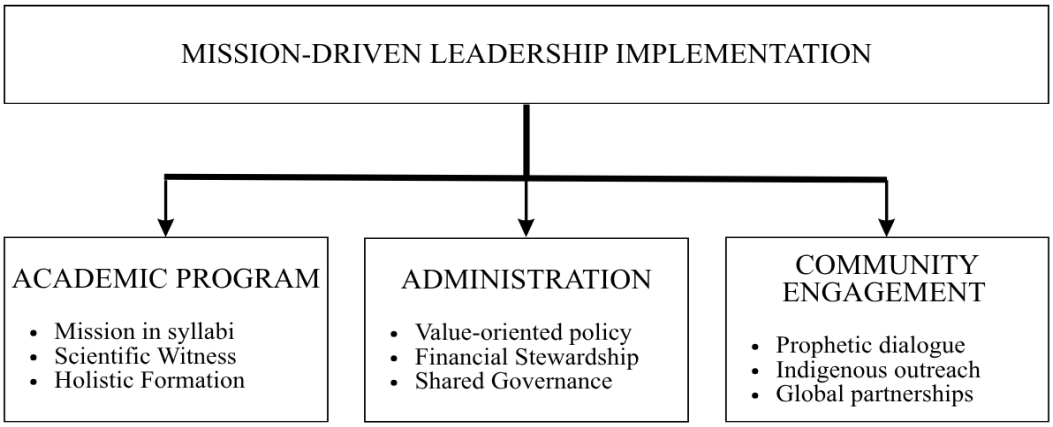


Figure 2: Mission-Driven Leadership Practices across Core Operational Domains

The table below outlines domain-specific practices observed across participating sites:

Table 5: Mission-Driven Leadership Practices across Functional Domains

Functional Domain	Key Operational Themes	Illustrative Practices Across Institutions
Academic Programs	Holistic Formation	School A: Syllabi integrate SVD core values; student retreats pair academic learning with spiritual formation.
	Mission Knowledge Production	School B: Curriculum embeds Christian ethics; faculty development includes faith-formation

	Scientific Witnessing	modules. School C: Offers specialized courses like "Education with a Mission" (EDM); research agendas prioritize community development.
Administrative Operations	Operationalizing Purpose	School A: Administrative procedures are reviewed for mission alignment; focus on fair employee welfare.
	Ethical Mission Governance	School B: Governance stresses participatory decision-making; finances are managed as "stewardship for mission".
	Resource Stewardship	School C: University statutes embed shared lay-religious governance; strategic planning uses mission KPIs.
Community Engagement	Transformative Outreach	School A: Community extension directly addresses rural socio-economic needs.
	Participatory Engagement	School B: Sustained extension serving Indigenous Mangyan communities through literacy and healthcare.
	Global & External Dialogue	School C: Expands engagement through global university networks and large-scale social development projects.

Cross-Case Comparative Analysis of Mission-Driven Leadership Challenges

A cross-case comparative analysis highlighting how institutional scale, geography, and resources shape core operational leadership tensions across Schools A, B, and C.

Table 6: Cross-Case Comparative Analysis of Mission-Driven Leadership Challenges

Challenge Domain	School A (Small / Rural)	School B (Medium / Regional)	School C (Large / Comprehensive)
Spirituality vs. Bureaucracy	Heavy operational demands threatening the spiritual focus needed to keep the Word of God at the center.	Heavy CHED and accreditation requirements taking time away from mission animation, charism, and spiritual reflection.	Paperwork, meetings, and bureaucratic routine diluting spiritual grounding as a living witness and creating resistance to mission integration.
Continuity vs. Change	Transmitting the SVD mission across generations while competing with sprouting local SUCs and community colleges.	Balancing traditional missionary identity with modern regional competition and evolving higher education demands.	Shifting paradigms from old methods to new investments while clarifying unique SVD identity alongside other religious orders.
Authority vs. Collaboration	Shifting from clerical, top-down decision-making to a shared leadership culture ("from employee to partner").	Addressing capacity gaps, lack of stakeholder dialogue, and breakdowns in participatory governance.	Managing role ambiguity, coordinator isolation ("I'm alone"), policy gaps, and time constraints in collaborative leadership.
Aspiration vs. Resource Limitations	Striving to keep programs thriving despite severe budget constraints and public institution growth.	Desiring to expand community extension and accessible education, but constrained by limited budgets and facilities.	Facing faculty turnover due to uncompetitive pay while coping with heavy administrative workloads in large departments.
Personal Conviction vs. Human Frailty	Sustaining personal commitment while navigating changing faith values and generational shifts among staff.	Leading amidst secularization, internal value diversity, and faculty who do not share the core missionary vision.	Managing personal limits, human frailty, relational strain from hard decisions, and aligning divergent views on mission expression.

The Enhanced Model of Mission-Driven Leadership

To synthesize empirical findings into an actionable framework, this study presents the Enhanced Model of Mission-Driven Leadership for SVD HEIs. Designed to bridge spiritual charism with university governance, the model is structured across five core components:



Figure 3: Enhanced Mission-Driven Leadership Model for SVD HEIs

Model Structural Breakdown

1. Core Identity: Witness to the Word. At the center of the framework is Witness to the Word, serving as the spiritual heart of leadership. Authority is derived from authentic personal and institutional witness to Gospel values. Two foundational orientations anchor this core:

Vocation over Position: Framing leadership as an apostolic service rather than a career ladder.

Incarnational Presence: Exercising relational, accessible leadership through active presence and personal accompaniment.

2. Four Leadership Dimensions: Mission-driven leadership within SVD higher education institutions is expressed through four interconnected leadership dimensions that guide institutional practice.

   Service-Oriented Leadership: Exercising authority as diakonia, emphasizing humility, empathy, and care for community members.

   Transformative Leadership: Driving academic quality and student formation through mentorship, faculty empowerment, and pedagogical renewal.

   Values-Centered Leadership: Integrating core SVD values into daily decision-making, ethical resource management, and intercultural dialogue.

   Purpose-Driven Leadership: Aligning administrative structures, academic curricula, and strategic visions with institutional mission.

3. Operational Pillars: The practical implementation of this leadership model can be further understood through three interrelated operational pillars that guide how leadership functions within SVD higher education institutions.

   Value Alignment: Translating abstract mission principles into measurable operational policies, hiring practices, and performance evaluations.

   Participatory Governance: Cultivating collaborative decision-making structures that unite religious administrators and lay professionals.

   Institutional Excellence through Witness: Maintaining academic quality and administrative rigor as a direct expression of faith and institutional credibility.

4. Functional Domains. The leadership model is operationalized across three major domains of institutional life.

   Academic Programs: Integrates SVD values and Christian perspectives into curriculum, teaching, and learning outcomes to pair academic excellence with moral and spiritual formation.

Administrative Operations: Implements ethical governance, policy development, and responsible stewardship grounded in justice, peace, and accountability to keep institutional management mission-oriented.

Community Engagement: Extends the SVD missionary purpose through outreach and partnerships that serve marginalized communities, using education to drive social transformation and solidarity.

5. Sustaining Mechanisms: To sustain mission-driven leadership and address contemporary institutional challenges, the framework incorporates several sustaining mechanisms.

   Continuous Formative Leadership: Ongoing spiritual, ethical, and professional development programs (retreats, leadership modules) for both religious and lay leaders.

   Inclusive-Participatory Governance: Structured dialogue platforms that ensure shared responsibility and succession planning across governance levels.

   Future-Oriented Mission Innovation: Discerning the ethical integration of emerging technologies (e.g., AI in education) and adapting to educational trends while safeguarding institutional identity.

Empirical Grounding of Model Components

The framework components are anchored in empirical findings gathered across the participating institutions:

Table 7: Empirical Grounding of Model Components

Model Component	Primary Qualitative Themes	Direct Verbatim Quotes / Empirical Data	Primary Source	Practical Application in SVD HEIs
Core Identity: Witness to the Word	Vocation, Incarnational Presence, Gospel Witness.	"I am a missionary... My identity as a priest, religious and missionary becomes the motivation for service."	Top Administrators & Middle Managers (Schools A, B, C).	Leadership Onboarding: Formulate mandatory orientation retreats grounded in SVD

		"Our identity is to be 'Witness to the Word'... our leadership style must be the first example."		missionary charism.
Dimension 1: Service-Oriented	Spiritual Accompaniment, Pastoral Care, Availability.	"To see that the spiritual formations and growth of the people... is taken care of." "Servant leadership is shown when you are ready to listen and assist whenever needed."	Top Administrators & Middle Managers (Schools A & B FGDs).	Governance Review: Establish employee wellness, pastoral care, and spiritual direction offices.
Dimension 2: Transformative	Faculty Mentorship, Human Growth, Mission Consciousness.	"I want to see my faculty growing, pursuing their PhDs. I follow up on them." "We transform the department by mentoring new teachers to align with the USC spirit."	Top Administrators & Middle Managers (School C Interviews & FGDs).	Succession Planning: Implement formal faculty mentorship pipelines and doctoral study grants.
Dimension 3: Values-Centered	Ethical Integrity, Fleshing Out Values, Interculturality.	"Mission-driven leadership is where we put some flesh into	Top Administrators & Middle Managers	Mission Alignment: Conduct ethical financial audits

		the values... show the face of our intervention." "I am the caretaker of the money of the school, not for me but for the mission."	(Schools B & C).	and mission-driven capital resource allocation.
Dimension 4: Purpose-Driven	Goal Alignment, Producing Missionaries, Evangelization.	"Every activity we plan must have a clear purpose that aligns with... evangelization through education." "As a missionary school, its product should also be missionaries."	Top Administrators & Middle Managers across all sites.	Curriculum Audit: Map course learning outcomes directly to SVD characteristic dimensions.
Operational Pillar 1: Value Alignment	Translating Vision to Tasks, SVD Branding.	"Making sure the students feel the SVD brand of education." "Integrate the core values of the institution into your daily tasks."	Middle Managers across sites.	Policy Integration: Embed core value rubrics into annual administrative performance appraisals.
Operational Pillar 2: Participatory	Prophetic Dialogue, Lay Partnership,	"Every individual person I call them	Top Administrators (Schools B &	Statute Revision: Formulate joint

Governance	Shared Leadership.	partners, there's no monopolization, everyone counsels." "Prophetic-Dialogical leadership... Dialogue is based on our faith."	C).	lay-religious governing councils and dialogical decision bodies.
Operational Pillar 3: Excellence through Witness	Scientia, Virtus, et Devotio, Academic Competence.	"Excellence in our field (Scientia) driven by a heart for the mission (Devotio)." "Achieving our objective to provide quality education inspired by St. Arnold Janssen."	Middle Managers (School C FGDs).	Quality Assurance: Balance regional accreditation standards with mission-impact assessment metrics.
Sustaining Mechanism 1: Formative Leadership	Spiritual Recharging, Continuous Formation, Burnout Prevention.	"We need a model that includes regular spiritual 'recharging' for leaders so we don't get burnt out." "There should be a continuous formation, not just for heads but	Middle Managers across sites.	Formation Modules: Institutionalize quarterly spiritual retreats and charism renewal workshops.

		for all employees."		
Sustaining Mechanism 2: Shared Succession	Mentorship Programs, Leadership Pipelines, Shared Vision.	"A mentorship program for the new leaders, so that the SVD charism... will continue." "Be a mentor to them, because in the long run, they will be the ones to run our educational apostolate."	Top Administrators & Middle Managers.	Leadership Pipeline: Create succession pathways for lay department chairs and deans.
Sustaining Mechanism 3: Belonging Culture	Inclusivity, Collective Direction, Organizational Retention.	"Cultivating a sense of belongingness from the cabinet level down to the students." Ensure even the lowest level of the organization feels they are part of the mission."	Middle Managers across sites.	Community Building: Design inclusive cross-departmental assemblies and staff recognition initiatives.
Sustaining Mechanism 4: Mission Innovation	Future-Oriented Leadership, EdTech, Tech Investment.	"The leadership model must shift... it must go beyond incorporating science, technology, and investment."	Middle Managers (School C FGDs).	Ethical Innovation: Develop institutional frameworks for ethical AI and emerging ed-tech integration.

LIMITATIONS AND FUTURE RESEARCH

Limitations

This study has several methodological limitations that frame its scope:

Bounded Context: Findings are derived specifically from three SVD-administered higher education institutions in the Philippines and may not fully generalize to non-SVD Catholic HEIs or secular universities.

Participant Scope: Data collection focused primarily on top-level administrators and middle-level managers. Perspectives from rank-and-file faculty, students, alumni, and community partners were not directly captured.

Self-Report and Social Desirability Bias: Participant accounts regarding leadership practices and spiritual values may reflect social desirability bias or idealized expectations rather than routine administrative behavior.

Preliminary Framework Status: The proposed Enhanced Model of Mission-Driven Leadership is derived directly from qualitative findings and institutional document analysis; it has not yet undergone formal external quantitative testing or empirical validation.

Future Research Directions

To extend the theoretical and empirical insights of this study, future research should explore:

1. Model Validation: Conduct expert panel evaluations and structural equation modeling (SEM) to quantitatively validate the proposed model's dimensions across wider SVD educational networks.
2. Comparative Studies: Execute comparative analyses evaluating mission-driven leadership models between SVD institutions and HEIs managed by other religious orders or diocesan authorities.
3. Broader Stakeholder Inclusion: Expand qualitative inquiry to capture student perspectives, faculty views, and community impact evaluations regarding leadership effectiveness.
4. Longitudinal Studies: Track the long-term impact of structured leadership formation programs on administrative retention, institutional culture, and mission alignment over time.

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

Mission-driven leadership within SVD higher education institutions in the Philippines is an identity-rooted vocation that integrates spiritual charism with academic governance.

Educational leaders operationalize this leadership through four core dimensions: Service-Oriented, Transformative, Values-Centered, and Purpose-Driven. These dimensions guide practice across academic programs, administrative operations, and community outreach. Navigating leadership requires resolving ongoing operational tensions between market competitiveness, regulatory demands, resource limits, and charism preservation. The proposed Enhanced Model of Mission-Driven Leadership provides an empirically grounded roadmap to ensure that academic rigor, administrative efficiency, and missionary identity remain mutually reinforcing.

Recommendations

1. Institutionalize Charism-Centered Formation: Establish structured, ongoing leadership formation modules for both religious and lay administrators, focusing on SVD charism, prophetic dialogue, and mission-aligned management.
2. Conduct Periodic Mission Audits: Implement systematic reviews of institutional policies, strategic plans, and resource allocations to verify alignment with SVD values and educational objectives.
3. Strengthen Shared Governance & Succession: Build inclusive governance frameworks that deepen collaboration between religious administrators and lay professionals, supported by mentoring pipelines.
4. Integrate Mission Across Curricula: Embed SVD core values and social responsibility metrics across degree syllabi, research agendas, and community engagement programs.
5. Establish Ethical AI & Tech Protocols: Formulate clear institutional guidelines for AI integration in research and administration that uphold data privacy, academic integrity, and human dignity.

References

Adamek, P. (2021). Challenge of the education ministry. Verbum SVD, 62(2–3), 235–249.

Baldera, P. R. (2025). Instructional leadership in practice: A qualitative exploration of public elementary master teachers' identity formation and influence in the Philippines. Educational Process: International Journal, 18, Article 482.

Benedict XVI. (2010). Verbum Domini: Post-synodal apostolic exhortation on the Word of God in the life and mission of the Church. Libreria Editrice Vaticana.

Bevans, S. B., & Schroeder, R. P. (2004). Constants in context: A theology of mission for today. Orbis Books.

Burns, J. M. (1978). Leadership. Harper & Row.

Cardona, P., & Rey, C. (2022). Missions-driven leadership. In Management by missions (pp. 131–145). Springer.

Chigbu, B. I., & Makapela, S. L. (2025). Data-driven leadership in higher education: Advancing sustainable development goals and inclusive transformation. Sustainability, 17(7), 3116.

Colwell, J. (2018). Mission-focused leadership in faith-based education. Journal of Catholic Higher Education, 37(2), 45–62.

Congregation for Catholic Education. (1977). The Catholic school. Vatican Publishing.

Cordero, C. A. (2018). Living the mission in education. In Studia Instituti Missiologici SVD (pp. 247–260). Franz Schmitt Verlag.

Davies, J. L. (2004). Mission and leadership in Catholic higher education. Current Issues in Catholic Higher Education, 23(1), 43–55.

Esogon, S. G. T., & Gumban, J. L. (2024). Transformational leadership of school heads in public elementary schools in Bacolod City, Philippines. International Journal of Research and Innovation in Social Science, 8(3S), 3244–3255.

Gallares, J. (2022). Paradigms of missionary spirituality. In Gifted to give: Proceedings of the Second National Mission Congress (pp. 212–230). CBCP–Episcopal Commission on Mission.

Greenleaf, R. K. (1977). Servant leadership: A journey into the nature of legitimate power and greatness. Paulist Press.

Guillaume, O., Honeycutt, A., & Savage-Austin, A. (2012). Servant leadership: An ideal model for public service. The Journal of Business & Economics Research, 10(2), 123–130.

Hannigan, T. (2008). Servant leadership for higher education. National Catholic Educational Association.

Hesselbein, F. (1996). The leader of the future: New visions, strategies, and practices for the next era. Jossey-Bass.

Honig, D., Dissanayake, R., & Plunkett, C. (2025). Mission readiness and public value creation in institutional governance. Journal of Public Administration and Governance, 15(1), 88–112.

Kraemer, H. M. J. (2011). Becoming the best: Essential leadership skills you can learn from how the best leaders lead. Jossey-Bass.

Lencioni, P. (2012). The advantage: Why organizational health trumps everything else in business. Jossey-Bass.

Pernia, A. M. (2019). Mission is life, life is mission: A theological-anthropological understanding of mission. Missio Inter Gentes, 5(1), 23–43.

Pillay, G. J. (2008). Education as mission: Perspectives on some new opportunities. In A. Walls & C. Ross (Eds.), Mission in the 21st century: Exploring the five marks of global mission (pp. 150–160). Orbis Books.

Saldivar, J. M. N. (2024). Mission-driven leadership: An emergent theory. Ignatian International Journal for Multidisciplinary Research, 2(9), 328–342.

SVD Generalate. (2024). Documents of the 19th General Chapter SVD 2024. SVD Publications.

Walls, A., & Ross, C. (Eds.). (2008). Mission in the 21st century: Exploring the five marks of global mission. Orbis Books.

Wright, C. J. H. (2006). The mission of God: Unlocking the Bible's grand narrative. IVP Academic.

Sub-Theme II

Data-Driven Quality Assurance: Innovations in Assessment and Accreditation

P26004

RU: AUN-QA DIGITAL TECHNOLOGY FOR INTERNAL QUALITY AT RAMKHAMHAENG UNIVERSITY

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ABSTRACT

The objectives of this study were to develop the RU AUN-QA digital technology to support internal quality assurance at Ramkhamhaeng University and to examine a 2-days RU AUN-QA platform training program for academic staff at Ramkhamhaeng University. The participants in the training program included 126 individuals who completed a two-day training program, while 50 participants who used the RU AUN-QA digital platform. The research methodology involved the development of the RU AUN-QA platform and the implementation of a 2-days RU AUN-QA platform training program. The research instruments consisted (1) the RU AUN-QA platform, (2) a 2-days RU AUN-QA platform training program for academic staff (3) a questionnaire for evaluating the RU AUN-QA digital platform. The results showed that (1) the RU AUN-QA digital platform provided a high level of efficiency and supported the preparation of self-assessment reports (SAR) and empirical evidence follow AUN-QA criteria. (2) Participants who used the RU AUN-QA platform enhanced competency in its use and a high level to understanding of the AUN-QA criteria (3) A total of 57 academic programs were evaluated based on the AUN-QA criteria, and the results indicated that the internal quality assurance assessment at the program level was at Level 2 or higher. The conclusion was that RU AUN-QA can effectively enhance internal quality assurance evaluation and prepare institutions for external quality assessment.

Keyword: RU AUN-QA digital technology, internal quality assurance, and training program

P26005

Guidelines for Developing Rajabhat Universities toward Excellence Based on the Education Criteria for Performance Excellence (EdPEx)

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ABSTRACT

This study aimed to examine the current state of implementation, analyze strengths, weaknesses, and key implementation issues, and formulate development approaches for advancing universities toward excellence based on the Education Criteria for Performance Excellence (EdPEx). A qualitative developmental research design was employed. Twelve key informants from Rajabhat Universities with experience in implementing EdPEx were selected, comprising six administrators or quality assurance personnel and six staff members involved in EdPEx implementation. Data were collected through in-depth interviews using a semi-structured interview protocol aligned with the EdPEx framework. Data were analyzed using content and thematic analysis, with triangulation across multiple informant sources. The synthesized development approaches were subsequently examined through a focus group discussion to assess their appropriateness and feasibility.The findings revealed that: (1) EdPEx implementation reflected an integrated management system covering all seven categories, with efforts to connect leadership, strategy, processes, and results; however, implementation levels varied, with limitations in data integration, strategic alignment, and staff participation; (2) key strengths included leadership and policy support, while major weaknesses and challenges involved insufficient systemic integration, siloed work practices, ineffective use of data, and uneven staff participation; and (3) advancing universities toward excellence requires an integrated, systemic approach that dynamically connects leadership, strategy, processes, data, workforce, and results, together with data-driven decision-making, workforce development, and continuous process improvement to achieve effective and sustainable outcomes.

Keywords: EdPEx; Rajabhat Universities; implementation; development approaches; organizational excellence

INTRODUCTION

Over the past decade, Thailand's higher education system has undergone significant changes driven by transformations in the economic, social, and technological landscape, as well as intensifying pressures from international competition. Higher education institutions are therefore required to move beyond their traditional role as providers of graduates and assume a more strategic role in developing human capital, generating knowledge and innovation, and improving the overall quality of life in society (Office of the Higher Education Commission, 2020). Within this context, traditional management approaches that primarily emphasize compliance with regulations and procedural requirements may no longer be sufficient to generate meaningful and sustainable outcomes in the long term. Consequently, the concept of Performance Excellence has increasingly been adopted as a framework for organizational development. The Education Criteria for Performance Excellence (EdPEx) provides a holistic framework for organizational assessment that encompasses seven key categories: leadership, strategy, customers, measurement, analysis, and knowledge management, workforce, operations, and results. These categories reflect a systems perspective that emphasizes the interrelationships among different dimensions of an organization. The framework is rooted in the Malcolm Baldrige Performance Excellence Framework, which promotes a systematic approach to organizational performance management by connecting leadership, strategy, learners and stakeholders, measurement and knowledge management, workforce, operations, and results. Accordingly, the application of EdPEx is not intended merely to assess the completeness of implementation within individual categories; rather, it emphasizes the integration of organizational components to generate improved outcomes and support continuous improvement (National Institute of Standards and Technology [NIST], 2021).

Although the Education Criteria for Performance Excellence (EdPEx) has been continuously adopted as a framework for quality development in Thai higher education institutions, Rajabhat Universities possess distinctive characteristics that differentiate them from other types of higher education institutions. They are mandated to serve as "higher education institutions for local development," with missions encompassing education, research, academic services, preservation of arts and culture, technology development and transfer, and teacher education and development. These multifaceted missions mean that the implementation of EdPEx in Rajabhat Universities should not be limited to improving internal organizational performance. Rather, it must also connect university performance with the value created for learners, stakeholders, and local communities. However, the existence of a quality framework alone does not automatically ensure effective implementation or desired outcomes. While such a framework establishes the components and principles that organizations should prioritize, it does not sufficiently explain how these principles can be connected and translated into actual practices at the organizational-unit and individual levels. This issue is particularly important in higher education institutions, which comprise diverse units with different missions, areas of expertise, administrative structures, and organizational cultures. Ruben and Gigliotti (2019) noted that applying the Baldrige framework in higher education requires consideration of the specific context, culture, and needs of each institution. Similarly, Ruben et al. (2007) found that Baldrige-based self-assessment in

higher education can support organizational learning, identification of strengths and areas for improvement, and commitment to organizational change.

These considerations indicate that the critical gap lies not in the absence of a framework for performance excellence, but in the limited understanding of the processes through which EdPEx can be connected from the policy and management levels to the actual practices of organizational units and personnel, while also linking internal organizational performance to value creation for learners, stakeholders, and local communities. Accordingly, this study sought to synthesize and develop approaches for implementing EdPEx that are responsive to the context of Rajabhat Universities. Specifically, it aimed to explain how leadership, strategy, processes, data, and workforce can be interconnected as a system and translated into continuous organizational development. A review of the literature indicates that relevant studies can be broadly categorized into three major groups. The first focuses on the components and principles of the Baldrige/EdPEx frameworks. The second examines organizational readiness for, or outcomes associated with, the adoption of performance excellence frameworks. The third focuses on self-assessment and organizational development based on performance excellence frameworks within higher education contexts. Nevertheless, three important gaps remain. First, although some studies have focused on measuring organizational readiness or performance outcomes, relatively limited attention has been given to explaining the processes through which policies are translated into implementation at the organizational-unit level. Second, while Ruben and Gigliotti (2019) highlighted the need to adapt performance excellence frameworks to the contexts of higher education institutions, further explanation is needed regarding how such frameworks can be implemented in universities whose missions and relationships with local communities differ from those of other types of universities. Third, previous research has primarily emphasized the components of quality frameworks, whereas limited attention has been given to explaining the interrelationships among leadership, policy translation, strategy, processes, data, and workforce within the context of Rajabhat Universities.

Therefore, the research gap addressed by this study is not the lack of a quality framework or principles of EdPEx, but rather an **implementation gap** that is, the lack of a clear explanation of how the components of EdPEx are interconnected and translated into sustained practices within the context of Rajabhat Universities. This study therefore aimed to explain the conditions and processes that enable EdPEx implementation to generate intended outcomes, as well as the factors contributing to gaps between policy and practice.

RESEARCH OBJECTIVES

1. To examine the current state of implementation of the Education Criteria for Performance Excellence (EdPEx) in Rajabhat Universities.

2. To analyze the strengths, weaknesses, and key issues associated with the implementation of the Education Criteria for Performance Excellence (EdPEx) in Rajabhat Universities.

3. To explore development approaches for advancing Rajabhat Universities toward excellence

based on the Education Criteria for Performance Excellence (EdPEx).

METHODOLOGY

This study employed a qualitative developmental research design with the aim of developing approaches for advancing universities toward excellence based on the Education Criteria for Performance Excellence (EdPEx). Data from an examination of the current state of implementation and an analysis of gaps, strengths, weaknesses, and systemic issues were used as the basis for synthesizing the development approaches. The research process consisted of three phases. Phase 1 examined the current state of implementation based on all seven categories of the EdPEx framework. Phase 2 analyzed the strengths, weaknesses, and implementation gaps identified from the current state of implementation. Phase 3 focused on developing approaches for advancing universities toward excellence by analyzing the relationships among the identified issues and implementation gaps and using these findings to formulate approaches for implementing EdPEx. The synthesized draft approaches were subsequently validated through a focus group discussion with the key informants. The discussion examined the appropriateness, clarity, and feasibility of the proposed approaches for practical implementation.

1. Target Population and Sampling

The target population comprised administrators and personnel in higher education institutions who were directly involved in the implementation of the Education Criteria for Performance Excellence (EdPEx). Purposive sampling was employed to select participants with direct experience and relevant roles in EdPEx implementation. The case selection was based on the participants' relevance to the research issues and their experience in implementing the EdPEx criteria, enabling them to provide in-depth information regarding implementation processes, challenges, and contextual conditions associated with the adoption of the criteria. A total of 12 key informants participated in the study, comprising six senior administrators or administrators responsible for quality assurance and six personnel directly involved in EdPEx implementation.

2. Research Instrument

The primary research instrument was a semi-structured interview protocol developed based on the seven categories of the EdPEx framework and key issues related to translating the framework into practice. These issues included organizational direction and leadership, strategy implementation, integration of processes and organizational units, data and results management, and workforce engagement. The interview protocol was reviewed by experts to establish content validity prior to data collection. In-depth interviews were conducted with each key informant. Interview data were recorded and transcribed verbatim based on the participants' responses, and the accuracy of the transcripts was checked against the original interview records. Key interview summaries were returned to the participants for confirmation of accuracy as part of the member-checking process.

3. Data Collection

Data were collected through semi-structured in-depth interviews with key informants directly

involved in EdPEx implementation, following informed consent and research ethics procedures. Interview protocols were developed based on the EdPEx framework, and interviews were conducted either face-to-face or electronically using probing questions. Data were recorded, transcribed, and verified through member checking and triangulation across multiple informant sources. The data were analyzed within and across the seven EdPEx categories to identify implementation conditions, strengths, weaknesses, and key issues. The synthesized findings were used to formulate draft development approaches, which were reviewed through a focus group discussion to assess their clarity, appropriateness, and feasibility.

4. Data Analysis

This study employed content analysis to analyze the qualitative data obtained from the in-depth interviews. The data analysis was conducted systematically through the following steps:

4.1 Data Preparation. The researcher reviewed and organized the data obtained from the in-depth interviews and identified the key issues for analysis based on the seven categories of the Education Criteria for Performance Excellence (EdPEx): leadership; strategy; customers; measurement, analysis, and knowledge management; workforce; operations; and results. These categories served as the analytical framework for organizing and interpreting the interview data.

4.2 Data Categorization. The interview data were categorized according to issues related to each EdPEx category. Particular attention was given to information reflecting the current state of implementation, strengths, weaknesses, problems, and operational constraints of the universities.

4.3 Data Synthesis and Interpretation. The researcher compared the key themes emerging from the interviews across individual informants to identify areas of convergence and divergence. The findings were then synthesized to provide an overall understanding of the universities' implementation of the EdPEx criteria.

4.4 Synthesis of Development Approaches. The findings regarding the current state of implementation, strengths, weaknesses, and key issues identified through content analysis were synthesized into draft approaches for advancing universities toward excellence based on the EdPEx criteria. The synthesis considered the contextual appropriateness of the proposed approaches and the issues identified through the study.

4.5 Validation and Refinement of the Analysis. The synthesized draft development approaches were presented in a focus group discussion with the key informants for critical review and feedback regarding their clarity, comprehensiveness, appropriateness, and feasibility for practical implementation. The feedback obtained from the discussion was subsequently incorporated to refine and synthesize the final development approaches.

Conceptual Framework

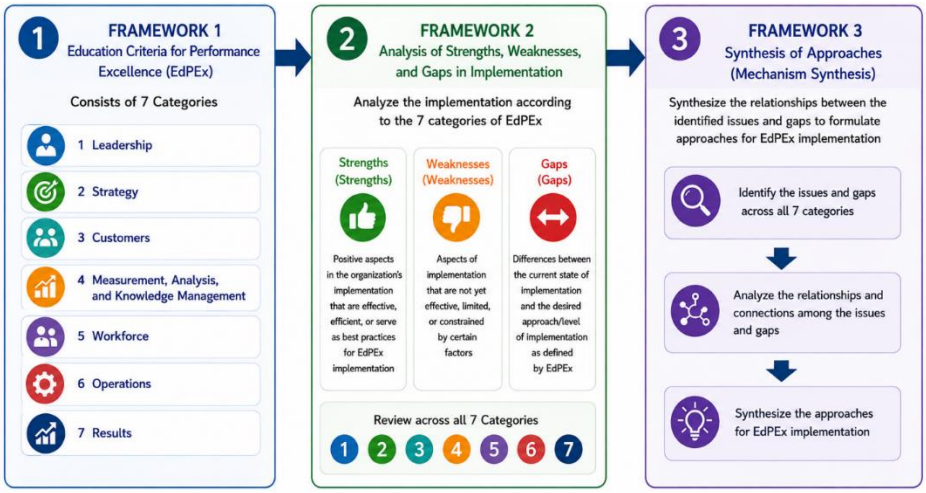


Figure 1. Research Conceptual Framework

RESEARCH FINDINGS

1. Current State of EdPEx Implementation in Rajabhat Universities

The findings revealed that the implementation of the Education Criteria for Performance Excellence (EdPEx) in Rajabhat Universities reflects an integrated management system development approach encompassing all seven categories of the framework. This indicates an effort by Rajabhat Universities to shift from fragmented operations toward a systemic management approach that emphasizes the interrelationships among inputs, processes, and outcomes. However, the level of implementation maturity varied across the seven categories. While some dimensions remained at an early stage of development, others had begun to develop in a more systematic manner. The current state of EdPEx implementation across the seven categories is described as follows.

Category 1: Leadership. Senior administrators played a critical role in establishing the university's vision, values, and strategic direction. Policies were communicated to various organizational units to promote shared understanding, and governance was exercised in accordance with principles of good governance. However, the translation of policies into practice varied across organizational units, resulting in inconsistencies in the level of implementation.

Category 2: Strategy. The universities had established strategic plans that were clearly aligned with their vision and missions and had made efforts to translate strategies into action plans through resource allocation and plan adjustments in response to changing circumstances. Nevertheless, the linkage among strategies, performance indicators, and outcomes remained incomplete, limiting the extent to which strategic achievement could be monitored and demonstrated through empirical evidence.

Category 3: Customers. The universities placed emphasis on learners and stakeholders by continuously gathering information on their needs, expectations, and satisfaction. The information

obtained was used to improve curricula and services. However, more sophisticated customer information management, such as learner segmentation and behavioral analysis, remained an area requiring further development.

Category 4: Measurement, Analysis, and Knowledge Management. The universities had established key performance indicators (KPIs) and continuously monitored performance, while data were maintained through information systems. However, the use of data for in-depth analysis and strategic decision-making remained constrained, particularly with regard to data integration across organizational units and the use of data to support innovation development.

Category 5: Workforce. The universities continuously developed workforce capabilities in relevant knowledge and skills and promoted workforce engagement through performance appraisal and reward systems. Nevertheless, some personnel still lacked sufficient understanding of the EdPEx criteria and their roles in driving organizational development, resulting in uneven levels of workforce participation.

Category 6: Operations. The universities had designed and developed work processes in alignment with their missions, particularly by connecting teaching and learning, research, and academic services. However, some processes remained redundant and lacked integration across organizational units, limiting operational efficiency and preventing the universities from fully realizing their potential.

Category 7: Results. The universities monitored and reported results across multiple dimensions, including learner outcomes, workforce outcomes, and organizational efficiency, and used the resulting information to support improvement and development. However, most reported results remained focused on outputs rather than outcomes that reflected value creation. In addition, benchmarking against other universities remained limited.

Overall, although the universities had made progress in adopting the EdPEx criteria and had begun to develop more systematic management practices across several dimensions, significant gaps remained in data integration, the linkage between strategy and outcomes, and workforce participation. These factors represent important conditions for advancing Rajabhat Universities toward genuine organizational excellence.

2. Findings on the Strengths, Weaknesses, and Key Issues in EdPEx Implementation

2.1 Strengths

The analysis revealed that Rajabhat Universities demonstrated significant strengths in leadership, which served as a key driver of EdPEx implementation. Senior administrators demonstrated clear awareness of and commitment to quality development by establishing directions, policies, and goals aligned with the principles of performance excellence. They also provided resources and designated responsible personnel to support implementation in a concrete manner. In addition, Rajabhat Universities had supporting structures or mechanisms, such as quality assurance or university development units, which served as central coordinating bodies for facilitating and driving EdPEx implementation. These structures contributed to greater clarity at the policy and strategic levels. In terms

of organizational culture, personnel had increasingly adapted to and embraced new concepts related to advancing the universities toward excellence, particularly systems thinking and an outcome-oriented approach. Policies were also continuously communicated and cascaded from senior management to organizational units, providing an important foundation for fostering workforce participation over the long term. However, these strengths remained largely potential strengths that required further development and consolidation to achieve broad and sustainable implementation at the operational level.

2.2 Weaknesses

Despite efforts to implement EdPEx, Rajabhat Universities continued to experience significant structural and operational weaknesses, particularly a lack of integration across the EdPEx categories. Operations remained largely characterized by silo-based practices, with individual units working according to their respective missions without sufficient integration of shared data, processes, and goals. Consequently, it remained difficult to establish a clear, system-wide view of university performance. Regarding the workforce, some personnel still lacked sufficient understanding of the EdPEx criteria and systems thinking in management. As a result, implementation tended to remain task-oriented rather than results-oriented, limiting workforce participation in driving university-wide development. In terms of knowledge and information management, although Rajabhat Universities possessed substantial amounts of data, they lacked effective systems for transforming data into information and knowledge that could be used to support strategic decision-making. Data were also fragmented and poorly interconnected, constraining the quality of analysis and planning. Overall, the primary weakness was the absence of effective systemic linkages across people, processes, and data.

2.3 Key Issues

The in-depth analysis enabled the researchers to synthesize the major issues as systemic issues, as follows.

2.3.1 Weak linkage between strategy and outcomes. Although the universities had established strategies and action plans, clear linkages among strategies, performance indicators, and outcomes remained limited, making it difficult to monitor and evaluate strategic achievement in a concrete manner.

2.3.2 Data limitations and underutilization of data. Rajabhat Universities lacked sufficiently in-depth information regarding learners and stakeholders, as well as robust systems for advanced data analysis. Consequently, decision-making continued to rely more heavily on experience than on evidence-based decision-making.

2.3.3 Organizational structures and work processes that constrained integration. University structures and work processes remained overlapping and insufficiently clear, resulting in duplicated tasks and reduced operational efficiency.

2.3.4 Gaps in policy translation into practice. Although senior administrators established clear policies, their translation into operational practices was not sufficiently continuous, resulting in variations in implementation across organizational units.

2.3.5 Limitations in workforce capacity and participation. Some personnel lacked the knowledge and skills required for EdPEx implementation, resulting in uneven workforce participation in driving university-wide development.

3. Development Approaches for Advancing Rajabhat Universities toward Excellence Based on EdPEx

The synthesis of the findings indicated that advancing universities toward excellence based on the EdPEx criteria requires an Integrated System Development approach encompassing leadership, strategy, processes, workforce, data, and results. These components need to be dynamically interconnected (Dynamic Linkage) to maximize organizational effectiveness. The development approaches can be described across seven dimensions as follows.

3.1 Strategy and Organizational Structure Development. Universities should transform strategic planning from a policy-oriented planning exercise into a mechanism for driving university development. This requires systematic strategy deployment into action plans, performance indicators, and budgets through organizational alignment. In addition, university structures should be redesigned to facilitate integrated operations, reduce silo structures, and promote cross-functional integration, thereby enabling strategies to be implemented more effectively.

3.2 Operations System Development. Operations system development should focus on designing core processes that integrate key missions, including teaching and learning, research, and academic services, into a coherent and integrated system. Clear operational standards and practices should be established, together with the adoption of continuous improvement to reduce duplication, enhance efficiency, and improve process quality.

3.3 Workforce Development. Workforce development should address both competency and engagement, particularly by strengthening personnel's understanding of the EdPEx criteria and their roles in driving university development. Universities should establish a continuous workforce development system, together with motivation and performance evaluation systems aligned with university goals, so that personnel can participate at the systemic level rather than merely at the operational level.

3.4 Leadership Development. University leaders should act as change leaders, going beyond establishing vision and policies to effectively communicating and translating them into practice at all organizational levels. Universities should also strengthen governance and performance monitoring systems to ensure clarity, transparency, and evidence-based management, thereby enhancing the credibility and effectiveness of university administration.

3.5 Measurement, Analysis, and Knowledge Management System Development. Universities should develop an integrated information system that connects data across organizational units and supports systematic data collection, analysis, and utilization. Strategic KPIs should be established to reflect strategic outcomes and provide meaningful measures of progress. Universities should also strengthen their analytics capability to support evidence-based decision-making.

3.6 Customer and Stakeholder Development. Universities should develop a more

systematic and in-depth Voice of Customer (VOC) system that captures the needs, expectations, and experiences of learners and stakeholders. These insights should be used to design and improve curricula, services, and organizational processes in order to create value and foster long-term engagement.

3.7 Results and Benchmarking Development. Universities should shift their approach to performance measurement from an emphasis on outputs toward outcomes and impacts that reflect the actual value created by the university. Performance should be benchmarked against comparable universities to identify performance gaps, while results should be used as a feedback loop for continuous improvement.

Based on these seven development approaches, the relationships among the approaches can be synthesized from the findings regarding the current state of implementation, strengths, weaknesses, and key implementation issues, as illustrated in the following framework.



Figure 2. Mechanisms Linking the Development Approaches

Mechanism 1: Leadership Mobilization. Senior administrators establish the university's direction, policies, and goals and allocate resources to support organizational change. The findings indicated that leadership and policy support represented key strengths of Rajabhat Universities.

Mechanism 2: Policy-to-Practice Translation. This mechanism translates managerial direction into organizational goals, action plans, performance indicators, and operational practices across organizational units. The findings demonstrated that leadership alone was insufficient to ensure effective EdPEx implementation at the operational level, as a gap remained between policy formulation and actual implementation within organizational units.

Mechanism 3: Strategic Alignment. This mechanism connects strategies with action plans, performance indicators, and resource allocation. The findings indicated that a significant gap existed in the linkage among strategies, performance indicators, and outcomes, limiting the extent to which strategic achievement could be effectively monitored and demonstrated through empirical evidence.

Mechanism 4: Cross-functional Integration. This mechanism addresses the need for integration across organizational units. The findings revealed a **silo-based mode of operation** and a lack of effective linkages among people, processes, and data.

Mechanism 5: Evidence-based Decision Making. The findings indicated that Rajabhat Universities possessed substantial amounts of data and numerous performance indicators but faced limitations in integrating data and using it for in-depth analysis to support strategic decision-making.

Mechanism 6: Workforce Engagement. This mechanism connects organizational change from the policy level to actual implementation at the operational level. The findings showed that some personnel still lacked sufficient understanding of EdPEx and their roles in organizational development, resulting in uneven workforce participation.

The six mechanisms therefore function as an interconnected system rather than as isolated components. The outcomes generated through implementation are fed back into the system to inform subsequent adjustments to strategies, processes, and resource allocation. This finding is consistent with the broader conclusion that advancing Rajabhat Universities requires dynamic linkages among leadership, strategy, processes, data, and results. The findings further indicated that the principal challenge in implementing EdPEx lies in the linking mechanisms among the various organizational components. Although universities already possess policies, strategic plans, performance indicators, information systems, and operational processes, the effectiveness of EdPEx implementation depends on the organization's capacity to connect these components into a continuous system of action extending from the policy level to the operational level. The analysis identified six key mechanisms: (1) Leadership Mobilization, (2) Policy-to-Practice Translation, (3) Strategic Alignment, (4) Cross-functional Integration, (5) Evidence-based Decision Making, and (6) Workforce Engagement. These mechanisms do not operate as discrete sequential stages; rather, they constitute an interconnected system in which each mechanism influences and reinforces the others. Leadership and policy support provide the initial driving force of the system, while policy-to-practice translation connects the policy level with operational implementation. Strategic alignment links strategies with action plans, performance indicators, and resources, whereas cross-functional integration reduces silo-based operations and connects processes across organizational units. At the same time, information systems and evidence-based decision making transform data from being used merely for performance reporting into a resource for decision-making and organizational improvement. The workforce serves as a critical mechanism for translating organizational change from the managerial level into actual practice. The outcomes of implementation are subsequently fed back into the system to inform the refinement of strategies, processes, and resource allocation in the next cycle.

DISCUSSION OF THE FINDINGS

1. Current State of EdPEx Implementation in Rajabhat Universities

The findings indicate that Rajabhat Universities have implemented the Education Criteria for Performance Excellence (EdPEx) across all seven categories, with an emerging tendency toward

systems-based management. In particular, the universities have increasingly sought to establish linkages among leadership, strategy, operational processes, and results. This finding is consistent with the concept of performance excellence, which emphasizes a systems perspective. However, the findings also indicate that the level of implementation across the seven categories remains uneven, with limitations in data integration, the translation of strategy into practice, and workforce participation. These findings are consistent with the framework of the National Institute of Standards and Technology (NIST, 2021), which emphasizes that organizational excellence based on the Baldrige Framework requires the systematic integration of all categories rather than isolated implementation of individual components. The findings are also consistent with Evans and Lindsay (2017), who noted that organizations in the early stages of adopting performance excellence approaches often develop their structures and processes before establishing clear systemic linkages among organizational components. Therefore, the findings suggest that Rajabhat Universities have made progress in establishing the fundamental components of EdPEx, but further development is required to strengthen the connections among these components and enable them to function as an integrated management system.

2. Strengths, Weaknesses, and Key Implementation Issues

The findings indicate that the major strengths of Rajabhat Universities lie in leadership and policy support. Senior administrators play an important role in establishing the direction of the universities and developing concrete mechanisms to support implementation. These factors constitute important foundations for advancing Rajabhat Universities toward excellence.cNevertheless, the major weaknesses and implementation issues concern the lack of system integration, particularly silo-based operations across organizational units, insufficient linkages among data, and uneven workforce participation. These findings are consistent with the organizational systems perspective of Katz and Kahn (1978), which conceptualizes organizations as systems whose effectiveness depends on the interrelationships among their various components. When these linkages are weak, overall organizational effectiveness may be constrained.The findings are also consistent with Oakland (2014), who argued that failures in organizational excellence initiatives often arise from insufficient alignment between strategy and operations and from inadequate use of data as a basis for decision-making. In the context of higher education, Sahney, Banwet, and Karunes (2008) similarly found that educational organizations implementing quality-oriented approaches commonly encounter fragmented operations and inadequate information systems to support strategic decision-making. Taken together, these findings suggest that the central challenge for Rajabhat Universities is not the absence of quality management components, but the limited capacity to integrate these components into a coherent organizational system.

3. Development Approaches for Advancing Rajabhat Universities toward Excellence Based on EdPEx

The findings indicate that effective EdPEx implementation depends not solely on the existence of a quality framework but also on the mechanisms that connect leadership, strategy, processes, data, and workforce and translate them into systematic practice. The findings therefore led

to the synthesis of six key mechanisms: Leadership Mobilization, Policy-to-Practice Translation, Strategic Alignment, Cross-functional Integration, Evidence-based Decision Making, and Workforce Engagement.cFirst, regarding Leadership Mobilization and Policy-to-Practice Translation, the findings indicate that leadership and policy support constitute strengths of Rajabhat Universities; however, a gap remains between policy formulation and implementation at the organizational-unit level. This finding is consistent with Kalyanamitra et al. (2021), who found that administrative and organizational factors were associated with readiness to implement EdPEx in Rajabhat Universities. It is also consistent with Phalakan et al. (2025), who found that communication and workforce participation were important to advancing EdPEx implementation in the Faculty of Communication Arts at Rambhai Barni Rajabhat University. The present study extends these findings by demonstrating that leadership contributes to effective EdPEx implementation when policies can be translated into operational goals, action plans, performance indicators, and responsibilities. Accordingly, Policy-to-Practice Translation is proposed as a mechanism linking organizational leadership with actual implementation.cSecond, regarding Strategic Alignment and Cross-functional Integration, the findings reveal gaps among strategies, action plans, performance indicators, and outcomes, as well as silo-based operations across organizational units. The findings concerning strategic planning are consistent with Kalyanamitra et al. (2021), who reported that strategic planning demonstrated a lower level of readiness than other categories. Meanwhile, the Baldrige framework emphasizes process integration, coordination across organizational units, and the linkage of results to organizational improvement (National Institute of Standards and Technology [NIST], 2021). In addition, Ruben and Gigliotti (2019) proposed that the implementation of performance excellence frameworks in higher education should be adapted to the specific culture and context of each institution. The present study extends these perspectives by proposing Cross-functional Integration as a mechanism that connects people, processes, data, and shared goals across organizational units, thereby reducing silo-based operations and enabling EdPEx to function as an integrated system. Third, regarding Evidence-based Decision Making and Workforce Engagement, the findings indicate that universities possess substantial amounts of data and numerous performance indicators but face limitations in integrating and analyzing these data to support decision-making. At the same time, some personnel lack sufficient understanding of EdPEx and their roles in advancing organizational development. These findings are consistent with the Baldrige principles emphasizing fact-based management, the integration of results into decision-making, and organizational learning (NIST, 2021). They are also consistent with Supawong (2024), who highlighted the importance of administrative support and workforce preparedness in applying EdPEx, as well as Sriwicha (2026), who found an association between workforce awareness and participation in organizational development based on EdPEx. However, the present study extends the existing perspective by conceptualizing data and workforce not merely as organizational components, but as mechanisms that facilitate implementation. Data function as a link between organizational results and decision-making, while the workforce functions as a link between organizational change at the policy level and its translation into actual practice. This perspective highlights that the effectiveness of EdPEx implementation depends on

the organization's ability to establish dynamic linkages among leadership, strategy, processes, data, and workforce, rather than simply developing each component independently.

References

Evans, J. R., & Lindsay, W. M. (2017). Managing for quality and performance excellence (10th ed., Asia ed.). Cengage Learning Asia.

Kalyanamitra, P., Tatiyalapa, D., & Ngamlamom, W. (2021). The causal relationship model of factors affecting the availability of Central Rajabhat University towards access to the Education Quality Criteria for Excellence. Asian Crime and Society Review, 8(2), 14–20. https://so02.tci-thaijo.org/index.php/IJCLSI/article/view/251335

Katz, D., & Kahn, R. L. (1978). The social psychology of organizations (2nd ed.). Wiley.

National Institute of Standards and Technology. (2021). 2021–2022 Baldrige Excellence Framework (Education): Proven leadership and management practices for high performance. U.S. Department of Commerce. https://www.nist.gov/baldrige/2021-2022-baldrige-excellence-framework-education

Oakland, J. S. (2014). Total quality management and operational excellence: Text with cases (4th ed.). Routledge.

Office of the Higher Education Commission. (2020). Education Criteria for Performance Excellence (EdPEx).

Phalakan, D., Sirinantana, A., & Keeratwasin, B. (2025). Guidelines for managing communication in internal educational quality assurance operations based on the Education Criteria for Performance Excellence (EdPEx): A case study of the Faculty of Communication Arts, Rambhai Barni Rajabhat University. Journal of Social Innovation and Mass Communication Technology, 8(1), 56–63. https://doi.org/10.14456/jsmt.2025.5

Ruben, B. D., & Gigliotti, R. A. (2019). The excellence in higher education model: A Baldrige-based tool for organizational assessment and improvement for colleges and universities. Global Business and Organizational Excellence, 38(4), 26–37. https://doi.org/10.1002/joe.21932

Ruben, B. D., Russ, T., Smulowitz, S. M., & Connaughton, S. L. (2007). Evaluating the impact of organizational self-assessment in higher education: The Malcolm Baldrige/Excellence in Higher Education framework. Leadership & Organization Development Journal, 28(3), 230–250. https://doi.org/10.1108/01437730710739657

Sahney, S., Banwet, D. K., & Karunes, S. (2006). An integrated framework for quality in education: Application of quality function deployment, interpretive structural modelling and path analysis. Total Quality Management & Business Excellence, 17(2), 265–285. https://doi.org/10.1080/14783360500450376

Sriwicha, S. (2026). Personnel awareness and participation in organizational development toward excellence based on EdPEx: A case study of the Faculty of Law, Rajabhat Mahasarakham University. Journal for Developing the Social and Community, 13(2), 305–322.

https://so03.tci-thaijo.org/index.php/rdirmu/article/view/302125

Supawong, T. (2024). Development of personnel potential in educational institutions using the EdPEx system. Journal of Social Sciences and Humanities, Kasetsart University, 50(2), 57–74. https://so04.tci-thaijo.org/index.php/socku/article/view/273087

P26013

DEVELOPMENT OF A PARENT'S GUIDE FOR PLAY-BASED CURRICULUM FROM STAKEHOLDERS' INSIGHTS

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ABSTRACT

This study focused on developing a parent's guide to inform stakeholders on the play-based curriculum in preschools in Legazpi City. Recognizing the crucial role of parents as partners in early childhood education, the study aimed to explore the perceptions of preschool parents in Legazpi City and early childhood experts regarding play-based learning in terms of socio-emotional, cognitive, and motor development. Using a descriptive-developmental research design, the study gathered insights from 46 preschool parents and 20 early childhood experts. Both qualitative and quantitative data were analyzed to develop the parent's guide, which aims to bridge the gap between home and school by enhancing parents' understanding of the benefits of play-based learning for their children's holistic development. The findings show a general consensus acknowledging play-based learning as a relevant and effective educational practice among all stakeholder groups. Overall, while it was widely perceived as highly effective, the study underscores the need for continuous stakeholder capacity-building and parent education. As revealed in the validation, the parent guidebook received a very satisfactory mean score of 3.80. The parent's guide was developed to provide stakeholders with accessible, research-backed information on play-based learning. It can serve as a resource for teacher education courses and community extension programs that involve families and communities, thereby fostering stronger institutional partnerships. The guide has the potential to support collaboration between home and school and recommend its further validation and implementation on a larger scale.

Keywords: Play-based Curriculum, Parent's Guide, Socio-Emotional Development, Cognitive Development, and Motor Development

Introduction

The growing understanding of early childhood development is reshaping education. Traditional teacher-led models that require passive, task-based learning have given way to approaches that recognize the early years as foundational to social, emotional, cognitive, and physical growth. Play-based learning has emerged as a prominent, developmentally appropriate strategy, with evidence supporting its role in academic skills, language, self-regulation, and executive function (Bitoy, 2021). The Philippine Department of Education has accordingly integrated play into the MATATAG curriculum, with Celedonio (2025) affirming its effectiveness in kindergarten learners' holistic development.

Beyond academics, free play fosters emotional intelligence, resilience, coping strategies, curiosity, problem-solving, and foundational math, literacy, and science skills, while active play refines motor coordination and dexterity (Ahmed et al., 2023).

Despite these benefits, free play is often reduced to non-essential downtime under academic pressure, and parents remain unaware of its educational value—a critical gap given BEDP 2030 and MATATAG mandates for family engagement (Awopetu, 2024). This UST-Legazpi initiative developed a contextually relevant Parent's Guidebook using insights from Legazpi City schools, demystifying play, equipping stakeholders with actionable home strategies, and positioning parents as active partners in fostering lifelong learning. Higher education institutions can utilize this parents' guidebook as a supplementary material discussed through Bachelor of Early Childhood Education courses (CMO No. 76, s. 2017), including Play and Developmentally Appropriate Practices and Family, School, and Community (Commission on Higher Education, 2017), to bridge the home-school divide via community extension.

Objectives of the Study

This study aims to develop a Parent's Guidebook to help stakeholders better understand the play-based curriculum. Specifically, it aims to:

1. Determine the perceptions of Legazpi City preschool parents on the play-based learning approach in terms of:

    a. Socio-emotional development
    b. Cognitive development
    c. Motor development

2. Determine the perceptions of early childhood practitioners on the play-based learning approach in terms of:

a. Socio-emotional development
b. Cognitive development
c. Motor development

3. Design and propose a structured parent's guide that aligns with the play-based curriculum.

Review of Related Literature

Play-based Learning and Parental Engagement

Global research confirms that play-based learning enhances holistic development, with parental involvement amplifying its effectiveness (Hisham & Ling, 2025; Ramasamy et al., 2023). The benefits span three domains: socio-emotionally, imaginative play builds resilience, self-confidence, emotion regulation, and social competence, especially with adult scaffolding (Severino et al., 2026; Skene et al., 2022; Chua et al., 2020); cognitively, structured and inquiry-based play fosters problem-solving, reasoning, and agency, while literacy-rich settings boost vocabulary, letter recognition, and phonemic awareness (Ahmad, 2024; Chen et al., 2024; Sakib, 2022; Zeng & Ng, 2024); and physically, outdoor and caregiver-guided activities refine gross and fine motor skills, locomotion, and coordination, providing a movement-rich foundation for well-being (Quinones & Opingo, 2025; Tepper, 2022).

Local Implementation and Persistent Challenges

Despite strong policy support, implementing play-based learning faces persistent conceptual, structural, and cultural barriers. Educators recognize play's benefits for engagement, collaboration, and emotional expression, yet struggle with material/space shortages, tight schedules, inadequate training, poor administrative support, and academic pressures favoring traditional benchmarks (Austria, 2024; Florita & Sabud, 2024). Moreover, teachers' lack of conceptual clarity in distinguishing free, guided, and structured play undermines program fidelity and assessment (Bodrova, 2023). Addressing these challenges requires not only physical resources and professional development but also sustained awareness-raising among parents and school stakeholders.

Descriptive-Developmental Approach

Employing a descriptive-developmental research model (analysis, design, development, and validation), this study addresses the need for instructional resources that help parents

understand and support play-based learning at home. Grounding parent-mediated interventions in stakeholder input is essential for building home-school partnerships, fostering shared responsibility, and optimizing early childhood education (Mullen & Skouteris, 2023). Yet while families globally value play, mixed attitudes, limited guidance, and a lack of accessible information leave many uncertain how to support it effectively at home (Wright et al., 2023). By utilizing descriptive data from parent and expert surveys to directly inform the guidebook design, this study ensures the resulting resource is a practical tool rooted in local families' needs, concerns, and strengths.

Conceptual Framework

As shown in figure 1, the developmental process began with gathering and thematically coding stakeholder perceptions to identify key knowledge gaps. These insights directly informed the guidebook's content and design, which features accessible language and authentic images of home and school play activities. The guidebook enhances parental understanding and engagement with support from teachers and HEIs, ultimately strengthening home-based support for holistic child development while enriching teacher education curricula and community extension programs.

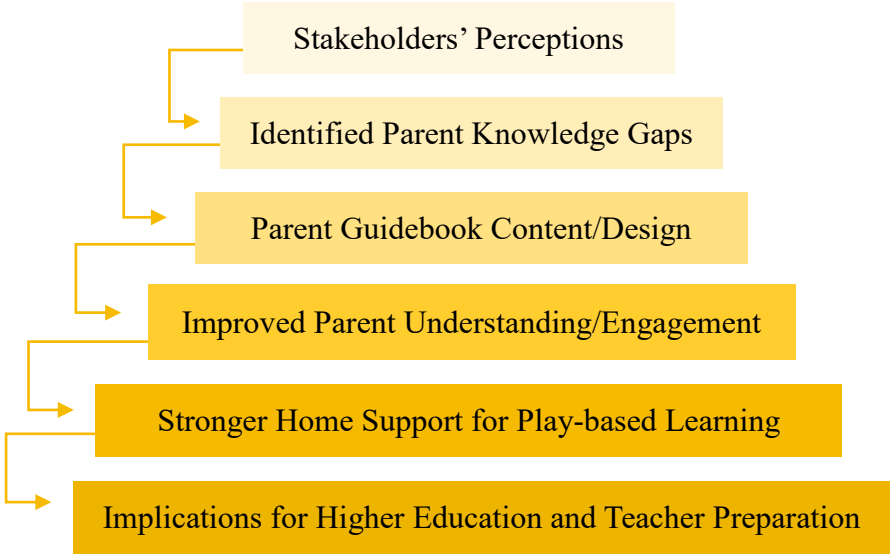


Figure 1. Conceptual Framework of the Development of the Parent's Guidebook (Magallanes et al., 2026)

Methodology

This section outlines the research design, sources of data, tools, procedures, and statistical treatment used for data analysis and interpretation.

Research Design

This study employed a descriptive-developmental research design, combining the systematic description of a target population with the design, development, and evaluation of instructional products (Formplus, 2021; Richey & Klein, 2005, as cited in Yusri et al., 2024). Quantitative data from checklists were analyzed using frequency counts and percentages to inform the parent's guide, while qualitative data from interview transcripts were analyzed descriptively to enrich and contextualize the quantitative findings.

Limitation

This study focused on the development and expert validation of the parent guidebook based on stakeholders from selected schools in Legazpi City. The guidebook has not yet been field-tested with parents; thus, its usability, acceptability, and effectiveness in improving parental understanding and engagement have yet to be established. Its potential adoption and integration into higher education teacher education programs have likewise not yet been evaluated.

Data Collection Tool

This study employed a mixed-methods design. Quantitative perceptions of parents and experts were measured using a modified checklist adapted from the study of Magallanes et al. (2025), originally grounded in literature and validated for face and content. Qualitative data were collected via semi-structured interviews (four open-ended questions for parents, five for experts) following standard protocol assurances including reading an approved memorandum from the Division office, and opening instructions. Sample items included statements on children’s social skills, confidence, problem-solving, literacy, numeracy, and fine and gross motor development. Transcripts were coded, categorized, and merged into central thematic patterns, with trustworthiness criteria mentioned in the study of Alexander (2019).

Data Gathering Procedure

This study employed a stratified cluster sampling design across 10 purposively selected kindergarten schools in Legazpi City (7 public, 3 private) to ensure balanced sectoral representation. Within each cluster, teachers were purposively selected based on direct

experience implementing play-based learning to provide in-depth insights for the guidebook. Parents were chosen via systematic random sampling from student rosters using a random start and a 5-parent interval. This strategy ensured practical feasibility, representative parent coverage, and inclusion of knowledgeable key informants.

Developmental Framework

This study adapted the developmental research framework of Magallanes et al. (2024), utilizing a three-phase descriptive-developmental approach: Analysis (problem identification and information gathering), Design (data consolidation, interpretation, and literature integration), and Development (creation of the printed Parent's Guide based on empirical findings). Figure 2 outlines this adapted framework. In the context of the current study, a fourth phase was added wherein the developed parents' guidebook underwent consequent validation.

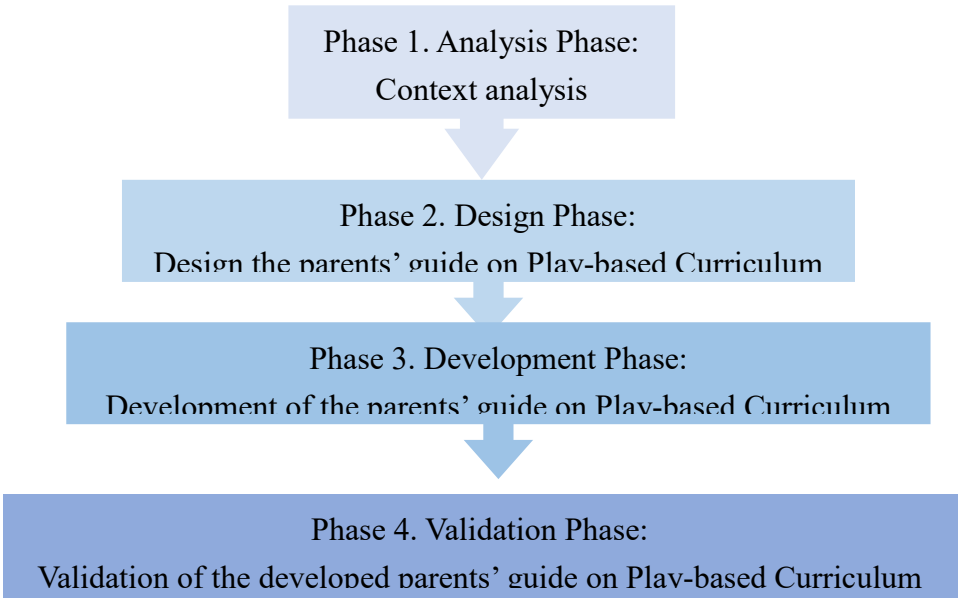


Figure 2. Summary of the Phases in the Developmental Research Framework (Magallanes et al., 2024)

Addressing the lack of localized parent's guidebook regarding play-based learning in Legazpi City, the analysis phase gathered insights across socio-emotional, cognitive, and motor domains to support the MATATAG Curriculum rollout. To ensure broad institutional and community utility, the study engaged parents, and early childhood experts. The design phase utilized survey data from 46 preschool parents and 20 experts to structure content around the three developmental domains. Finally, the development phase synthesized these findings into

a printed Parent's Guide for Legazpi City, directly pairing identified knowledge gaps with tailored topic areas for all stakeholders.

Validation Tool

Validation, the study's final phase, was conducted by six early childhood education experts holding master's degrees with expertise in home collaboration, teaching, and curriculum development. They evaluated the guidebook using an adapted tool, Evaluation Rating Sheet for Print Resources, for material refinement (DepEd SDO Naga City, 2019). The evaluation covered four core areas modified from DepEd's print resource sheet: (1) Content and Pedagogical Alignment (adapted from "Content"), measuring home application, play principles, values, engagement, and safety; (2) Visual, Layout, and Technical Aspects (updated from "Format and Technical Aspects"), retaining five criteria; (3) Language and Presentation (revised from "Presentation and Organization"), condensed from five to four criteria; and (4) Accuracy and Reliability (modified from "Accuracy and Up-to-datedness"), with two added items to align with study objectives.

Pointing System

A 1-to-4 scale (Poor to Very Satisfactory) was adapted to quality-assure the guidebook (DepEd SDO Naga City, 2019). Maximum and passing scores were recomputed per factor based on item modifications: Factor 1 (Max: 28, Passing: 21), Factor 2 (Max: 20, Passing: 15), Factor 3 (Max: 16, Passing: 12), and Factor 4 (Max/Passing: 16). Unlike standard DepEd protocols where failing a single factor disqualifies a resource, this study did not enforce strict disqualification at this stage, as the guidebook will proceed to a subsequent phase focusing on stakeholder implementation and evaluation regarding usability, acceptability, and effectiveness.

Table 1. Rating Scale and Interpretation of Validation Results (Magallanes et al., 2026)

Scale	Mean Range	Descriptive Rating	Interpretation
4	3.26 – 4.00	Very Satisfactory	Highly valid; meets or exceeds quality standards.
3	2.51 – 3.25	Satisfactory	Valid; acceptable quality. Minor revisions may be applied.
2	1.76 – 2.50	Fair	Partially valid; needs explicit revisions based on comments.
1	1.00 – 1.75	Poor	Invalid; major overhaul required.

To align with the objectives and answer the research problems, the gathered data were organized into tabular form, computed, and statistically analyzed. The following statistical tools were utilized for proper data interpretation:

$$P = \frac{x}{n} \ 100 \qquad (1)$$

Where P is the percentage, x is the frequency of the score, and n is the total number of respondents.

The following statistical tools were used in the validation of the Parent's Guidebook:

Mean ($\bar{X}$): Used to determine the average evaluation rating per criterion, factor, and overall guidebook.

$$(\bar{X}): \ = \frac{\sum_{i=1}^{n} X_i}{n} \qquad (2)$$

($\bar{X}$) : Represents the sample mean rating.

X_i : Represents the individual evaluation rating provided by validator i.

n : Represents the total number of expert validators (n = 6).

Item Content Validity Index (I-CVI): Determines the proportion of validators giving a favorable rating (3 or 4), an I-CVI of at least 0.83 indicates that a minimum of five (5) out of six (6) experts agreed on the item's relevance and appropriateness (Malik & Hasan, 2026).

$$\text{I-CVI} = \frac{n_{\text{agree}}}{N} \qquad (3)$$

n_agree : The total count of experts giving a favorable rating (rating ≥ 3).

N : The total number of expert validators (N = 6).

Scale Content Validity Index Average (S-CVI/Ave): Calculated to assess the overall validity of the 20-item guidebook evaluation tool against the ≥ 0.90 standard threshold (Malik & Hasan, 2026).

$$\text{S-CVI/Ave} = \frac{\sum_{j=1}^{k} \text{I-CVI}_j}{k} \qquad (4)$$

I-CVI_j : The Item Content Validity Index calculated for item j.

J: The item number, ranging from 1 to k.

k : The total number of items evaluated in the instrument (k = 20).

Results and Findings

This section presents and interprets the data based on the objectives of the study. Tables and figures are used to present and summarize the findings. The results are organized according to each research objective.

Table 2. Perceptions of Preschool Parents in Legazpi City on the Play-Based Learning Approach (Magallanes et al., 2026)

Domain & Stakeholders' Findings	Identified Need & Learning Outcome	Guide Sec.	Supporting Literature
Before Play-Based Learning (Initial Perceptions)			
Socio-Emotional: • 100% saw socio-emotional benefits. • Initial anxiety regarding child shyness, social adaptability, and play as non-educational.	Need: Clear orientation on emotional resilience and home strategies for social integration. Outcome: Appreciate play-based benefits and gain confidence in a child's emotional growth.	p. 3-4	Severino et al. (2026)
Cognitive: • 91.30% recognized thinking growth. • Misconception that structured play lacks academic value ('just play'); 8.69% preferred another method.	Need: Conceptual clarity on how play builds problem-solving; comparative advantages over traditional teaching. Outcome: Realize play effectively fosters critical thinking.	p. 5, 9	Sakib (2022)
Physical & Motor: • 86.96% acknowledged motor benefits. • Concerns over physical independence and structured activity participation.	Need: Reiterate motor gains and provide home-based physical routines. Outcome: Become proactive initiators of home physical play and self-help chores.	p. 11	Tepper (2022)
After Engaging in Play-Based Learning			

Socio-Emotional: • 82.61% reported children excited for school. • 26.09% observed improved emotion regulation and social confidence.	Need: Sustained home routines to reinforce emotional regulation and peer expression acquired at school. Outcome: Actively guide emotional expression and behavior regulation at home.	p. 7, 8,10,13-14	Severino et al. (2026)
Cognitive: • 71.74% noted enriched vocabulary. • 34.78% observed better problem-solving, literacy/numeracy, and decision-making.	Need: Strategies to seamlessly integrate academic concepts (literacy/math) into daily play. Outcome: Foster active conversation and critical thinking play at home.	p. 8,12	Ahmad (2024)
Physical & Motor: • 76.09% saw improved fine motor skills. • 23.91% emphasized kinesthetic learning, self-care independence, and physical fitness.	Need: Structured home play for physical independence and fine/gross motor exercises. Outcome: Provide fine motor materials (clay, blocks) and establish active daily routines.	p. 6, 9	Quinones & Opingo (2025)

Prior to experiencing play-based learning, parental consensus strongly favored its benefits for socio-emotional (100%), cognitive (91.30%), and motor (86.96%) development, though minor hesitation (4.35%–8.69%) and misconceptions ('just play') persisted. Post-engagement, parents reported marked positive transformations, particularly in school enthusiasm (82.61%), fine motor skills (76.09%), and vocabulary enrichment (71.74%).

Parents fostered socio-emotional skills through turn-taking, politeness modeling, and encouragement; cognitive growth via board games, puzzles, activity sheets, and questioning; and motor skills through fine motor tasks and outdoor obstacle courses. Key concerns included speech delays, tracking tangible learning outcomes, and balancing literacy focus with play. Recommendations favored digital feedback tools to bridge home-school communication.

Table 3: The Perceptions of Preschool Experts in Legazpi City on the Play-Based Learning Approach (Magallanes et al., 2026)

Domain & Stakeholders' Findings	Identified Need & Learning Outcome	Guide Sec.	Supporting Literature
Before Play-Based Learning (Initial Expert Perceptions)			
Socio-Emotional: • 95% endorsed benefits (0% negative). • Shifted from viewing play as 'just fun' or conflicts as 'misbehavior' to key self-regulation tools.	Need: Assist parents in reframing peer conflicts as essential social learning moments. Outcome: Reframe play as a vital tool for emotional regulation and communication.	p. 17-18	Chua et al. (2020)
Cognitive: • 95% endorsed cognitive benefits (10% initial hesitation). • Shifted from direct instruction preference to guided play as an academic foundation.	Need: Explicit pedagogical framing showing guided play builds literacy, math, and reasoning skills. Outcome: Understand how guided play constructs academic foundations.	p. 17, 19, 20	Chen et al. (2024);
Physical & Motor: • 90% supported motor benefits (5% initial hesitation). • Shifted from viewing physical play as 'burning energy' to intentional motor planning.	Need: Actionable strategies for elevating physical play to intentional motor-planning and counteracting screen time. Outcome: Utilize structured physical play for spatial awareness and strength.	p. 21, 22	Quinones & Opingo (2025)
After Engaging in Play-Based Learning			
Socio-Emotional: • 80% noted high social engagement. • 35% noted school happiness. • Recognized play as an	Need: Home routines sustaining school-acquired social confidence and emotional role-play processing. Outcome: Provide guided environments for peer interaction and anxiety alleviation.	p. 24-26, 31, 32, 36	Skene et al. (2022)

anxiety buffer building empathy and role-play skills.			
Cognitive: • 75% observed critical thinking skills. • 30% noted enriched vocabulary, early literacy (3-syllable words), and 3-digit numeracy.	Need: Practical strategies to seamlessly integrate math and literacy into home play activities. Outcome: Reinforce academic concepts through storytelling, counting, and decision-making.	p. 27, 28, 33, 37, 40	Zeng & Ng (2024)
Physical & Motor: • 75% observed gross motor gains & active movement. • 5% noted healthy/hygienic habit adoption, enhanced fine control, and self-care.	Need: Structured outdoor routines promoting physical movement, sensory coordination, and hygiene habits. Outcome: Encourage independent self-care, bike riding, and reduced screen reliance.	p. 29, 34, 38	Quinones & Opingo (2025)

Experts universally endorsed play-based learning across socio-emotional (95%), cognitive (95%), and motor (90%) domains prior to implementation. Observations after engagement confirmed major developmental advances, particularly in social engagement (80%), critical thinking (75%), and gross motor skills (75%).

Experts recommended cooperative role-play, storybooks, and guided group activities for socio-emotional skills (empathy, turn-taking, regulation); integrated learning centers, board games, open-ended materials, and structured inquiry for cognition; and active play zones, traditional games, fine motor tasks (lacing, clay), and reduced screen time for motor development. They affirmed play as indispensable for holistic development, brain maturation, and foundational academics.

Designed and Proposed Parent's Guide Aligned with the Play-Based Curriculum

Aligned with the MATATAG Curriculum, Legazpi City schools adopted a play-based preschool approach, receiving positive feedback from parents and experts. However, many parents remain unfamiliar with play as a learning method, often equating education with worksheets and structured lessons. To address this, a printed parent guide was developed using

local insights, illustrating how play fosters exploration, creativity, problem-solving, and socio-emotional security (Seo & Munsell, 2022). The guide promotes holistic development, supports home-based play, and serves HEIs as an instructional resource for early childhood courses and a material for community extension.

Table 4. Parent's Guidebook Contents (Magallanes et al., 2026)

Page Number	Title/Sub-Title
i	Title Page: Play-Full: How a Day of Play Builds a Lifelong Learning
ii	Introduction
iii	Table of Contents
1	Parent's Journey: A Guide to Play-Based Learning
2	Parents' Perceptions
3	Socio-Emotional Expectations
4	Cognitive and Motor Concerns
7	What to Expect (The Results)
9	Cognitive and Physical Breakthroughs
10	Supporting Your Child at Home
13	Important Reminders for Parents
16	Experts Initial Perceptions
23	Experts Current Perceptions
30	Beyond the Basics: Expanding the Value of Play (The Benefits)
35	Guiding Play at Home and in School (Experts Recommendation)
39	The Heart of Play (Importance of Play)

The guidebook is structured around parent and expert perceptions, knowledge, and engagement. It opens with an introduction to play-based learning, followed by parental insights and domain-specific concerns (cognitive, socio-emotional, motor). Subsequent sections detail concrete strategies, outcomes, and breakthrough findings to address these concerns, then present expert perspectives, concluding with a reinforcement of play's intrinsic value and actionable home integration recommendations.

Description of the Parts of the Parent's Guide



Figure 3. Cover Page of the Parent's Guide (Magallanes et al., 2026)

The front cover features the authors' names and the title, "Play Full," which reflects how play brings richness and fullness to a child's life while highlighting play as an essential developmental process. To clarify its purpose, the subtitle, "How a Day of Play Builds a Life of Learning," provides context, emphasizing how the guide helps parents understand the lifelong impact of a play-based curriculum.

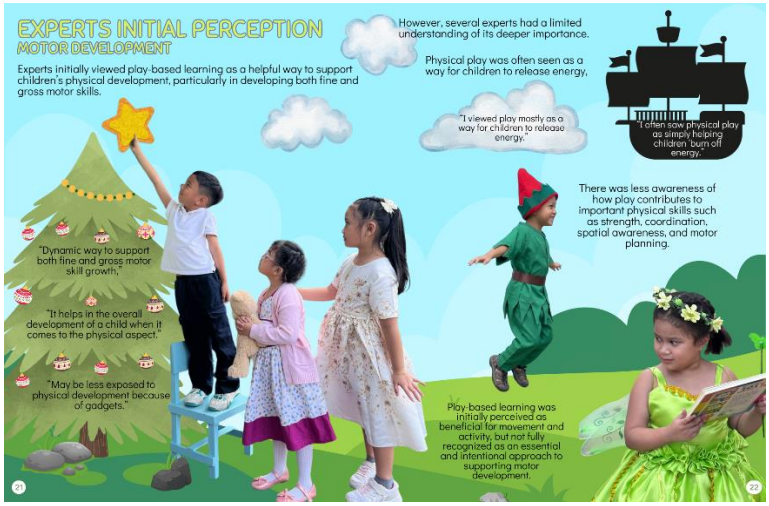


Figure 4. Body Section of the Parent's Guide (Magallanes et al., 2026)

Body. This section contains the essential information intended for parents. This section contains essential information that is intended to help parents better understand the play-based curriculum.

The design of the book was made mostly of solid design elements to create a light and welcoming reading experience for parents. Pictures were added to showcase every detail of the content. The content itself was from the experience and knowledge of the parents and experts alike. It was consolidated by the researchers to become coherent and easy to understand from parents' perspectives.

Validation of the Parent's Guidebook

This section shows the results of the validated parents' guidebook presented in tabular form along with their respective descriptions.

Table 5. Evaluation Factor Passing & Benchmark Compliance (Magallanes et al., 2026)

Evaluation Factor	Max Points	Min Passing Score	Actual Mean Points (Sum across 6 Validators)	Factor Mean (1-4)	Remarks
Factor 1: Content & Pedagogical Alignment	28	21	27.00	3.86	Passed
Factor 2: Visuals, Layout & Technical Aspects	20	15	18.50	3.70	Passed
Factor 3: Language & Presentation	16	12	15.33	3.83	Passed
Factor 4: Accuracy & Reliability	16	16	15.17	3.79	Needs Revision
Total Overall Score	80	64	76.00	3.80	Passed

Table 5 presents the overall evaluation score of 76.00/80 (mean: 3.80/4), comfortably exceeding the 64-point threshold. Three factors passed with strong performance: Content & Pedagogical Alignment (27.00/28), Visuals, Layout & Technical Aspects (18.50/20), and Language & Presentation (15.33/16). However, Factor 4 (Accuracy & Reliability) scored 15.17/16, falling 0.83 points below the passing mark and requiring revision. Despite high overall quality, targeted factual and reference corrections are needed before final approval.

Table 6. Overall Mean Score and Content Validity Index (Magallanes et al., 2026)

Metric	Result	Benchmark Target	Interpretation
Overall Mean Score (1-4 Scale)	3.80	≥ 3.26	Very Satisfactory
Item Content Validity Index (I-CVI)	0.83 – 1.00	≥ 0.83	Passed
Scale-CVI Average (S-CVI/Ave)	0.97	≥ 0.90	Passed

The results shown in table 6 demonstrate highly satisfactory outcomes and strong content validity. The overall mean score (3.80) exceeded the 3.26 benchmark, and both the I-CVI (0.83–1.00) and S-CVI/Ave (0.97) passed their respective thresholds of ≥0.83 and ≥90.

Strengths of the Parent's Guidebook

Formative evaluation confirms the guidebook as a valid, research-backed tool translating Piagetian and Vygotskian theories into practical cognitive, socio-emotional, physical, and early literacy activities. It reframes play as a core learning mechanism, resolving common misconceptions. Clean formatting, white space, and clear dividers ensure readability across literacy and socioeconomic levels. Developed without generative AI and validated by independent experts without structural revisions, the resource holds high scientific integrity.

Experts' Suggestions for Improvement

Targeted content revisions include enhancing home play safety (with supervision guidelines for traditional games like luksong tinik), replacing informal terms (e.g., "playtunities" → "play opportunities"), adding full expert citations, and updating section headers. Visual and layout adjustments involve increasing font size and contrast, fixing alignment and density, correcting Table of Contents for pagination, and eliminating blank pages. Minor grammatical edits and localized, culturally relevant illustrations will finalize the material before dissemination.

Higher Education Implications

This parents' guidebook takes into consideration the perceptions and opinion of parents regarding play-based learning which is then backed up by expert insights which serves as a unique resource for the local community which was previously non-existent. The study provides Higher Education Institutions (HEIs) with a localized resource that can support teacher education, early childhood instruction, and community extension programs. The Parent's Guide may be integrated into early childhood education courses to help pre-service

teachers understand how play-based learning can be supported at home and how parents can be engaged as partners in children's learning. It may also serve as a reference for HEI-led community extension initiatives that promote parent education and school–community collaboration.

Conclusion

In conclusion, parents and early childhood experts in Legazpi City overwhelmingly hold positive perceptions of play-based learning across socio-emotional, cognitive, and motor domains, though lingering parental hesitations highlight the need for ongoing education. Addressing this gap, the study produced the research-grounded guidebook *"Play Full: How a Day of Play Builds a Life of Learning."* Beyond aligning home and school perspectives, the guide provides higher education institutions (HEIs) with a practical resource for Bachelor of Early Childhood Education (BECEd) coursework and a framework for community extension programs, fostering stronger collaboration among parents, educators, and institutions.

Recommendation

Based on the study's findings, conclusions, and limitations, the following recommendations are proposed: field-testing the Parent's Guide among Legazpi City parents to measure its usability, acceptability, and overall impact on home engagement; designing and assessing structured home-based play activities to evaluate their direct effect on children's multi-domain development; and expanding future research by broadening the geographical sample, using longitudinal measures, and testing the guide's integration within HEI teacher education programs.

References

Ahmad, N. K. (2-24). Play-based learning activities of kindergarten learners for reading readiness. *IMCC Journal of Science*, *5*(1), 18–31. https://myjournal.imcc.edu.ph/publication/gsp-3/

Ahmed, S., Khan, D. S., & Mehmood, A. S. (2023). Let them play: A systematic review investigating the benefits of free play in emotional development of children. Academy of Education and Social Sciences Review, 3 (4), 509–520. https://doi.org/10.48112/aessr.v3i4.660

Alexander, A. P. (2019). Lincoln and Guba's quality criteria for trustworthiness. *IDC International Journal, 6*(4), 1–6. https://idcinternationaljournal.com/0ct-2019/Article_6_manuscript_IDC_August_October_2019_Dr_Annie_full.pdf

Austria, M. (2024). Lived experiences of international teachers in integrating play-based learning: Towards the development of an action plan [Unpublished master's thesis]. Philippine Christian University.

Awopetu, A. V. (2024). The significance of play in promoting child development and strong parent-child bonds. *European Journal of Research and Reflection in Educational Sciences, 12*(2), 58–66.

Bitoy, R. (2021). "The Vital Benefits of Play". Master's Theses & Capstone Projects. 412. https://nwcommons.nwciowa.edu/education_masters/412

Bodrova, E., Leong, D. J., & Yudina, E. (2023). Play is a play, is a play, is a play. . . or is it? Challenges in designing, implementing, and evaluating play-based interventions. Frontiers in Psychology, 14, 1034633. https://doi.org/10.3389/fpsyg.2023.1034633

Celedonio, A. M. N. (2025). Effectiveness in integrating play-based learning within the MATATAG curriculum to the kindergarten learners' performance. International Journal of Advanced Multidisciplinary Studies, 5(3).

Chen, M. Y., Rouse, E., & Morrissey, A. (2023). Intentionality and the active decision-making process in play-based learning. *The Australian Educational Researcher*, *51*(4), 1373–1388. https://doi.org/10.1007/s13384-023-00644-6

Chua, C. H., Kosnin, A. B. M., & Yeo, K. J. (2020). Pre-University Teacher's perceptions on play-based pedagogy in the classroom. *psychosocial.com*. https://doi.org/10.61841/wm872855

Commission on Higher Education. (2017). *CMO No. 76, s. 2017: Policies, standards and guidelines (PSG) for the Bachelor of Early Childhood Education (BECEd).* https://ched.gov.ph/wp-content/uploads/2017/11/CMO-No.-76-s.-2017.pdf

Department of Education, Schools Division Office of Naga City. (2019, October 1). Guidelines and processes for LRMDS assessment and evaluation of locally developed and procured materials (Division Memorandum No. 441, s. 2019).

Department of Education. (2022, May 30). Adoption of the Basic Education Development Plan 2030 (DepEd Order No. 024, s. 2022). Republic of the Philippines. https://www.deped.gov.ph

Florita, D. N., & Sabud, M. C. (2024). *A Phenomenological Account of Early Childhood Education Teachers in Implementing Play-Based Learning. European Journal of Education Studies, 11*(9). Retrieved from https://oapub.org/edu/index.php/ejes/article/view/6142

Hisham, N. A. B., & Ying, L. S. (2025). Incorporating play-based learning into the curriculum for preschools in Malaysia: Challenges and practical recommendations. Journal of Business and Economic Perspectives

Magallanes, M. F. G., Napay, A. E. E., Aycardo, L. J. B., & Barajas, K. L. (2024). Development of a parent's guide for UST-Legazpi preschool: Stakeholders' perspective on the implementation of a play-based curriculum (Unpublished manuscript).

Malik, I. S., & Hasan, M. (2026). Mastering content validation: A guide to calculating the Content Validity Index (CVI). *Educational Quest: An International Journal of Education and Applied Social Sciences, 17*(1), 21–27. https://doi.org/10.30954/2230-7311.1.2026.3

Moon-Seo, S. K. & Munsell, S. E. (2022). Play as a medium for children's learning from parents' perspectives. https://files.eric.ed.gov/fulltext/EJ1352344.pdf

Mullen, R., & Skouteris, H. (2023). How parents and school staff conceptualize parental engagement: A primary school case study. *Frontiers in Education*, 8, 990204.

Nyangwete, Sichula & Kalinde, (2025) Nurturing Minds through Play: Family Perceptions of Play-Based Learning A Case Study of Mazabuka District, Zambia https://rsisinternational.org/journals/ijriss/articles/nurturing-minds-through-play-family-perceptions-of-play-based-learning-a-case-study-of-mazabuka-district-zambia/

Quinones, H. M., & Opingo, K. M. (2025). The Influence of Play Behavior on the Motor Skills of Preschoolers. *Journal of Learning and Development Studies*, *5*(6), 08-14. https://doi.org/10.32996/jlds.2025.5.6.2

Ramasamy, R., Hussain, Y., Fernando, Y., & Kamarudin, D. (2023). Parent's Involvement In Preschool and Its Influences on Children's Learning Activities. https://Www.Researchgate.Net/Publication/376805409_

Sakib, N. (2022). The effect of play-based learning on the cognitive development of kindergarten students. *Cultural Communication Journal*, *10*(1), 40–58. https://doi.org/15.28490/ccj.01.2022.10.22

Severino, G. R., Cabatic, E. T., & Molina, M. M. (2024). The role of play in children's development. *Asian Journal of Education and Human Development*, *5*(1), 62–73. https://doi.org/10.69566/ajehd.v5i1.100

Skene, K., O'Farrelly, C. M., Byrne, E. M., Kirby, N., Stevens, E. C., & Ramchandani, P. G. (2022b). Can guidance during play enhance children's learning and development in educational contexts? A systematic review and meta-analysis. *Child Development*, *93*(4), 1162–1180. https://doi.org/10.1111/cdev.13730

Tepper, D. L., Howell, T. J., & Bennett, P. C. (2022). Executive functions and household chores: Does engagement in chores predict children's cognition? *Australian Occupational Therapy Journal, 69*(6), 636–647. https://doi.org/10.1111/1440-1630.12822

Wright, C. A., Pasek, J., Lee, J. Y., Masters, A. S., Golinkoff, R. M., Thomsen, B. S., & Hirsh-Pasek, K. (2023). U.S. parents' attitudes toward playful learning. Frontiers in Developmental Psychology, 1. https://doi.org/10.3389/fdpys.2023.1267169

Yusri, A. A., Zainal, M. Z., & Zulprianto, Z. (2024). Enhancing Malay language education: Usability evaluation of the Kia ArPoly Kit for Malay figurative compound nouns. https://www.researchgate.net/publication/383516967_Enhancing_Malay_Language_Education
Usability_Evaluation_of_the_Kia_ArPoly_Kit_for_Malay_Figurative_Compound_Nouns

Zeng, H. Q., & Ng, S. C. (2024). Free Play Matters: Promoting Kindergarten Children's Science Learning Using Questioning Strategies during Loose Parts Play. *Early Childhood Education Journal*, *53*(7), 2373–2388. https://doi.org/10.1007/s10643-024-01741-6

P26035

Exploring the Latent Structure of Interdisciplinary Competencies among University Students: An Exploratory Factor Analysis

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ABSTRACT

This study examined the latent structure of interdisciplinary competence among university students using exploratory factor analysis (EFA). Although interdisciplinary competence has been widely recognized as a multidimensional construct, previous studies have proposed diverse competency frameworks, and no consensus has yet been reached regarding its underlying dimensional structure. Based on a synthesis of existing theoretical and empirical literature, an initial instrument comprising seven theoretically derived competency dimensions and 34 questionnaire items was developed. Data were collected from 1,043 undergraduate students enrolled in a university-wide interdisciplinary curriculum at a private university in Taiwan. Principal axis factoring with Promax rotation was employed to examine the latent structure of students' perceived interdisciplinary competence. The initial analysis revealed a separate factor composed exclusively of reverse-worded items, suggesting a wording-related method effect. After removing these items, a revised three-factor solution emerged, consisting of Interdisciplinary Knowledge Integration, Reflective and Self-directed Problem Solving, and Collaborative Communication. The findings suggest that university students tend to organize their perceptions of interdisciplinary competence into broader and more integrated competency domains than those proposed by existing theoretical frameworks. This study provides an empirical perspective on the conceptualization of interdisciplinary competence and offers a more parsimonious framework for future instrument development and competency assessment in higher education.

Keywords: interdisciplinary learning, interdisciplinary competency, exploratory factor analysis, higher education

P26036

Exploring the Relationships between Sociocultural and Academic Adaptation with Career Decisions among International Students: A Case Study of a Public University of Technology in Taiwan

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ABSTRACT

Taiwan is facing a population decline and a labor shortage, and one of Taiwan's government policies is to recruit international graduates after they graduate from universities in Taiwan, making Taiwan's universities another hub for selecting and training an international labor force. However, international workers and students are found to struggle with cross-cultural adaptation, language barriers, and low social support. These cultural challenges may result in reduced involvement in work or earlier return to home countries. This creates a leakage of human capital during the transition from study to work. Therefore, this study aims to examine how sociocultural and academic adaptation are associated with career commitment and career intention of international students in a public university of technology in Taiwan. It also tests the mediating effect of self-efficacy on the relationship between adaptation and career decisions. A quantitative research design was employed using an online survey distributed to international students, and 128 responses were collected. The findings indicate that international students show stronger career commitment when they have better sociocultural and academic adaptation. Self-efficacy also fully mediates the relationship between sociocultural adaptation and career commitment, while academic adaptation directly impacts career commitment. However, sociocultural and academic adaptation do not affect the intention to stay in Taiwan. Based on these findings, universities should offer a range of programs to help international students strengthen their sociocultural and academic adaptation. Meanwhile, these multiple programs offered by universities could be developed with an emphasis on providing experiences that further build students' self-confidence and strengthen their overall career development.

Keywords: Sociocultural Adaptation, Academic Adaptation, Career Commitment, Career Intention, Self-Efficacy

Introduction

Globally, there is a projected trend of population decline and aging societies due to lower birth rates (United Nations, 2019), which may cause economic contraction and labor shortages (Scheijgrond & Donovan, 2024). Taiwan is also facing similar challenges, including a forecasted labor shortage of 400,000 workers by 2030 (National Development Council, 2023). In response, Taiwan's government has implemented several strategies to recruit and retain international workers, such as reducing the bureaucratic process for applying for employment gold cards (Taiwan Employment Gold Card Office, 2020).

In addition to directly recruiting new international workers and retaining existing ones, the government actively attracts international students by providing various scholarships (Ministry of Education, 2021) and expanding exchange programs (Executive Yuan, 2019). As a result, the number of international students has grown 300 percent in 1 decade. In 2010, only 8,801 foreign students pursued a degree in Taiwan, but by 2022, the number had risen to 37,062 (Ministry of Digital Affairs, 2024). Also, international students are eligible to apply for a 1-year job-seeking visa after graduation, which can be extended for up to 2 years (Office of International Affairs, n.d.-b), creating opportunities for them to transition into the workforce.

Foreigners who graduated from Taiwanese universities have more advantages over other categories of foreigners, such as language learners or those holding degrees from abroad. They are better adapted to life in the host country than those who have just arrived (Ziguras & Law, 2005), and their experience of taking internships or part-time jobs during their studies may also help them be more familiar with Taiwanese work culture and policies. Therefore, international students who graduate from Taiwanese universities should also be the main target for the long-term foreign labor force.

However, empirical studies in global contexts highlighted that international workers and students are found to struggle with cross-cultural adaptation (Takeuchi et al., 2007; Ward et al., 2001), language barriers (Hendrickson et al., 2011; Rhein & Jones, 2020), as well as low social support and discrimination (Tartakovsky, 2012; Yang et al., 2023). These cultural challenges may result in lower psychological well-being, reduced involvement in work or earlier return to home countries (Rhein & Jones, 2020; Takeuchi et al., 2007).

Therefore, this paper aims to examine whether international students intend to transition into Taiwan's workforce by exploring how sociocultural and academic adaptation affect their career intentions and commitment. It also tests the mediating effect of self-efficacy on the relationship between adaptation and career intentions. Ultimately, this paper seeks to provide insights that can contribute to more effective policies that enhance the study-to-work transition for international personnel in Taiwan and further strengthen the comprehensiveness of national labor planning.

Literature Review

Sociocultural Adaptation

Scholars have studied cross-cultural adaptation among international students and foreign workers to understand how adaptation occurs in different cultural contexts. One of the earliest theories on cross-cultural adaptation is Oberg's (1960) Culture Shock Theory. Oberg introduced the concept of culture shock to describe the psychological and social challenges individuals face when relocating to a new cultural environment. Instead of treating adaptation as a linear process, as Oberg did, Kim (2001) proposed the Cross-Cultural Adaptation Theory to describe it as a continuous, complicated, dynamic pattern of change and growth.

Meanwhile, cross-cultural adaptation may be too broad to fully explain its causes and consequences. To address this, Searle and Ward (1990) suggested that cross-cultural adaptation should be divided into two key dimensions: psychological and sociocultural adaptation. Psychological adaptation is examined using stress-coping models, focusing on emotional well-being and factors such as personality traits, life changes, and relationships with host nationals. In contrast, sociocultural adaptation, studied through a social learning framework, refers to the acquisition of social skills necessary for behavioral competence in a new cultural environment.

Based on empirical studies, sociocultural adaptation is influenced by various factors including length of stay (Searle & Ward, 1990; Ward & Kennedy, 1994; Furnham, 2010; Wilson, 2013), interactions with host nationals (Ward et al., 2001; Ward & Kennedy, 1994; Yu, 2020), knowledge of the host country's culture (Masgoret & Ward, 2006; Wilson, 2013), cultural distance (Hofstede, 1980; Ward & Kennedy, 1993b; Alemu & Cordier, 2017; Yang et al., 2023), language fluency (Ward & Kennedy, 1993b, 1994; Alemu & Cordier, 2017; Yu, 2020), and acculturation strategies (Lai et al., 2023).

Academic Adaptation

According to Anderson et al. (2016), academic adaptation comprises three aspects: academic lifestyle, academic achievement, and academic motivation. Academic lifestyle refers to a student's overall satisfaction, including enjoyment of their role, perceived value of education, and concerns about academic abilities. Academic achievement reflects a student's perceived performance, confidence in academic abilities, and satisfaction with learning progress. Academic motivation relates to a student's motive to complete their degree, pursue personal goals, and achieve desired career after graduation. Van Rooij et al. (2018) emphasize the

outcomes of academic adaptation, such as GPA, number of credits earned, and intention to continue studying, defining academic adaptation as the ability to meet institutional requirements to achieve academic success.

However, the definitions of academic adaptation mentioned by Anderson et al. (2016) and Van Rooij et al. (2018) overlooked cultural influences. Empirical studies show that international students encounter cultural difficulties, such as a lack of host language skills (Wang & Hannes, 2014), unfamiliar teaching styles in the classroom (Cortazzi & Jin, 1997), and different teacher-student relationships (Yerken & Nguyen Luu, 2022), which affect international students' academic adaptations. Being less understanding of lecture content, not confident to actively participate in class, and receiving less support from teachers may lead to "study shock", academic stress resulting from different educational systems, especially in a foreign country (Burns, 1991, p. 71). This may result in depression, low academic achievement, and higher dropout rates (Burns, 1991; Smith & Khawaja, 2011).

Career Commitment

Career commitment is defined as the process of planning, identifying, and continuously dedicating energy to personal career goals (Colarelli, & Bishop, 1990). It comprises three components: career resilience, which reflects persistence; career identity, which provides direction and emotional engagement; and career planning, which serves as the energizing factor (Carson & Bedeain, 1994).

Intention to work in Taiwan

Studying abroad also offers more opportunities to work in the host country. There are economic reasons motivating students to work in the host country after graduation, including differences in GDP levels between home and host countries (Becker, 1994, as cited in Cao, 2022). Another reason is the push-pull economic factor, which refers to the perceived advantages of the host country and disadvantages of the home country such as income levels, encouraging students to stay in the host country and leave the country of origin (Schoorl et al., 2000, as cited in Cao, 2022). Therefore, if the host country offers higher income, students' career intentions in the host country will also increase. Therefore, Taiwan ranked 14th in the world in GDP and 5th in Asia in 2024 (OCAC, 2024; Stampfl, 2025) and may also attract some international students.

Moreover, internal factors such as life satisfaction and positive impressions of the host country also play an important role in encouraging students to stay in the host country (Tartakovsky,

2012; Istad et al., 2021; Cao, 2022). On the other hand, external factors, such as supportive immigration policies, also motivate international students to remain in the host country (Department of Home Affairs, n.d.). Regarding the outcomes of sociocultural adaptation, research has found that it also influences career decisions (Tsang & Nguyen, 2023). As sociocultural adaptation reflects how well individuals manage daily life challenges and interact with local people in a new environment, it may play a crucial role in shaping international students' career intentions in the host country.

Self-Efficacy

Self-efficacy is defined by Bandura (1997) as an individual's belief in their ability to manage actions to achieve goals. Luszczynska et al. (2005) further explained that self-efficacy includes setting personal goals, putting in consistent effort, staying persistent in the face of obstacles, and bouncing back from failures. Bandura (1986) highlighted that the most effective source to develop self-efficacy is previous successful experience, which increases individual perceptions of their own competence, leading to better outcomes. Conversely, failure experience lowers self-efficacy. Sociocultural and academic adaptation can serve as a previous successful experience. Research has found that studying abroad positively increases both sociocultural and academic adaptation, thereby enhancing international students' self-efficacy (Cubillos & Ilvento, 2012). Also, self-efficacy has been shown to influence career intention through direct experience (Isaac et al., 2015).

Methodology

Research Framework and Hypotheses

This research aims to examine how sociocultural adaptation and academic adaptation can influence career intention and career commitment. This study adopts self-efficacy as a mediating variable, reflecting the belief in one's ability to succeed in a new cultural and academic environment. The research framework is shown in Figure 1. Also, based on the literature review and research framework, the following hypotheses are formulated for this study:

H1: Adaptation (sociocultural and academic) directly predicts career commitment.

H2: Adaptation (sociocultural and academic) directly predicts the intention to work in the host country (Taiwan).

H3: Self-efficacy mediates the relationship between adaptation (sociocultural and academic) and career commitment.

H4: Self-efficacy mediates the relationship between adaptation (sociocultural and academic) and the intention to work in the host country (Taiwan).

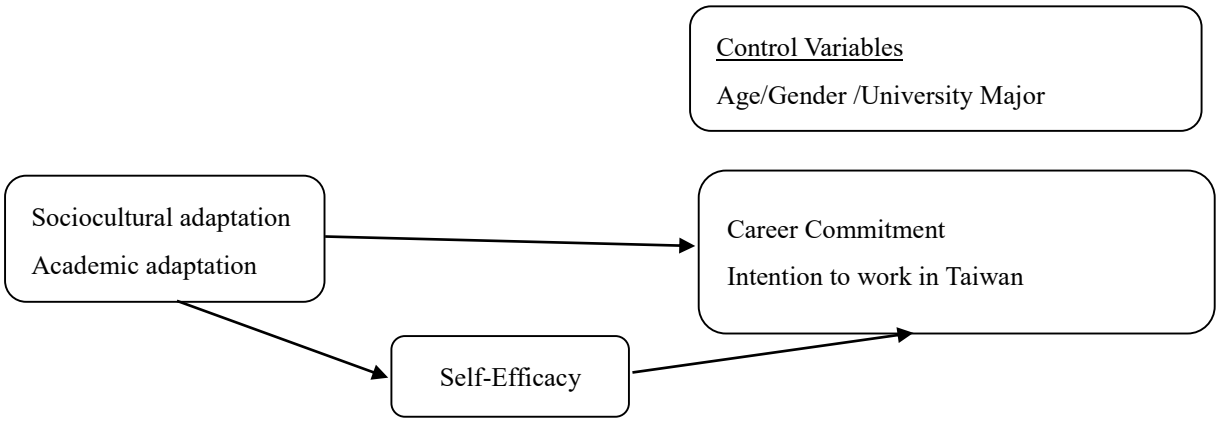


Figure 1: Research Framework

Survey Design and Sample

The survey for this study was created using Google Forms, an online survey platform that is easily and conveniently accessible to potential participants, especially university students with smartphones and internet access. The online survey link was distributed through the international student associations and student social media groups. There are 4 sections in the survey, including (1) personal information, (2) sociocultural and academic adaptation, (3) self-efficacy, and (4) intention to stay in Taiwan and career commitment. The first part, personal information, focuses on demographic details. Parts (2), (3), and (4) use a five-point Likert scale (1 = strongly disagree, 5 = strongly agree) to collect responses. Out of a total population of 1,024 eligible degree-seeking international students enrolled at one public vocational university in Northern Taiwan, 128 complete responses were collected, yielding a response rate of 12.5%.

Research Ethics and Data Protection

Strict ethical procedures were followed during the data collection process. Prior to accessing the survey items, all prospective participants were presented with an informed consent form on the initial page of the Google Form. This form clearly outlined the study's purposes and emphasized that participation was voluntary. To ensure privacy and confidentiality, all responses were collected anonymously, and no personal identifying information (such as names

or student ID numbers) was gathered. All data were encrypted and secured, used exclusively for academic research purposes, and aligned with institutional research integrity frameworks.

Measures

The sociocultural adaptation measure proposed by Ward and Kennedy (1999) is adopted in this study, and the Cronbach's alpha is 0.885. The items for international students' academic adaptation were originally developed by Zhu (2011), as cited in Mao (2024). The Cronbach's value is 0.885. The survey items for career commitment were adapted from the Three-Component Model of Commitment (Meyer & Allen, 1991; 1997), and the Cronbach's alpha is 0.819. The survey assessing intention to work in the host country (Taiwan) was adapted from Shariff et al. (2018), and their Cronbach's alpha is 0.925. The self-efficacy items proposed by Schwarzer et al. (1997) were selected, and the Cronbach's alpha was 0.920.

Data Analysis Strategy

To test the research framework and the hypothesized pathways, path analysis and mediation analysis were conducted using jamovi (Version 2.8; The jamovi project, 2024). Specifically, the jAMM (jamovi Advanced Mediation Models) module (Gallucci, 2020) was employed, which utilizes the lavaan package (Rosseel, 2012) as its underlying statistical engine to perform robust path estimations. This approach allows for the simultaneous estimation of all total, direct, and indirect effects within a single path-analytic model while controlling demographic variables (gender, age, and major). To evaluate the statistical significance of the indirect mediation effects, bias-corrected bootstrapping with 5,000 resamples was used to calculate 95% confidence intervals (CIs). An indirect effect is considered statistically significant if its 95% confidence interval does not include zero. Before performing the path analysis, multicollinearity among the independent variables was evaluated. The results indicated that the Variance Inflation Factors (VIF) for sociocultural adaptation and academic adaptation were well below the conservative threshold of 5.0 (with Tolerance values above 0.10), confirming that multicollinearity was not a serious concern in this study.

Discussion

Descriptive and Correlation Analysis

Table 1 summarizes the respondents' characteristics, and Table 2 presents the means and standard deviations for each variable from the correlation analysis. In addition, regarding

language proficiency, respondents rated their Mandarin skills as poor or very poor at the following rates: 54.7% for listening, 61.7% for speaking, 71.9% for reading, and 78.9% for writing. In contrast, a significant portion of respondents reported good or excellent English skills: 89.8% for English listening, 76.6% for speaking, 86.7% for reading, and 78.9% for writing.

Table 1: Profile of Respondents

Variables	Characteristics	Frequency	Percentage	Chi-square Test
Gender	Male	66	51.2%	0.125
	Female	62	48.0%	(p<0.724)
Age	18 – 22 years old	18	14.1%	
	23–27 years old	74	57.8%	79.750
	28–32 years old	28	21.9%	(p<0.000)
	33 years old and above	8	6.3%	
University Major	Business-related	38	29.7%	
	Engineering	53	41.4%	
	Information Technology & Computer Science	21	16.4%	26.688 (p<0.000)
	Other	16	12.5%	
Education Level	Bachelor's Degree	12	9.4%	
	Master's Degree	95	74.2%	97.234 (p<0.000)
	PhD	21	16.4%	
Nationality	Indonesian	49	38.3%	
	Thai	24	18.8%	12.313
	Vietnamese	27	21.1%	(p<0.006)
	Non-Asian	28	21.9%	
Length of Stay	1-6 months	40	31.3%	
	7-12 months	21	16.4%	
	12-24 months	38	29.7%	26.937
	24-36 months	12	9.4%	(p<0.000)
	36 months above	15	11.7%	
	Data missing	2	1.6%	

Table 2: Summary of Correlation Results

Variable	M	SD	1	2	3	4	5
1.Sociocultural Adaptation	4.00	0.65	1				
2. Academic Adaptation	4.09	0.64	.73**	1			
3. Career Commitment	4.00	0.72	.58**	.59**	1		
4. Intention to Work in Taiwan	3.95	1.00	.34**	.32**	.39**	1	
5. Self-Efficacy	3.82	0.81	.67**	.54**	.50**	.22*	1

**Correlation is significant at the 0.01 level (2-tailed). *Correlation is significant at the 0.05 level (2-tailed).

Path Analysis for Career Commitment

Table 3 presents the path analysis results examining the total, direct, and indirect effects of sociocultural and academic adaptation on career commitment, with self-efficacy acting as the mediator. Regarding the total effects, both sociocultural adaptation ($\beta = 0.238$, $z = 2.466$, $p = .014$, 95% CI [0.056, 0.485]) and academic adaptation ($\beta = 0.402$, $z = 4.218$, $p < .001$, 95% CI [0.222, 0.673]) were positive and statistically significant predictors of international students' career commitment. These findings support Hypothesis 1, indicating that better overall adaptation is associated with a stronger career commitment.

The mediation framework was further evaluated through direct and indirect effect pathways. Sociocultural adaptation exerted a significant indirect effect on career commitment through self-efficacy ($\beta = 0.125$, $z = 2.359$, $p = .018$), and the 95% bias-corrected bootstrap confidence interval did not include zero (95% CI [0.025, 0.307]). Crucially, when controlling for the mediator, the direct effect of sociocultural adaptation on career commitment was no longer statistically significant ($\beta = 0.113$, $z = 1.073$, $p = .283$, 95% CI [-0.104, 0.353]). This pattern indicates that self-efficacy fully mediates the relationship between sociocultural adaptation and career commitment.

In contrast, academic adaptation maintained a strong and statistically significant direct effect on career commitment ($\beta = 0.374$, $z = 4.008$, $p < .001$, 95% CI [0.198, 0.631]). However, its indirect effect on career commitment via self-efficacy was statistically non-significant ($\beta = 0.028$, $z = 1.195$, $p = .232$, 95% CI [-0.018, 0.119]), demonstrating that self-efficacy does not mediate the path from academic adaptation. Among the control variables, gender showed a

significant direct effect on career commitment (β = -0.207, z = -3.197, p = .001), while major (β = 0.136, p = .034) was also significant; age (β = 0.091, p = .167) did not reach significance. Collectively, these results partially support **Hypothesis 3**: self-efficacy fully mediated the effect of sociocultural adaptation on career commitment but did not mediate the impact of academic adaptation.

Table 3: Path Analysis Results for the Mediation of Self-Efficacy on Career Commitment

Variable/Path	Estimate	SE	β	z	95% CI	
					Lower	Upper
Indirect Effects						
Xsocio →SE → Career Commitment	.137	.058	.125	2.359*	.025	.307
Xacademic →SE → Career Commitment	.032	.027	.028	1.195	-.018	.119
Direct Effects						
Xsocio→ Career Commitment	.124	.116	.113	1.073	-.105	.353
Xacademic→ Career Commitment	.419	.105	.374	4.008***	.198	.631
SE→ Career Commitment	.198	.077	.224	2.579*	.028	.362
Total Effects						
Xsocio → Career Commitment	.261	.106	.238	2.466*	.056	.485
Xacademic → Career Commitment	.451	.107	.402	4.218***	.222	.673
Control Variables						
Gender→ Career Commitment	-.295	.092	-.207	-3.197**	-.491	-.113
Major→ Career Commitment	.100	.047	.136	2.117*	-.012	.199
Age→ Career Commitment	.086	.062	.091	1.383	-.033	.216

Note. N= 128. β represents completely standardized effect sizes. Confidence intervals (Cis) were computed using 5,000 bias-corrected bootstrap samples. SE = Self-Efficacy; Xsocio= Sociocultural Adaptation; Xacademic= Academic Adaptation. * p < 0.05; ** p < 0.01; *** p < 0.001

Path Analysis for Intention to Work in Taiwan

Table 4 displays the path analysis results for the second outcome variable, international students' intention to work in Taiwan, examining the total, direct, and indirect effects mediated through self-efficacy. Regarding the total effects, the results indicated that neither sociocultural adaptation (β= 0.201, z = 1.657, p = .098, 95% CI [-0.094, 0.755]) nor academic adaptation (β= 0.173, z = 1.441, p = .150, 95% CI [-0.104, 0.623]) was a statistically significant predictor of the intention to work in the host country. Consequently, the data did not support Hypothesis 2, showing that a student's high level of adaptation within the university context does not automatically translate into a desire to remain in Taiwan's workforce.

When examining the mediation pathways, self-efficacy did not have a significant direct effect on the intention to work in Taiwan (β = -0.017, z = -0.154, p = .878, 95% CI [-0.319, 0.308]). Furthermore, the indirect effects computed via bootstrap resampling confirmed that self-efficacy did not mediate the relationships. Specifically, the indirect path from sociocultural adaptation (β= -0.010, z = -0.154, p = .878, 95% CI [-0.246, 0.211]) and the indirect path from academic adaptation (β= -0.002, z = -0.153, p = .879, 95% CI [-0.104, 0.056]) both failed to reach statistical significance, with their 95% bias-corrected confidence intervals safely straddling zero. Additionally, none of the demographic control variables—including gender (β= -0.046, p = .584), major (β= 0.146, p = .079), and age (β= -0.063, p = .460)—exerted a significant direct impact on the intention to work in Taiwan. Based on these non-significant coefficients, Hypothesis 4 was completely rejected.

Table 4: Path Analysis Results for the Mediation of Self-Efficacy on Intention to Work in Taiwan

Variable/Path	Estimate	SE	β	z	95% CI	
					Lower	Upper
Indirect Effects						
Xsocio →SE → Work in TW	-.015	.096	-.010	-.154	-.246	.211
Xacademic →SE → Work in TW	-.003	.022	-.002	-.153	-.104	.056
Direct Effects						
Xsocio→ Work ub TW	.323	.209	.211	1.549	-.144	.834
Xacademic→ Work in TW	.274	.189	.175	1.454	-.108	.654

SE→ Work in TW	-.021	.138	-.017	-.154	-.319	.308
Total Effects						
Xsocio →	.309	.186	.201	1.657	-.094	.755
Work in Taiwan						
Xacademic →	.271	.188	.173	1.441	-.104	.623
Work in Taiwan						
Control Variables						
Gender→	.-091	.166	-.046	-0.547	-.427	.213
Work in TW						
Major→	.149	.085	.146	1.756	-.034	.331
Work in TW						
Age→	-.083	.112	-.063	-.739	-.318	.182
Work in TW						

Note. N= 128. β represents completely standardized effect sizes. Confidence intervals (Cis) were computed using 5,000 bias-corrected bootstrap samples. SE = Self-Efficacy; Xsocio= Sociocultural Adaptation; Xacademic= Academic Adaptation. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Conclusion

The findings show that international students show stronger career commitment when they have better sociocultural and academic adaptation. It indicates that when students feel comfortable in the new environment, such as easily navigating the transportation system, handling daily tasks, or communicating with local people, they show better outlooks on their career development. Meanwhile, students also show similar career outlooks as they gain momentum in academic settings, such as understanding course materials, expressing ideas comfortably in class, or performing well on exams. Furthermore, self-efficacy fully mediates the relationship between sociocultural adaptation and career commitment. Therefore, when international students increase their sociocultural adaptation, it enhances their self-efficacy, leading them to show greater resistance, identification, and direction toward their careers. However, academic adaptation directly predict career commitment, and self-efficacy does not mediate this relationship.

On the other hand, sociocultural and academic adaptation do not affect the intention to stay in Taiwan. One reason might be the study's sample limitation, since the sample size is small and all participants come from the same university. However, this non-significant relationship between adaptation and host-country intention represents an interesting challenge in the study-

to-work transition. Even if international students successfully adapt internal career attributes, such as career self-efficacy and career commitment, it does not mean that internal adaptation automatically translates into stay or migration intentions. This divergence may be explained by structural barriers in the host country's labor market that go beyond individual adaptation.

Consistent with previous studies in similar East Asian contexts (Cao, 2022; Istad et al., 2021), international graduates facing highly rigid demand-side factors often lower their host-country workforce retention intentions regardless of how well they have integrated into university life. In Taiwan, small and medium enterprises (SMEs) dominate the job market. These employers heavily prioritize high-level Mandarin proficiency for workplace communication and are often deterred by the complex, unfamiliar administrative procedures associated with visa sponsorship. Therefore, individual cultural and academic integration alone is insufficient; host-country employment intentions are bounded by systematic friction, including perceived employer openness and institutional immigration frameworks. This highlights that expanding university-level adaptation programs must be paired with macro-level policy interventions to effectively smooth the study-to-work transition.

This study has several implications for universities serving as a buffer between study and work. First, universities should offer a range of programs, such as cross-cultural training, peer support systems, and developmental guidance, to help international students strengthen their sociocultural adaptation. Second, universities might also provide academic support, including comprehensive new-student orientation, tutoring, or academic intervention when international students show signs of difficulty adapting academically. Third, the multiple programs offered by universities could be developed with an emphasis on providing experiences that further build students' self-confidence and strengthen their overall career development. Overall, the mission of modern universities is not only to provide students with academic experiences but also to enhance their employability and contribute to the transformation of the national labor structure.

Reference

Alemu, A. M., & Cordier, J. (2017). Factors influencing international student satisfaction in Korean universities. *International Journal of Educational Development*, *57*, 54-64. https://doi.org/10.1016/j.ijedudev.2017.08.006

Anderson, J. R., Guan, Y., & Koc, Y. (2016). The academic adjustment scale: Measuring the

adjustment of permanent resident or sojourner students. *International Journal of Intercultural Relations*, *54*, 68-76. https://doi.org/10.1016/j.ijintrel.2016.07.006

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory.* Prentice-Hall, Inc.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W H Freeman/Times Books/ Henry Holt & Co.

Burns, R. B. (1991). Study and Stress among First Year Overseas Students in an Australian University. *Higher Education Research & Development*, *10*(1), 61-77. https://doi.org/10.1080/0729436910100106

Cao, N. T. K. (2022). Determinants of international students' decision to remain in Japan to work after graduation. *Journal of Asian Economics*, *82*, 101529. https://doi.org/10.1016/j.asieco.2022.101529

Carson, K. D., & Bedeian, A. G. (1994). Career commitment: Construction of a measure and examination of its psychometric properties. *Journal of Vocational Behavior, 44*(3), 237–262. https://doi.org/10.1006/jvbe.1994.1017

Colarelli, S. M., & Bishop, R. C. (1990). Career commitment: Functions, correlates, and management. *Group & Organization Studies, 15*(2), 158–176.

Cortazzi, M., & Jin, L. (1997). Communication for learning across cultures. In D. M. R. Harris (Ed.), *Overseas students in higher education (pp. 76–90)*. Routledge.

Cubillos, J., & Ilvento, T. (2012). The Impact of Study Abroad on Students' Self-Efficacy Perceptions. *Foreign Language Annals*, *45*. https://doi.org/10.1111/j.1944-9720.2013.12002.x

Department of Home Affairs. (n.d.). *Temporary graduate visa (subclass 485): Post-higher education work*. Retrieved 30 June from https://immi.homeaffairs.gov.au/visas/getting-a-visa/visa-listing/temporary-graduate-485/post-higher-education-work

Executive Yuan. (2019). *New Southbound Policy*. Retrieved August 10, 2024, from https://english.ey.gov.tw/News3/9E5540D592A5FECD/2ec7ef98-ec74-47af-85f2-9624486adf49#:~:text=To%20diversify%20Taiwan's%20risks%20and,fully%20into%20the%20regional%20economy.

Furnham, A. (2010). The SAGE Encyclopedia of Intercultural Competence. In. Hendrickson, B., Rosen, D., & Aune, R. K. (2011). An analysis of friendship networks, social connectedness, homesickness, and satisfaction levels of international students. *International Journal of Intercultural Relations*, *35*(3), 281-295. https://doi.org/10.1016/j.ijintrel.2010.08.001

Gallucci, M. (2020). jAMM: jamovi Advanced Mediation Models [jamovi module]. Retrieved from https://jamovi-amm.github.io/

Hendrickson, B., Rosen, D., & Aune, R. K. (2011). An analysis of friendship networks, social connectedness, homesickness, and satisfaction levels of international students. *International Journal of Intercultural Relations*, *35*(3), 281-295. https://doi.org/10.1016/j.ijintrel.2010.08.001

Hofstede, G. (1980). Culture and Organizations. *International Studies of Management & Organization*, *10*(4), 15-41. https://doi.org/10.1080/00208825.1980.11656300

Isaac, V., Walters, L., & McLachlan, C. S. (2015). Association between self-efficacy, career interest and rural career intent in Australian medical students with rural clinical school experience. *BMJ Open*, *5*(12). https://doi.org/10.1136/bmjopen-2015-009574

Istad, F., Varpahovskis, E., Miezan, E., & Ayhan, K. J. (2021). Global Korea Scholarship students: Intention to stay in the host country to work or study after graduation.

Kim, Y. (2001). *Becoming Intercultural: An Integrative Theory of Communication and Cross-Cultural Adaptation*. SAGE Publications, Inc. https://doi.org/10.4135/9781452233253

Lai, H., Wang, D., & Ou, X. (2023). Cross-cultural adaptation of Chinese students in the United States: Acculturation strategies, sociocultural, psychological, and academic adaptation. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.924561

Luszczynska, A., Scholz, U., & Schwarzer, R. (2005). The General Self-Efficacy Scale: Multicultural Validation Studies. *The Journal of Psychology*, *139*, 439-457. https://doi.org/10.3200/JRLP.139.5.439-457

Mao, Y., Wang, R., & Ji, H. (2023). Acculturation and Academic Adjustment of Student Sojourners in the Chinese Higher Education Context. *Journal of Studies in International Education*, *28*, 102831532211501. https://doi.org/10.1177/10283153221150114

Masgoret, A.-M., & Ward, C. (2006). Culture learning approach to acculturation. In *The Cambridge handbook of acculturation psychology.* (pp. 58-77). Cambridge University Press. https://doi.org/10.1017/CBO9780511489891.008

Meyer, J. P., & Allen, N. J. (1991). A three-component conceptualization of organizational commitment. *Human Resource Management Review*, *1*(1), 61–89.

Meyer, J. P., & Allen, N. J. (1997). *Commitment in the workplace: Theory, research, and application.* SAGE Publications.

Ministry of Digital Affairs. (2024). *Statistics of the number of international students studying in Taiwan at each academic year*. https://data.gov.tw/en/datasets/42158

Ministry of Education. (2021). *Taiwan Scholarship Program*. Ministry of Education, Republic of China. Retrieved August 10, 2024, from https://english.moe.gov.tw/cp-24-16833-23C09-1.html

National Development Council. (2023). *Talent Taiwan Officially Launches – NDC Aims to Support Foreign Professionals in Taiwan with Comprehensive One-stop Services* https://www.ndc.gov.tw/en/nc_8455_37509

Oberg, K. (1960). Cultural shock: Adjustment to new cultural environments. *Practical Anthropology, 7*(4), 177–182.

OCAC. (2024). *Taiwan ranked world 14th richest country*. Retrieved 27 May, 2024 from https://www.ocac.gov.tw/OCAC_OLD/Eng/Pages/Detail.aspx?nodeid=329&pid=69211777

Office of International Affairs. (n.d.-a). *NTUST Scholarships*. National Taiwan University of Science and Technology. https://oia-r.ntust.edu.tw/p/412-1060-8931.php?Lang=eOn

Rhein, D., & Jones, W. (2020). The impact of ethnicity on the sociocultural adjustment of international students in Thai higher education. *Educational Research for Policy and Practice*, *19*. https://doi.org/10.1007/s10671-020-09263-9

Rosseel, Y. (2012). lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software, 48(2), 1-36.*

Scheijgrond, J.-W., & Donovan, P. (2024). *Demographic shifts: How to steer towards economic growth*. World Economic Forum. Retrieved August 10. 2024, from

https://www.weforum.org/stories/2024/10/demographic-shifts-ageing-population-economic-growth/

Schwarzer, R., Bäßler, J., Kwiatek, P., Schröder, K., & Zhang, J. X. (1997). The assessment of optimistic self-beliefs: Comparison of the German, Spanish, and Chinese versions of the General Self-efficacy Scale. *Applied Psychology: An International Review*, *46*(1), 69-88. https://doi.org/10.1111/j.1464-0597.1997.tb01096.x

Searle, W., & Ward, C. (1990). The prediction of psychological and sociocultural adjustment during cross-cultural transitions. *International Journal of Intercultural Relations*, *14*(4), 449-464. https://doi.org/10.1016/0147-1767(90)90030-Z

Shariff, N., Krishnaswamy, J., Abdullah, D., & CHAU, A. W. (2018). The influence of new economic model on intention to work abroad: An empirical study to address brain drain issue in Malaysia. *Editorial Board*, *101*.

Smith, R. A., & Khawaja, N. G. (2011). A review of the acculturation experiences of international students. *International Journal of Intercultural Relations*, *35*(6), 699-713. https://doi.org/10.1016/j.ijintrel.2011.08.004

Stampfl, B. (2025). *Economic Freedom: An Unheralded Driver of Taiwanese Prosperity*. Global Taiwan Institute. Retrieved 27 May, 2025 from https://globaltaiwan.org/2025/02/economic-freedom-an-unheralded-driver-of-taiwanese-prosperity/

Taiwan Employment Gold Card Office. (2020). *What is the Taiwan Employment Gold Card?* Retrieved August 10, from https://goldcard.nat.gov.tw/en/about/

Takeuchi, R., Tesluk, P., Yun, S., & Lepak, D. (2007). An Integrative View of International Experience. *Academy of Management Journal*, *48*. https://doi.org/10.5465/AMJ.2005.15993143

Tartakovsky, E. (2012). Factors affecting immigrants' acculturation intentions: A theoretical model and its assessment among adolescent immigrants from Russia and Ukraine in Israel. *International Journal of Intercultural Relations*, *36*(1), 83-99. https://doi.org/10.1016/j.ijintrel.2011.02.003

The jamovi project (2026).jamovi.(Version 28) [Computer Software]. Retrieved from

https://www.jamovi.org

Tsang, S.-S., & Nguyen, T. V. T. (2023). Sociocultural adaptation and job satisfaction as mediators between cultural competence and intention to stay among Vietnamese workers in Taiwan. *Humanities & Social Sciences Communications*, *10*(1), 292. https://doi.org/10.1057/s41599-023-01798-5

United Nations. (2019). *Shifting Demographics*. Retrieved August 10, 2024, from https://www.un.org/en/un75/shifting-demographics

Van Rooij, E. C. M., Jansen, E. P. W. A., & van de Grift, W. J. C. M. (2018). First-year university students' academic success: the importance of academic adjustment. *European Journal of Psychology of Education*, *33*(4), 749-767. https://doi.org/10.1007/s10212-017-0347-8

Wang, Q., & Hannes, K. (2014). Academic and socio-cultural adjustment among Asian international students in the Flemish community of Belgium: A photovoice project. *International Journal of Intercultural Relations*, *39*, 66-81. https://doi.org/10.1016/j.ijintrel.2013.09.013

Ward, C., Bochner, S., & Furnham, A. (2001). *The psychology of culture shock, 2nd ed*. Routledge.

Ward, C., & Kennedy, A. (1993b). *Where's the "culture" in cross-cultural transition? Comparative studies of sojourner adjustment* [doi:10.1177/0022022193242006]. Sage Publications.

Ward, C., & Kennedy, A. (1994). Acculturation strategies, psychological adjustment, and sociocultural competence during cross-cultural transitions. *International Journal of Intercultural Relations*, *18*(3), 329-343. https://doi.org/10.1016/0147-1767(94)90036-1

Ward, C., & Kennedy, A. (1999). The measurement of sociocultural adaptation. *International Journal of Intercultural Relations*, *23*(4), 659-677. https://doi.org/10.1016/S0147-1767(99)00014-0

Yang, F., He, Y., & Xia, Z. (2023). The effect of perceived discrimination on cross-cultural adaptation of international students: moderating roles of autonomous orientation and integration strategy. *Current Psychology*, *42*(23), 19927-19940.

https://doi.org/10.1007/s12144-022-03106-x

Wilson, J. K. (2013). Exploring the Past, Present, and Future of Cultural Competency Research: The Revision and Expansion of the Sociocultural Adaptation Construct.

Yerken, A., & Nguyen Luu, L. A. (2022). A stepping stone to the "West": Academic adaptation of international students from post-Soviet countries in Hungary. *International Journal of Intercultural Relations*, *89*, 183-194. https://doi.org/10.1016/j.ijintrel.2022.06.005

Yu, Y. (2020). From universities to Christian churches: agency in the intercultural engagement of non-Christian Chinese students in the UK. *Higher Education*, *80*(2), 197-213. https://doi.org/10.1007/s10734-019-00474-5

Ziguras, C., & Law, S. (2005). *Recruiting International Students As Skilled Migrants: The Global 'Skills Race' As Viewed from Australia and Malaysia* (Vol. 4). https://doi.org/10.1080/14767720600555087

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OPERATIONAL RISK MANAGEMENT PRACTICES AND RESILIENCE OF SELECTED CATHOLIC HIGHER EDUCATIONAL INSTITUTIONS IN THE PHILIPPINES

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ABSTRACT

This multi-method study investigated operational risk management (ORM) and resilience within selected Philippine Catholic private higher educational institutions. Analyzing data from 96 surveyed and 8 interviewed administrators, the research assessed institutional variables such as budget, manpower, and accreditation to determine their influence on risk practices. Findings revealed a "great extent" of ORM implementation and a "higher-than-average" degree of resilience. The Mann-Whitney U test did not show significant differences in the ORM practices across institutional profiles; resilience levels also remained consistent across various characteristics. Crucially, the study found a positive, significant, but non-causal correlation between strong ORM and higher resilience. Qualitative insights identified prevalent financial and non-financial risks, noting that while risk management practices exist, they require greater formalization. The study concludes that while these HEIs demonstrate strong commitment, formalizing risk structures is essential for long-term stability. These results not only provide a framework for developing structured ORM plans to enhance institutional endurance but also equip accreditation bodies, planners, audit committees, continuity planners, and governance boards with empirical evidence and practical frameworks to integrate operational risk management systematically.

Keywords: Operational Risk Management Practices, School Resilience, Catholic private higher educational institutions, Multi-Methods Research, Philippines

Introduction

Operational risk management and institutional resilience are intrinsically linked to the Sustainable Development Goals, specifically serving as essential drivers for achieving SDG 4 by ensuring safe, continuous, and quality education (Rivadeneira Moreira & Nerizalde Vera,

2025; Goh, 2023). While operational risk management mitigates internal and external threats to protect finances, legal standing, and personnel safety (James, 2023; Curacubby Team, 2023), school resilience provides the capacity to function efficiently under unfavorable conditions, safeguarding physical infrastructure and facilitating post-disaster recovery (Pinskaya et al., 2018; Subedi & Subedi, 2020 cited in Vinogradov et al., 2022; Parajuli et al., 2020). Across Asia, where education serves as a vital vehicle for social mobility, external shocks and institutional vulnerabilities—such as pandemic-driven school closures in Japan (Ichinose & Oda, 2022) and the rising prioritization of risk governance in China (Institute of Risk Management [IRM], 2019)—highlight the urgent need for resilient educational systems (Asian Development Bank [ADB], 2023).

To elevate educational quality standards, Philippine higher education institutions increasingly seek accreditations and certifications, such as PAASCU's Leadership and Governance standard requiring formal risk management systems (PAASCU, 2021) and ISO 31000 guidelines for comprehensive risk treatment (ISO, 2023), alongside CHED mandates like Learning Continuity Plans and hybrid models to ensure academic stability during national crises (CHED, 2022). Within Catholic higher education institutions run by religious congregations, these regulatory demands are compounded by frequent natural disasters, health emergencies, large student populations, and cyber threats, underscoring an urgent need to strengthen operational frameworks to endure and recover from diverse disruptions.

Several studies have assessed schools' operational risk management practices and resilience. Studies on operational risk management in schools include those of Porras (2021), Molchanova (2023), and Wang et al. (2020). Meanwhile, several studies have also examined school resilience: Parajuli et al. (2020), San Miguel and Pascual (2021), Li and Yeung (2019), and Amos et al. (2022). Of the studies mentioned above, only a few attempted to correlate operational risk management practices and school resilience specifically in the context of selected Catholic higher education institutions, a gap this study sought to address.

This study was conducted not only to address the scarcity of studies correlating operational risk management practices and school resilience but also to identify the extent to which the selected Catholic higher education institutions apply operational risk management practices and the degree of resilience of these schools. Studying Catholic higher education institutions provides unique insights into operational risk management and resilience due to their values-driven governance, religious congregations, and dual accountability to secular and church standards. This focus addresses a significant research gap by showing how faith-based missions and distinct environmental challenges shape institutional endurance differently from secular private counterparts. The study's findings guided the researcher in preparing the

Operational Risk Management Plan for the selected Catholic higher educational institutions in the Philippines.

Theoretical Framework

This study is primarily anchored in the ISO 31000 / Enterprise Risk Management (ERM) framework, which provides comprehensive guidelines for systematically identifying, assessing, treating, monitoring, and communicating risks to achieve organizational objectives and enhance resilience (ISO, 2023). ISO 31000 emphasizes a structured, proactive approach to risk management and promotes integrating risk processes into institutional governance, strategic planning, and decision-making. Its principles advocate leadership commitment, continual improvement, and transparent communication, thereby enabling higher education institutions to effectively anticipate and mitigate operational disruptions, safeguard resources, and sustain academic and financial stability.

Operational Risk Management (ORM) in higher education institutions encompasses a systematic process of identifying, assessing, mitigating, and monitoring risks that can affect an institution's ability to achieve its objectives. The dimensions of ORM typically include risk identification, risk assessment, risk measurement and mitigation, and risk monitoring and reporting.

Risk identification proactively detects potential disruptions across internal, external, and operational domains through continuous environmental scanning and stakeholder consultation. Risk assessment then evaluates these identified risks using qualitative and quantitative methods to determine their likelihood, impact, and priority for resource allocation. Risk measurement and mitigation follow by implementing targeted controls, contingency plans, and policies while continually refining their effectiveness. Finally, risk monitoring and reporting ensure ongoing oversight of threat landscapes and compliance, enabling transparent communication to leadership for informed decision-making. These dimensions reflect the integrated and cyclical nature of ORM emphasized by ISO 31000 guidelines and align with the practices observed in the selected Catholic higher educational institutions studied.

Resilience in educational institutions refers to their capacity to anticipate, prepare for, respond to, and recover from disruptions while ensuring the continuity of operations and quality education. The study identified four core dimensions of this institutional resilience: leadership involvement, continuous improvement, resource management, and process standardization and flexibility. Leadership involvement assesses how actively institutional leaders engage in resilience-building, promote risk awareness, and drive the strategic direction

and resource allocation essential for preparedness. Supported by literature, strong leadership ensures an aligned vision and organizational commitment to fostering a resilient culture. Continuous improvement reflects an institution's dedication to learning from past experiences, evaluating ongoing processes, and enhancing operational resilience. Grounded in Total Quality Management principles, this dimension emphasizes perpetual learning and adaptation to respond to evolving risks and uncertainties. Resource management evaluates how effectively an institution oversees its physical, financial, human, and technological assets to maintain stability during crises. Because resources underpin an institution's capacity to absorb shocks, strategic allocation is vital to prevent vulnerabilities from being exacerbated. Process standardization and flexibility balance consistent operational procedures with the agility needed to adapt workflows in response to unexpected conditions without sacrificing core quality. Finally, the study's data empirically confirmed these four indicators as significant contributors to institutional resilience within Catholic Higher Education Institutions.

Complementing this primary framework, the study also adopts Deming's Total Quality Management (TQM) Theory as a supporting lens to enrich the cultural and process-oriented dimensions of organizational resilience (Deming, 2000). TQM reinforces continuous improvement, employee empowerment, and customer (student and stakeholder) satisfaction. Through Deming's 14 Points, TQM nurtures a quality-centered culture that prioritizes systemic process enhancement over individual blame, aligning well with ISO 31000's risk management emphasis on holistic organizational integration.

By integrating ISO 31000 / ERM with TQM principles, Catholic higher education institutions in the Philippines can establish strong, formalized risk management frameworks grounded in strategic leadership and foster a culture of continuous learning and stakeholder engagement. Catholic higher education institutions in the Philippines have distinct foundational models in which mission-driven orientations integrate faith, reason, and social justice to guide holistic education and compassionate stewardship. Congregation-led leadership fosters servant governance and ethical decision-making that naturally aligns with Total Quality Management principles of employee empowerment and student focus. Layered governance structures balance canonical directives with national educational standards to ensure transparent accountability and disciplined quality assurance practices. Furthermore, stewardship responsibilities emphasize the long-term, prudent management of institutional resources to ensure operational sustainability and community trust. Ultimately, these intrinsic cultural and spiritual dimensions uniquely position Catholic HEIs to achieve operational excellence and enduring institutional resilience. This dual theoretical perspective equips institutions to systematically identify vulnerabilities, design effective risk treatment plans, and build adaptive capabilities that enhance both operational stability and institutional resilience.

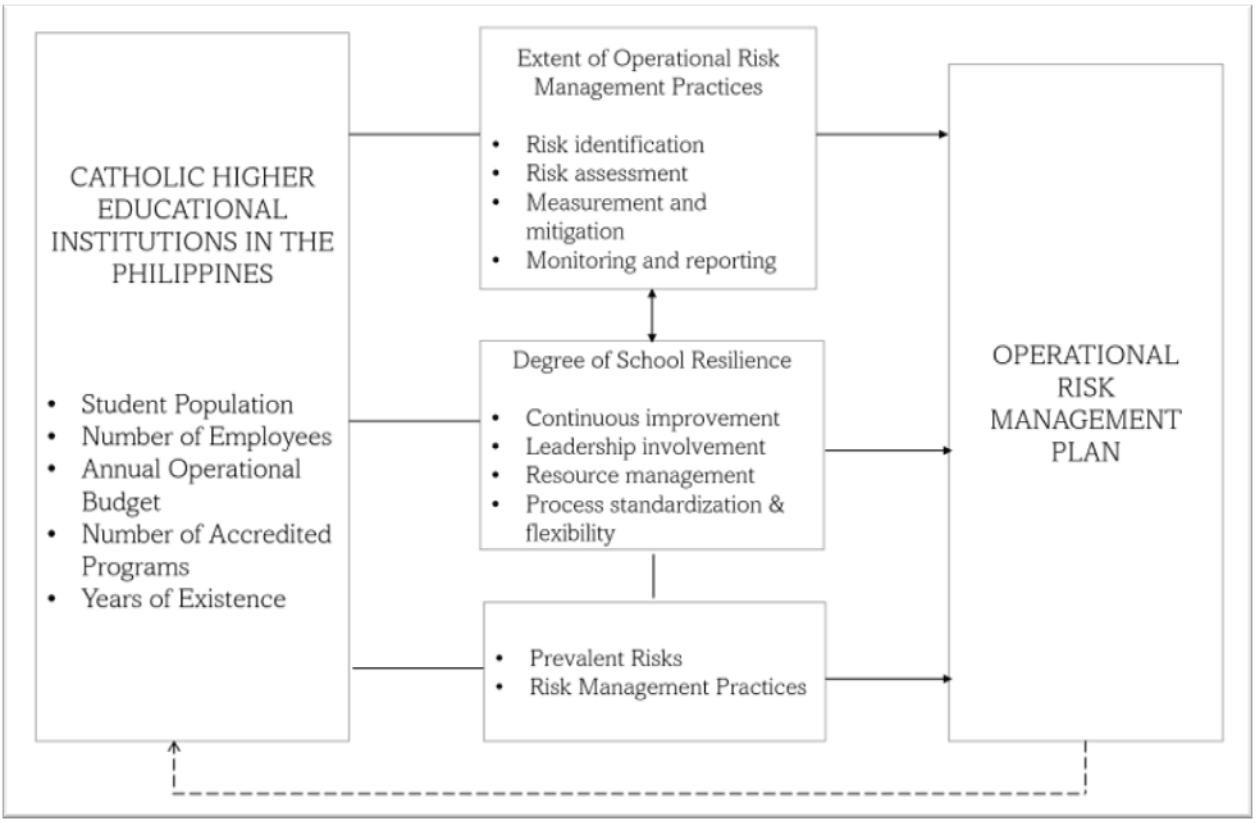


Figure 1. Conceptual Model of the Study

Methodology

Research Design

This study employed a multi-method research design, combining quantitative and qualitative approaches to gather data, analyze results, and answer the research questions. Creswell and Plano Clark (2018) define multi-method research design as using multiple methods or approaches in a single study to gather and analyze data, enhancing breadth and depth of understanding and ensuring more robust and reliable findings. This design is particularly suitable for this study because it provides a comprehensive understanding of a complex issue like operational risk management and school resilience, enhances the validity and reliability of findings by triangulating data from multiple sources, and offers a deeper insight into the relationships between different variables.

For the quantitative approach, the descriptive, comparative, and correlational research design was utilized. The descriptive design describes a situation or state of affairs regarding the

specified variables (Creswell & Creswell, 2018). It was used to determine the extent of operational risk management practices and degree of resilience of selected Catholic higher educational institutions in the Philippines as assessed by the administrators when the schools are taken as a whole and grouped according to student population, number of employees, annual operational budget, number of accredited programs, and years of existence. Meanwhile, the comparative design was utilized to determine whether a significant difference exists in the extent of operational risk management practices and in the degree of resilience of the selected Catholic higher educational institutions in the Philippines when they are grouped according to student population, number of employees, annual operational budget, number of accredited programs, and years of existence. Moreover, the correlational design was used to assess whether a significant relationship exists between operational risk management practices and school resilience.

Qualitative research, on the other hand, explores and understands people's experiences, perceptions, and motivations and focuses on gathering non-numerical data, such as words, images, and observations, to gain insights into social and human behavior (Creswell & Creswell, 2018). This approach identified the prevalent risks and risk management practices of the selected Catholic higher education institutions.

Respondents and Sampling

This study utilized stratified random sampling to select 96 religious and lay administrators from a total population of 127 across Catholic higher education institutions in Cebu, Bacolod, Manila, and Cavite, stratifying respondents by school. The response rate was 100%. Meanwhile, purposive sampling was employed to select eight (8) individual interview participants for the qualitative phase based on specific inclusion criteria: holding a current administrative position, having served as a religious or lay administrator for at least 5 years, and holding at least a master's degree.

The study grouped participating Catholic higher educational institutions based on key institutional profile variables to examine differences in operational risk management and resilience. *Student population* refers to the total number of students enrolled in the selected Catholic higher educational institutions in the Philippines; those with 13,678 or fewer were classified as having a smaller student body, while those with more than 13,678 were classified as having a larger *student body*. *The number of employees* refers to the total count of individuals working for the selected Catholic higher educational institutions in the Philippines; those with 507 or fewer were classified as having a smaller workforce, while those with more than 507 were classified as having a larger workforce. *Annual operational budget* is a

financial plan that outlines every selected Catholic higher educational institution's expected income and expenses for a specific year and serves as a roadmap for managing their resources and making informed decisions throughout the year; those with Php 243,842,987.30 or less were classified as having lower budget capacity, while those with more than Php 243,842,987.30 were classified as having higher budget capacity. *Number of accredited programs* refers to the total count of academic programs at each selected Catholic higher educational institution in the Philippines that have been officially recognized and approved by a recognized accrediting agency; those with 16 or fewer were classified as having fewer accredited programs, while those with more than 16 were classified as having more accredited programs. Years of existence refers to the total number of years each selected Catholic higher educational institution in the Philippines has been in operation; those with 75 or fewer years of existence were classified as younger institutions, while those with more than 75 years of existence were classified as legacy institutions.

Research Instrument

The quantitative phase utilized a researcher-made instrument divided into three parts: institutional profile (Part I), Likert-type statements assessing the extent of operational risk management practices (Part II), and Likert-type statements measuring school resilience (Part III). Adapted from related literature, the instrument underwent rigorous validation, achieving a very high content validity ratio (CVR = 0.95) evaluated by ten experts, and demonstrated excellent internal consistency through a pilot test yielding a Cronbach's alpha of 0.991 with excluded pilot participants.

The following scales guided the interpretation of the results:

Interpretative Scale for the Extent of Operational Risk Management Practices

Scale	Mean Range	Verbal Description	Verbal Interpretation
4	3.26 – 4.00	Very Great Extent	The organization's operational risk management practices are always observed.
3	2.51 – 3.25	Great Extent	The organization's operational risk management practices are often observed.
2	1.76 – 2.50	Poor Extent	The organization's operational risk management practices are sometimes observed.

1	1.00 – 1.75	Very Poor Extent	The organization's operational risk management practices are never observed.

Interpretative Scale for the Degree of School Resilience

Scale	Mean Range	Verbal Description	Verbal Interpretation
4	3.26 – 4.00	Very High Degree	The school demonstrates exceptional levels of resilience, demonstrating a strong capacity to withstand and recover from challenges.
3	2.51 – 3.25	High Degree	The school exhibits satisfactory levels of resilience, indicating a good ability to adapt and bounce back from difficulties.
2	1.76 – 2.50	Low Degree	The school has average levels of resilience, suggesting that it can cope with challenges to some extent but may require additional support or interventions.
1	1.00 – 1.75	Very Low Degree	The school demonstrates poor levels of resilience, indicating a vulnerability to challenges and a potential need for significant improvements.

Data Collection Procedure

To collect quantitative data, the procedure began with a letter seeking approval from the presidents of the selected Catholic higher education institutions to conduct the study. After approval, the researcher selected an enumerator from each school to help disseminate information about the online survey and secure the list of administrators and their email addresses. An online orientation was conducted among the enumerators to ensure that the nature and procedure employed in the study were clearly understood. Individual letters were sent with attached informed consent and survey material. Upon the approval of the administrator to participate in the study, he or she was asked to sign the informed consent electronically, answer the survey, and submit the same online. Constant follow-up was done by the researcher to ensure that the survey materials were responded to and submitted to her as

soon as possible. For those who answered the survey in person, the researcher ensured that data-collection protocols were observed. After retrieving all survey materials, the researcher tabulated the responses and submitted them to an accredited statistician for analysis.

Meanwhile, the following data-collection procedure was observed for the qualitative aspect of the study. The researcher sought approval from the HEI presidents regarding the involvement of some of their administrators in the online interview. Once permission was granted, data collection began. The researcher conducted individual interviews with administrators who met the study's inclusion criteria. The researcher began by establishing rapport with participants by asking about their role in the HEI and the length of service they have given to the institution. Then, the researcher gave a brief explanation of the procedure and obtained informed consent. Also, an assurance of the confidentiality of information or data to be shared by the participant was given by the researcher. The interview began only after participants consented by indicating their approval on the informed consent form. During the interview, the researcher observed mind bracketing by consciously setting aside pre-existing assumptions about the phenomenon under study. Data collection involved in-depth probing using a series of follow-up questions designed to elicit the "what," "how," and "why" of each participant's experiences. Data saturation was achieved when participants' responses showed consistent redundancies and no new insights emerged from subsequent interviews. After the interview, the researcher debriefed by returning to table talk and engaging in more relaxed conversations with the participants about plans and programs the institution has for the upcoming year. The researcher thanked the participants and offered tokens of appreciation for their participation. The researcher transcribed the participants' responses and proceeded with data analysis.

Data Analysis Procedure

Descriptive, comparative, and correlational analyses were employed to answer the specific problems in the quantitative aspect of this study. Descriptive analysis was employed to analyze the data as to the extent of operational risk management practices and the degree of resilience of the selected Catholic higher educational institutions when they are taken as a whole and grouped according to student population, number of employees, annual operational budget, number of accredited programs, and years of existence. Shapiro-Wilk test results showed that neither operational risk management practices nor the degree of resilience followed a normal distribution. For operational risk management practices, the test indicated a significant result ($W=0.960$, $p=0.007$), whereas for the degree of resilience, it also exhibited a significant deviation from normality ($W=0.966$, $p=0.018$). Since both p-values are below the 0.05 alpha level, these results indicate that both variables were not normally distributed and

will therefore be better analyzed using non-parametric statistical methods. Comparative analysis was used to examine significant differences in the extent of operational risk management practices and the degree of resilience of the selected Catholic higher educational institutions when grouped according to student population, number of employees, annual operational budget, number of accredited programs, and years of existence. The Mann-Whitney U test showed that operational risk management practices differed significantly across institutional profile groups because the data on the extent of operational risk management practices and degree of resilience did not follow a normal distribution. In contrast, correlational analysis was used to test the significant relationship between operational risk management practices and school resilience. Since the data did not follow a normal distribution, Spearman rank correlation was employed to determine the relationship between operational risk management practices and the resilience level assessed by the administering respondents.

Meanwhile, for the qualitative data, thematic analysis using Lichtman's (2013) 3Cs (coding, categorizing, and conceptualization) was employed. In initial coding, transcripts were read, and various codes that represent different elements within the data were derived. This included listening to audio recordings and reviewing transcripts multiple times, making notes and reflections in the margins, and creating first-level codes focused on the content in the data. This coding phase was essential for breaking down the data into manageable pieces, allowing researchers to identify patterns and themes. Once initial codes were established, the next step was to categorize them into broader themes or categories. This involved organizing codes into major topics and identifying subsets under these topics, using methods like constant comparative analysis to refine categories by comparing data relevant to each code, and revisiting categories to remove redundancies and clarify critical elements. This categorization helped structure the findings and connect different pieces of data. The final step was moving from categories to concepts. The study identified key concepts or themes that encapsulated the meaning derived from the data. This involved synthesizing information from categories to articulate overarching themes and understanding how these concepts relate to the research questions and objectives.

Data Trustworthiness

To ensure trustworthiness, the study applied Lincoln and Guba's (1985) criteria of credibility, transferability, dependability, and confirmability. Credibility was established through methodological triangulation (interviews, documents, and observations), peer debriefing, negative case analysis, and member-checking, which involved emailing transcripts to participants for review. Transferability was achieved by providing thick, rich descriptions of

the research context, participants, and specific institutional examples. Dependability was maintained through a transparent audit trail of recordings, field notes, and stable digital communication to ensure data integrity. Finally, confirmability was observed by maintaining a detailed paper trail of the analytical process, ensuring consistent coding, and practicing researcher reflexivity and bracketing to minimize personal bias.

Ethical Considerations

To ensure ethical soundness, the researcher upheld the principles of respect for persons, beneficence, and justice. Before accessing the survey, participants provided informed consent either in person or electronically, affirming their voluntary participation and right to withdraw at any time without penalty. Survey access was strictly restricted until consent was secured. While online administration minimized physical risks—with strict protocols observed for the single school completing physical copies—potential psychological or emotional risks were mitigated by utilizing clear, concise materials designed to foster a friendly, non-threatening environment. The study strictly maintained privacy and confidentiality by omitting identifying information, using data exclusively for research, and securing records electronically and in print for proper disposal after publication. Furthermore, the study fully complies with the Data Privacy Act of the Philippines.

Results and Discussion

Extent of Operational Risk Management Practices

Data in Table 1 show that overall, the extent of operational risk management practices is great (M=2.65; SD=0.86). Of the four areas of operational risk management practices, risk identification scored the highest (M=2.71; SD=0.81); risk assessment ranked second (M=2.68; SD=0.89); risk measurement and mitigation followed (M=2.63; SD=0.90); and monitoring and reporting placed last (M=2.57; SD=0.92). This "great" extent of operational risk management practices means the organizations' operational risk management practices are often observed and suggests that organizations are, on average, proactively and frequently engaged in managing operational risks.

The positive trend in operational risk management implies a strong commitment to stability and security within higher education institutions. However, variability and lagging performance among younger organizations highlight clear opportunities for maturity development, supported by Libo-on (2017) on risk awareness; Kondić et al. (2020) and Wessels and Sadler (2015) on systematic frameworks like ISO 31000; and Indarbaev and Kapustina

(2023) on proactive, continuous assessment. Syed et al. (2021) and Molchanova (2023) confirm that institutions frequently lag in monitoring and reporting despite active identification and assessment.

When grouped by student population, both groups reported mean scores interpreted as great, although institutions with larger student bodies had higher means (M=2.70; SD=0.86) than those with smaller student bodies (M=2.55; SD=0.86). The positive correlation between larger student populations and more extensive operational risk management practices reflects how complex operations, greater resources, and heightened risk profiles drive institutions to develop solid frameworks, whereas smaller schools often maintain simpler operations with lower formal needs (Odlin et al., 2021; Libo-on, 2017), which is further supported by Wessels and Sadler (2015) regarding the adoption of ISO-compliant frameworks in larger operational scopes and Holtermann et al. (2021) demonstrating that larger institutions engage more systematically in risk management maturity.

When grouped by employee count, organizations with larger workforces scored higher (M=2.70; SD=0.86) than those with smaller workforces (M=2.55; SD=0.86). Organizations with more employees exhibit more intensive and active operational risk management practices, driven by resource availability, specialized personnel, and structured approaches. In contrast, smaller organizations often rely on limited resources and less formal processes (Libo-on, 2017), which is further supported by Holtermann et al. (2021) regarding the resource capacity of larger staffs to execute systematic mitigation, Odlin et al. (2021) highlighting resource advantages for formal risk assessments, and Wessels and Sadler (2015) noting a higher likelihood of adopting formalized frameworks like ISO 31000 due to available workforce expertise.

When grouped by annual operational budget, those with higher budget capacity showed a higher mean (M=2.81; SD=0.81) than those with lower budget capacity (M=2.58; SD=0.87); financial capacity directly drives operational risk management performance, as larger budgets enable institutions to invest in specialized personnel, advanced technology, training, and strong systems, whereas lower budgets create resource constraints that hinder implementation (Mukherjee, 2019; Zang, 2022). Furthermore, Cotelnic (2023) emphasizes that adequate resource allocation is vital for sustaining quality and risk protocols, and Wessels and Sadler (2015) note that institutions with greater financial flexibility are better equipped to adopt sophisticated, ISO-compliant frameworks.

Table 1

Extent of Operational Risk Management Practices as Assessed by the Administrator Respondents

Variable	Risk Identification			Risk Assessment			Risk Measurement and mitigation			Monitoring and Reporting			Operational Risk Management Practices		
	M	SD	Int	M	SD	Int	M	SD	Int	M	SD	Int	M	SD	Int
Student Population															
Smaller Student Body	2.58	0.77	Great	2.58	0.91	Great	2.59	0.90	Great	2.46	0.93	Poor	2.55	0.86	Great
Larger Student Body	2.78	0.82	Great	2.73	0.88	Great	2.65	0.91	Great	2.63	0.91	Great	2.70	0.86	Great
Number of Employees															
Smaller Workforce	2.58	0.77	Great	2.58	0.91	Great	2.59	0.90	Great	2.46	0.93	Poor	2.55	0.86	Great
Larger Workforce	2.78	0.82	Great	2.73	0.88	Great	2.65	0.91	Great	2.63	0.91	Great	2.70	0.86	Great
Annual Operational Budget															
Lower Budget Capacity	2.64	0.82	Great	2.62	0.92	Great	2.58	0.92	Great	2.49	0.92	Poor	2.58	0.87	Great
Higher Budget Capacity	2.88	0.75	Great	2.81	0.80	Great	2.76	0.86	Great	2.77	0.88	Great	2.81	0.81	Great
Number of Accredited Programs															
Fewer Accredited Programs	2.64	0.82	Great	2.62	0.92	Great	2.58	0.92	Great	2.49	0.92	Poor	2.58	0.87	Great
More Accredited Programs	2.88	0.75	Great	2.81	0.80	Great	2.76	0.86	Great	2.77	0.88	Great	2.81	0.81	Great
Years of Existence															
Younger Institutions	2.63	0.81	Great	2.62	1.00	Great	2.63	0.99	Great	2.52	1.00	Great	2.60	0.92	Great
Legacy Institutions	2.73	0.81	Great	2.69	0.87	Great	2.63	0.89	Great	2.58	0.90	Great	2.66	0.85	Great
Whole	***2.71***	***0.81***	***Great***	***2.68***	***0.89***	***Great***	***2.63***	***0.90***	***Great***	***2.57***	***0.92***	***Great***	***2.65***	***0.86***	***Great***

Mean Range: 1.00-1.75=Vey Poor, 1.76-2.50=Poor, 2.51-3.25=Great, 3.26-4.00=Very Great

When grouped according to the number of accredited programs, those with more accredited programs scored higher (M=2.81; SD=0.81) than those with fewer accredited programs (M=2.58; SD=0.87). The link between program accreditation and operational risk management suggests that rigorous accreditation standards drive institutions to establish systematic practices, strengthen documentation, and improve quality assurance across operations. In contrast, institutions with fewer accredited programs could benefit from adopting these structured approaches (Machuca et al., 2021). Thi et al. (2020) further support this, emphasizing accreditation as a vital quality management tool for monitoring and improving institutional processes. Parajuli et al. (2020) note that structured, measurable indicators align closely with accreditation standards to foster overall institutional resilience.

When grouped by school age, legacy institutions scored higher (M=2.66; SD=0.85) than younger institutions (M=2.60; SD=0.92). Institutional age and experience contribute significantly to operational risk management performance, as legacy institutions leverage extended histories, accumulated institutional memory, and refined processes to build systematic practices, whereas younger schools often remain in foundational development stages (Porras, 2021; Machuca et al., 2021). Furthermore, Alhamad (2021) highlights that established institutions possess more mature frameworks for managing academic and financial risks effectively, while Wessels and Sadler (2015) confirm that older, experienced organizations with robust governance are better equipped to implement comprehensive risk and quality management standards.

Degree of Resilience of Selected Catholic Higher Educational Institutions in the Philippines

Table 2 shows that, overall, the selected schools' degree of resilience is high (M=3.25; SD=0.48). Of the four areas of resilience, leadership involvement ranked first (M=3.37; SD=0.56), followed by continuous improvement (M=3.26; SD=0.49). Resource management (M=3.18; SD=0.58) and process standardization and flexibility (M=3.18; SD=0.50) came third with similar mean scores. This suggests the institutions under study are generally well prepared to withstand and adapt to disruptions. The ranking of the four resilience areas highlights strengths in active administrative engagement and learning cultures—specifically through top-ranked leadership involvement and continuous improvement—which are critical for fostering a resilient organizational culture (Storms et al., 2019; Gamble & Crouse, 2020; Lim & Gaerlan, 2022). However, the slightly lower and tied scores for resource management and process standardization suggest potential vulnerabilities during crises, indicating that institutions must focus on streamlining operations, optimizing resource allocation, and balancing standardization with flexibility (Kondić et al., 2020).

Table 2

Degree of Resilience and Its Indicators as Assessed by the Administrator Respondents

Variable	Continuous Improvement			Leadership Involvement			Resource Management			Process Standardization and Flexibility			Degree of Resilience		
	M	SD	Int	M	SD	Int	M	SD	Int	M	SD	Int	M	SD	Int
Student Population															
Smaller Student Body	3.13	0.50	High	3.28	0.62	Very High	3.04	0.69	High	3.07	0.43	High	3.13	0.49	High
Larger Student Body	3.34	0.47	Very High	3.42	0.52	Very High	3.25	0.50	High	3.25	0.53	High	3.31	0.47	Very High
Number of Employees															
Smaller Workforce	3.13	0.50	High	3.28	0.62	Very High	3.04	0.69	High	3.07	0.43	High	3.13	0.49	High
Larger Workforce	3.34	0.47	Very High	3.42	0.52	Very High	3.25	0.50	High	3.25	0.53	High	3.31	0.47	Very High
Annual Operational Budget															
Lower Budget Capacity	3.23	0.50	High	3.38	0.61	Very High	3.18	0.62	High	3.14	0.51	High	3.23	0.50	High
Higher Budget Capacity	3.33	0.46	Very High	3.35	0.45	Very High	3.16	0.46	High	3.28	0.47	Very High	3.28	0.44	Very High
Number of Accredited Programs															
Fewer Accredited Programs	3.23	0.50	High	3.38	0.61	Very High	3.18	0.62	High	3.14	0.51	High	3.23	0.50	High
More Accredited Programs	3.33	0.46	Very High	3.35	0.45	Very High	3.16	0.46	High	3.28	0.47	Very High	3.28	0.44	Very High
Years of Existence															
Younger Institutions	3.11	0.49	High	3.41	0.57	Very High	3.07	0.84	High	3.18	0.41	High	3.19	0.49	High
Legacy Institutions	3.30	0.48	Very High	3.36	0.56	Very High	3.20	0.50	High	3.19	0.52	High	3.26	0.48	Very High
Whole	***3.26***	***0.49***	***Very High***	***3.37***	***0.56***	***Very High***	***3.18***	***0.58***	***High***	***3.18***	***0.50***	***High***	***3.25***	***0.48***	***High***

Mean Range: 1.00-1.75=Very Low, 1.76-2.50=Low, 2.51-3.25=High, 3.26-4.00=Very High

When grouped by student population, those with larger student bodies scored very high (M=3.31; SD=0.47), while those with smaller student bodies scored high (M=3.13; SD=0.49). Larger institutions develop more systematic resilience practices because of greater resources, complex structures, and the need to manage diverse populations, whereas smaller schools face relative disadvantages that signal an opportunity to adopt strategies from their larger peers (Ungar et al., 2019; Kondić et al., 2020). This is further supported by Storms et al. (2019), who noted that comprehensive institutional infrastructure and systems bolster performance, and Kenno et al. (2021), who highlighted that decentralized structures in larger organizations facilitate strategic resource allocation and effective resilience planning.

When grouped by workforce size, those with larger workforces had a very high mean (M=3.31; SD=0.47), while those with smaller workforces had a high mean (M=3.13; SD=0.49). Human capital and organizational scale significantly drive resilience practices, as institutions with larger workforces have the specialized personnel and resources needed for comprehensive frameworks, whereas smaller organizations face relative disadvantages that targeted training and formalized processes can mitigate (Kenno et al., 2021; Storms et al., 2019). Furthermore, Kondić et al. (2020) emphasize that a larger workforce provides a broader array of skills to implement multifaceted resilience strategies, a view reinforced by Ungar et al. (2019), who highlight how increased personnel foster robust support networks and adaptive capacity.

When grouped by annual operational budget, those with higher budget capacity had a very high mean (M=3.28; SD=0.47), while those with lower budget capacity had a high mean (M=3.23; SD=0.50). The minimal difference in resilience levels across varying budgets indicates that financial capacity is not a decisive factor, proving that effective practices rely more on leadership, efficiency, and institutional commitment than monetary outlays (Campbell et al., 2020; Lim & Gaerlan, 2022). Furthermore, Poltarykhin et al. (2020) emphasize that well-designed organizational processes enable high performance regardless of budget size, allowing resource-constrained institutions to succeed while prompting wealthier ones to spend efficiently.

When grouped by number of accredited programs, those with more accredited programs scored very high (M=3.28; SD=0.44), while those with fewer accredited programs scored high (M=3.23; SD=0.50). The minimal performance difference across program accreditation counts indicates that while rigorous accreditation standards foster quality, they are not the sole determinant of success, allowing institutions with fewer accredited programs to still achieve high standards by adopting universal quality assurance principles (Alhamad, 2021; Machuca et al., 2021). Furthermore, Thi et al. (2020) and Zhang and Luo (2023) emphasize that

structured evaluation and continuous improvement are essential, transferable tools that drive organizational resilience regardless of an institution's total number of accredited programs.

When grouped by years of existence, legacy institutions had a very high mean (M=3.26; SD=0.48), while younger institutions scored high (M=3.19; SD=0.49). Institutional age and experience contribute to resilience levels, as legacy institutions leverage extended histories, accumulated institutional memory, and refined processes to build robust operational foundations, whereas younger schools are still progressing through earlier developmental stages (Lim & Gaerlan, 2022; Kondić et al., 2020). Furthermore, Wessels and Sadler (2015) confirm that institutions with longer operational histories possess a more mature knowledge base, positioning them to better adopt and sustain effective risk management and resilience strategies over time.

Difference in the Extent of Operational Risk Management Practices as Assessed by the Administrator Respondents

Table 3

Difference in the Extent of Operational Risk Management Practices as Assessed by the Administrator Respondents

Variable	U	z	p
Student Population	844.000	-1.054	0.292
Number of Employees	844.000	-1.054	0.292
Annual Operational Budget	736.000	-1.214	0.225
Number of Accredited Programs	736.000	-1.214	0.225
Years of Existence	593.000	-0.448	0.654

Note: The difference in the means is significant when p≤0.05 (less than or equal to).

The Mann-Whitney U test showed that operational risk management practices did not differ significantly when grouped by institutional profile variables. Table 3 showed no significant differences by student population [U=844.000, p=0.292], number of employees [U=844.000, p=0.292], annual operational budget [U=736.000, p=0.225], number of accredited programs [U=736.000, p=0.225], or years of existence [U=593.000, p=0.654]. This means the extent of operational risk management practices did not differ significantly by institutional characteristics.

Consistent performance across varying student populations, employee counts, budgets, accredited programs, and institutional ages challenges the assumption that larger, wealthier, or older institutions hold a monopoly on effective risk management, proving instead that success

is driven by internal governance, leadership commitment, and strategic culture rather than resource scale (Libo-on, 2017; Wessels & Sadler, 2015; Mukherjee, 2019). Furthermore, Syamsia et al. (2021), Molchanova (2023), Drahein et al. (2019), and Lim and Gaerlan (2022) reinforce that intentional methodologies and systematic approaches enable institutions of any size or capacity to achieve high standards, making effective risk management an attainable goal for all rather than a privilege of the few.

Difference in the Degree of Resilience and Its Indicators as Assessed by the Administrator Respondents

The study analyzed resilience and its indicators for significant differences using the Mann-Whitney U test on groups formed based on varying institutional profile variables. Results showed no significant differences by students' population [U=769.000, p=0.096], number of employees [U=769.000, p=0.096], annual operational budget [U=863.000, p=0.901], number of accredited programs [U=863.000, p=0.901], or number of years of existence [U=581.500, p=0.573]. The results indicate that administrator respondents' stated resilience level does not differ significantly by institutional characteristics.

The uniformity of resilience levels across institutional profiles challenges the assumption that resilience stems exclusively from organizational scale, wealth, or history, showing instead that resilience is a cultivated trait driven by internal factors such as leadership quality, culture, and strategic planning (Zhang & Luo, 2023; Campbell et al., 2020). Furthermore, Ungar et al. (2019), Lim and Gaerlan (2022), Karlsson and Offord (2023), and Rasli et al. (2022) confirm that internal adaptive capacities and strategic responses are far more determinative than external characteristics, ensuring that smaller, younger, or less affluent institutions can achieve equal resilience through intentional internal processes.

Table 4

Difference in the Degree of Resilience and Its Indicators as assessed by the Administrator Respondents

Variable	U	z	p
Student Population	769.000	-1.666	0.096
Number of Employees	769.000	-1.666	0.096
Annual Operational Budget	863.000	-0.124	0.901
Number of Accredited Programs	863.000	-0.124	0.901
Years of Existence	581.500	-0.564	0.573

Note: The difference in the means is significant when p≤0.05 (less than or equal to).

Relationship between Operational Risk Management Practices and School Resilience

Spearman rank correlation was employed to determine the relationship between operational risk management practices and the resilience level assessed by the administering respondents. Table 5 shows a highly significant correlation between the two variables [$r_s(90)=0.660$, $p=0.000$], suggesting that institutions with more developed operational risk management also demonstrate greater resilience. This suggests that stronger risk management improves an institution's ability to adapt and recover from disruptions.

The strong positive correlation between operational risk management and institutional resilience demonstrates that practices like risk identification, assessment, mitigation, and monitoring are fundamental drivers of an institution's ability to adapt to and recover from disruptions (Libo-on, 2017; Indarbaev & Kapustina, 2023). This direct relationship highlights that prioritizing and formalizing risk management frameworks is the most effective strategy for administrators seeking to strengthen organizational stability and crisis-response capacity. Furthermore, this is supported by Molchanova (2023) regarding loss minimization and stability, Wessels and Sadler (2015) emphasizing ISO-compliant frameworks for strategic resilience, Zagorcheva-Koycheva (2022) noting the role of comprehensive procedures in operational continuity, and Syamsia et al. (2021) confirming that proactive risk mitigation directly reduces institutional vulnerabilities.

Table 5

Relationship between Operational Risk Management Practices and School Resilience

Variable	r_s	df	p
Operational Risk Management Practices x Degree of Resilience	0.660*	90	0.000

*Note: *correlation is significant when p≤ 0.05 (less than or equal to)*

Prevalent Risks

Financial Risks. Qualitative findings show that financial risks—driven by demographic shifts, enrollment declines, and funding shortages—pose severe threats to higher education institutions, often prompting reactive cost-cutting because many lack formal risk frameworks (Tamrat & Teferra, 2020; Khaw & Teoh, 2023). Consequently, institutions must transition toward proactive financial strategies, such as revenue diversification, reserve creation, contingency planning, and early warning systems, to secure long-term operational viability (Lyalyuk, 2019; O'Leary et al., 2020).

Declining enrollment. Declining enrollment is a major concern for these institutions, with some facing the issue for up to 15 years. It is considered one of the top three significant risks. The decline is attributed to several factors, including competition from local government schools that offer free education and an increase in the number of schools in the provinces. Since tuition fees are the main source of income, lower enrollment directly leads to lower income. One school experienced a significant drop in its college population, having only about 6,000 tertiary students at one point.

> There are several risks, including financial risks. Whether you like it or not, many projects need financing, especially with a new building. Enrollment has been going down. So, we will check where we will get our resources... Yes, because tuition fees are the main source of income. With lower enrollment, income is lower. (LAY1, online interview, April 9, 2025, number lines 50-52; 56-57)

> And one of the very… what do you call that… major concerns here is how to address the continuous decline in enrollment. That is one thing… we focus so much on that… on how to address on that aspect. Definitely… the impact of this is more on the financial… okay? Well… well… concerning with the financial aspect, it is in terms of providing financial resources to our different activities. (LAY2, online interview, April 12, 2025, number lines 49-51; 59-61)

Insufficient funding and cost-cutting. Related to declining enrollment, institutions face insufficient funding and the need to cut costs. To manage this, schools have had to trim expenses and prioritize spending to avoid affecting operations. Limited resources can also affect facility maintenance, leading to old, dilapidated equipment, deteriorating buildings, and non-competitive salaries compared to government schools. One institution mentioned the need to cut costs to clarify priorities and trim expenses without affecting operations. The demand for a higher facilities budget is risky because tuition income is low.

> We have to… really… cut on costs to see our priorities, and if possible, trim down the expenses that will not affect the operations, we will cut on those expenses… And then another thing is, the the infrastructure because we have very limited resources because when when we are in, when able to assure infrastructure quality and and human resources as one then then the risk in terms of clientele. (LAY1, online interview, April 9, 2025, number lines 61-62; 199-202)

> Let us say, the salaries and benefits are raised to be at par with other institutions, but this would mean an imbalance in the allocation of fees. The school might suffer on the improvement of facilities. (LAY4, personal communication, May 2, 2025, number lines 73-75)

Human Resources Risks. Qualitative findings indicate that human resources risks—particularly high employee turnover driven by uncompetitive compensation and a lack of formal succession planning—severely disrupt educational quality, create leadership gaps, and threaten organizational continuity (Tamrat & Teferra, 2020; Khaw & Teoh, 2023). Addressing these vulnerabilities requires proactive strategies such as competitive compensation structures, professional development, performance incentives, and clear leadership pipelines to enhance staff retention and ensure long-term resilience (O'Leary et al., 2020).

Employee turnover and competitiveness. The risk of employee turnover and competitiveness is a significant concern for the institutions. This risk is characterized by high turnover, lack of competitiveness, employee poaching, impacts on quality, and stagnant salaries.

> Aside from finances, we also have human resources because the pay in other institutions, especially the government schools, are higher… Human resources are very important to make the institution successful, so if you have a dearth of resources… ahhh… there is no motivation, then school would face resignation, not necessarily mass resignation, but resignation of those who are really good because they are attracted by outside sources. (LAY1, online interview, April 9, 2025, number lines 52-54; 66-69)

> Ahhh… what else… faculty and staff turnover, like administrators, faculty, staff turnover… okay… ummm… what else?... For the past two years, my office experiences risk such as staff turnover… not just staff but faculty turnover… Oh. OK, if I am not mistaken, last year was the very high turnover. Almost 15 of our administrators… faculty… transferred… (LAY2, online interview, April 12, 2025, number lines 35-36; 55-56; 151-152)

Lack of succession planning and leadership issues. Based on the interviews, the lack of succession planning and leadership issues are a significant concern for the institutions. This risk stems from the absence of formal plans, leadership gaps, and cultural shifts.

> During our planning, one of the things that I raised was to come up with a really formal process on how to do that… *Iba talaga pag face-to-face, so we trace out if this is about… leadership? Isa sa mga issues is leadership. Yun na yun ang kailangan talaga. Ahhh… religious… and the administrators… you could imagine kasi during the last five years, you heard naman no,*

> *ako isa na lang ako sa mga natitira*… (It is different when it is face-to-face, so we try to trace if this is about… leadership? One of the issues is leadership. That is what is really needed. Ahhh… religious… and the administrators… you could imagine because during the last five years, you have probably heard, I am the only one left…) (LAY2, online interview, April 12, 2025, number lines 50-51; 99-102)

> Human resource, financial management, sudden drop of enrolment, competitions with other schools, outdated laboratories and equipments, the prevalent effects of globalization, and biases, *pabag-o bago nga and inconsistent government regulations and policies* (ever-changing and inconsistent government regulations and policies). All these are inside the web of risks and are interconnected. (LAY4, personal communication, May 2, 2025, number lines 45-48)

Operational and Management Risks. Qualitative findings indicate that operational and management risks are often handled through reactive, ad hoc problem-solving rather than systematic mitigation, driven by a lack of formal systems and restrictive communication channels that limit organizational transparency and delay responses (Lyalyuk, 2019; O'Leary et al., 2020). To overcome these vulnerabilities and build resilience, institutions must formalize their practices by adopting proactive strategies such as environmental scans, SWOT analyses, structured risk registers, and regular monitoring.

Reactive vs. proactive risk management. Effective risk management is essential for institutional stability and growth, yet organizations often struggle to balance reactive responses with proactive planning. The distinction lies in whether actions are taken after a problem manifests or before it occurs. While some interviewees describe proactive measures, such as conducting SWOT analyses and environmental scans to anticipate threats, a recurring theme suggests a tendency toward reactive strategies, where action is taken only "when there is a problem."

> What happens here is that when there is a problem, we are reactive, not proactive. When we see a problem, that is the time we look for a solution. It is that we are not proactive; this situation might happen, we have options supposedly, but many times, we are caught unaware. (LAY1, online interview, April 9, 2025, number lines 87-90)

> These are new standards of the PAASCU, and after some time, it has already become a reality that we will have to address, but it is a challenge here to really come up with an operational manual on how to address… there were some kind of like emergency, but it was more of a reactive than a proactive, but these are not yet the so-called risk management. (LAY2, online interview, April 12, 2025, number lines 44-49)

Inadequate communication. A significant barrier to effective risk management is the inadequate or inconsistent communication of potential risks and mitigation strategies across all organizational levels. While formal risks are addressed through high-level discussions, such as immediate meetings called by the school head and reports to the School Board or Board of Trustees, the routine flow of information appears disjointed. Communication is often handled on a "case-to-case basis" and restricted based on the scope or perceived "confidentiality" of the issue. This often results in critical information being "communicated to the top management level" but "not to the lower" levels, unless a specific incident has already occurred (LAY2).

> If institutional, we have to inform the whole school. But if it involves only a particular level, then it is contained where it happened. That is usually on a case-to-case basis. Meaning, if it is institutional, we inform everyone, but if not, then it stays at their level. That is because we consider confidentiality of the issues also. (LAY1, online interview, April 9, 2025, number lines 109-112)

> It's not… what do you call that… regularly done. Meaning, there are times that it is just communicated to the top management level. *Sa below, hindi. It is communicated to the below kung may mga pangyayari… so, ganun…* (Not to the lower. It is communicated to the below if there are incidents… so, it is like that…) (LAY2, online interview, April 12, 2025, number lines 125-127)

Other Significant Risks. Qualitative data reveal that physical security incidents, reputational crises, and intense external competition from nearby public and private institutions pose critical threats to enrollment stability and institutional continuity (Zakharova & Karmalova, 2023; Tamrat & Teferra, 2020). Mitigating these complex external pressures requires institutions to integrate proactive safety measures, robust digital crisis communication, and comprehensive contingency plans into their overarching management frameworks (Lyalyuk, 2019).

Security and reputational risks. Institutional integrity hinges on effectively managing both immediate physical security risks and their potential to cascade into severe reputational damage. One institution is consistently exposed to multiple, varied threats, from direct security incidents like past arson attempts to the dangers posed by an unsafe school location, while another faces critical maintenance and financial failings that have left CCTVs nonfunctional and facilities that pose immediate safety threats to students and personnel. Compounding these internal vulnerabilities is the exposure to external hazards; however, the most profound risk lies in how these situations are managed, as neglecting fundamental safety

and maintenance standards—or mishandling stakeholder engagement—directly jeopardizes the school's standing, placing "the name of the school is at stake" and threatening catastrophic reputational risks if an accident were to occur.

> Ahhh… once we had an incident on arson. *May taong may problema sa utak tried to… ahhh… pumunta sa… somewhere sa property banda ng university… nagsindi ng match at mga dahoon… there was an attempt at arson, and that was a security risk. Kung security risks, madami, as you can see the location of the school is not very safe although it is also safe because we have a connection with the barangay and the police department, and meron talagang mga security around, pero hindi lahat nakikita eh.* (A man with mental problems tried to… ahhh… went to… somewhere in the property of the university… lit a match and leaves… there was an attempt at arson, and that was a security risk. Talking about security risks, there are many, as you can see the location of the school is not very safe, although it is also safe because we have a connection with the barangay and the police department, and there are security personnel around, but not everything can be seen or captured.) (LAY1, online interview, April 9, 2025, number lines 115-120)

> *Meron, last year lang nangyari.* (There was one which happened last year.) The crisis management committee had to meet and present the problem to the School Board, and then, eventually we presented it to the BOT… not really to the BOT, but to the Provincial and the ---- President, and they called the BOT and informed of the problem. *Pero nabigyan naman ng solution.* (But it was given a solution.) (LAY1, online interview, April 9, 2025, number lines 131-134)

Competition and external factors. The institution faces significant risk stemming from intense competition and rapidly shifting external factors that directly threaten its sustainability and enrollment base. A major challenge is the influx of public sector education, including the growth of local government schools offering free education, and the opening of nearby public universities with similar programs. This is compounded by rivalry from other private institutions, particularly those viewed as being "generally for business" and focused on competitiveness.

> Faculty we have a ranking instrument*, but ganun lang, which is too far*... (but it was only that, which is too far...) I mean we we did we we did actually the the study on the competitiveness of our salary. Even first study was to conduct on the top schools. *Well, we do not want to do that because it's very tough, layo, more or less with equal equivalent within the area.* (Well, we do not want to do that because it's very tough, very far, more or less with equal equivalent within

the area.) We are second to the bottom. (LAY2, online interview, April 12, 2025, number lines 162-165)

Mataas talaga! (It was really high!) 10 years ago, 15 years ago. Oh my gosh. We were very competitive. *Marami talagang gustong pumasok dito.* (Many wanted to come here.) But no… one of the reasons there is the ----- University. It is not just the -----. *Many schools looked at us before as… in a way… hindi… oh my gosh!* (Many schools looked at us before as… in a way… but no… oh my gosh!) (LAY2, online interview, April 12, 2025, number lines 167-170)

Operational Risk Management Practices

Financial and Enrollment Management Practices. Qualitative data show that higher education institutions combat financial and enrollment risks by diversifying income through partnerships and entrepreneurial ventures, offering scholarships and discounts, exercising cost control, and improving infrastructure, with targeted marketing and non-tuition revenue streams buffering against fluctuations (Tamrat & Teferra, 2020; Zakharova & Karmalova, 2023). Furthermore, Lyalyuk (2019) highlights that stronger marketing, financial aid programs, and strategic infrastructure investments are essential to attract students and ensure long-term institutional appeal and sustainability.

Diversification of income and partnerships. Faced with the profound threat of financial risk driven by low enrollment and insufficient tuition revenue, the institutions are strategically pursuing measures centered on diversification and partnerships to ensure long-term viability. The current financial fragility of one school is highlighted by its need to be subsidized by a larger entity, underscoring the urgency of generating self-sustaining income. In response, implemented strategies include strengthening the marketing and outreach programs, particularly leveraging digital platforms, and employing comprehensive marketing plans involving all university units. Early indicators suggest that these concerted marketing efforts may already be yielding positive results. Furthermore, the institution is actively strengthening external relations through partnerships with feeder schools and exploring internal operational adjustments to maximize resource use and student flexibility. For long-term financial resilience, the university needs to channel funds into lasting investments like infrastructure and employee training.

… one of the solutions there is to come up with a block section. The semester is divided into two, two blocks, no? If you look at it there are two semesters and one summer. Iyan ang ginagawa to address the impact of it. (… one of the solutions there is to come up with a

> block section. The semester is divided into two, two blocks, okay? If you look at it there are two semesters and one summer. This is what is done to address the impact.) (LAY2, online interview, April 12, 2025, number lines 67-69)

> We have implemented several strategies such as strengthening our marketing and outreach programs especially through digital platforms and have enhanced partnerships with feeder schools. (LAY3, online interview, June 16, 2025, number lines 87-89)

Scholarship and discount programs. Recognizing that the institution's human capital is a key competitive asset, scholarship and discount programs have become a multi-faceted risk-mitigation and strategic investment priority. The institution is actively using attractive scholarship packages and flexible payment options as a key strategy to boost enrollment and compete effectively in the market. Beyond student recruitment, the institution has a distinct focus on faculty development, which it recognizes as an immediate response to institutional risk. However, the evidence suggests a current limitation in this area. At the same time, while leadership is very conscious of supporting faculty development programs, there is a critical need to intensify efforts to secure scholarships for faculty, especially for those pursuing advanced studies, as current availability appears insufficient. This twin focus—using scholarships to attract and retain students while simultaneously seeking greater resources for faculty development—underscores a strategic commitment to investing in talent to secure both immediate enrollment goals and long-term academic excellence.

> *Of course, the support… very conscious to support the faculty development programs, we don't have scholars studying abroad, no?... One thing also is that to… to is, isa sa mga dapat i address natin is the the data and involve other other ways really to find scholarships for our faculty.* (Of course, the support… very conscious to support the faculty development programs, we don't have scholars studying abroad, right?... One thing also is that to… to is, one thing to address is the data and involve other other ways really to find scholarships for our faculty.) (LAY2, online interview, April 12, 2025, number lines 60-71; 236-237)

> We have implemented several strategies, such as strengthening our marketing and outreach programs, especially through digital platforms, and enhancing partnerships with feeder schools. We are also offering more attractive scholarship packages and flexible payment options. (LAY3, online interview, June 16, 2025, number lines 87-90)

Cost control and financial prudence. In response to persistent financial pressures, the institutions have adopted a rigorous approach to cost control and financial prudence designed to safeguard essential operations and prioritize core commitments. This strategy

includes a strict mandate to "cut on costs" by identifying and trimming non-essential expenses without compromising operational continuity. Central to this fiscal discipline is the strong, strategic guidance of financial leadership, which manages expense releases to prevent shortfalls. Salary payments remain the top priority, ensuring employee stability. Beyond mere expense reduction, the institution has implemented structural adjustments to optimize resource utilization.

> We have to… really… cut on costs to see our priorities, and if possible, trim down the expenses that will not affect the operations, we will cut on those expenses. Then, our controller is really very good. He knows how to… look into the bigger picture so that we can move around. (LAY1, online interview, April 9, 2025, number lines 61-64)

> *Then, for finances… ahhh… we really program the release of our expenses, para we will not be gipit. Basta first priority talaga yung salaries; the others would follow. The VP-Finance has priorities too, to know the actual picture.* (Then, for finances… ahhh… we really program the release of our expenses, so that we will not be short of anything. The priority would always be the salaries; the others would follow. The VP-Finance has priorities too, to know the actual picture.) (LAY1, online interview, April 9, 2025, number lines 82-85)

Human Resources and Employee Development Practices. Qualitative findings indicate that higher education institutions combat high employee turnover and external staffing competition by reviewing salary scales, offering performance incentives, providing professional development, and granting employee and dependent scholarships to foster organizational loyalty and stability (Tamrat & Teferra, 2020; Zakharova & Karmalova, 2023). Furthermore, Nguyen et al. (2021) highlight that targeted financial incentives and advanced study opportunities effectively motivate staff and mitigate attrition against aggressive market pressures from government and private competitors.

Employee welfare and incentives. The institution is addressing human resource risks, particularly talent loss due to uncompetitive compensation, through a focused strategy on employee welfare and incentives. A dedicated committee on compensation and benefits has been established to review and potentially improve the salary scale and benefits package, with the explicit goal of aligning it with the salary scale of other schools. Beyond basic pay adjustments, we are implementing strategic changes to the compensation structure, including adjusting hiring rates based on qualifications and working to mitigate salary distortion during internal ranking processes. Furthermore, we are taking proactive measures to improve retention and stability, such as introducing special scholarship programs for single parents and extending benefits, like scholarships for dependents, to single employees.

> For our risk management strategies, if we look at the human resources first… ahhh… we have… the administration has identified a committee on compensation and benefits. The said committee is reviewing our salary scale, our benefits, so that these benefits can be improved, so that we can be at par with the salary scale of other schools. (LAY1, online interview, April 9, 2025, number lines 79-82)

> *Another strategy we are working on is that may mga iniba… may mga rates na iniba... no? may mga rates depending on the qualifications, hiring rate. Hiring rate muna, iba… so so that once after, after you will be one year or two years, magpapa rank ka. Minsan, hindi pa rin magbabago ang salary mo… kasi nga distortion… To add more, more development programs for our employees…* (Another strategy we are working on is that we applied changes in some rates where hiring rates are based on the qualifications. The hiring rate was first improved. After one or two years, you will apply for ranking. Because sometimes, there is no change in the salary because of the distortion. We also want to add more, more development programs for our employees…) (LAY2, online interview, April 12, 2025, number lines 212-217)

Professional development and training. A cornerstone of mitigating institutional risk and ensuring long-term competitiveness is a strong commitment to professional development and training for both faculty and employees. While there is a strong expressed commitment to supporting faculty development programs, the current focus seems to be shifting toward more substantial investments. Evidence suggests the administration understands the value of sending employees to training and echo seminars, even abroad, for program implementation. Moreover, there is a clear strategic push to significantly increase this investment, exemplified by the proposal to nearly double the budget for the Faculty Development Scholarship.

> Of course, the support… very conscious to support the faculty development programs, we still don't have scholars studying abroad. (LAY2, online interview, April 12, 2025, number lines 69-71)

> Imagine, we sent a lot on trainings and echo seminars. We send our employees, even abroad, for the implementation of programs… (LAY4, personal communication, May 2, 2025, number lines 90-91)

Operational and Management Practices. Qualitative findings show that higher education institutions manage operational risks by formalizing procedures through manuals and ISO certification efforts, conducting routine planning assessments, utilizing SWOT analyses and environmental scans, upgrading infrastructure, and strengthening governance

(Khaw & Teoh, 2023). While these structured frameworks are still evolving from informal routines, adopting quality standards and environmental scanning enhances strategic decision-making, stability, and stakeholder confidence by fostering a culture of continuous operational improvement (Johanson et al., 2019; ISO, 2015).

Formalizing risk management. The transition toward formalizing risk management within these institutions reflects an ongoing shift from reactive, intuitive routines to structured, documented frameworks driven by external quality standards. Interview data reveals that while many schools possess functional "working routines" and committee-based problem-solving models, they largely lack a centralized, highly formalized framework or a dedicated operational manual. Currently, the drive toward formalization is primarily fueled by Quality Assurance (QA) initiatives, specifically through ISO certification and management audits, which compel schools to map potential threats against strategic goals and utilize standardized forms to identify risks at the office and cluster levels.

> How? Sometimes… ummm… during planning sessions or during meetings. Different administrators share some problems and risks they encounter, so the school would know what are the risks they are facing. For example… ummm… particular problems occurred at the athletics office, they identified the problem, then a committee, yes because we have a risk management committee that looks into it, evaluates, and looks for possible solutions, if there are things to be remedied. (LAY1, online interview, April 9, 2025, number lines 37-42)

> More or less, there is, but not really so… since we are still undergoing ISO. So, through ISO, we are making documentation supposedly for everything, but we are not done yet. (LAY1, online interview, April 9, 2025, number lines 45-46)

Communication and reporting. While the institution engages in various risk-related activities, it still needs to formalize and standardize a comprehensive risk management framework. Existing efforts include systematic, office-by-office risk identification, followed by clustering and alignment with institutional goals through planning sessions. Furthermore, a risk management committee has been established to evaluate specific issues, and a Quality Assurance Office monitors standards.

> If institutional, we have to inform the whole school. But if it involves only a particular level, then it is contained where it happened. That is usually on a case-to-case basis. Meaning, if it is institutional, we inform everyone, but if not, then it stays at their level. That is because we consider confidentiality of the issues also. (LAY1, online interview, April 9, 2025, number lines 109-112)

> *It is papel lang, but one thing now with Father----- compared with previous administrations, we are now experiencing every now and then townhall meeting. So, harap harapan… so, that is one thing that we introduced in the last three years townhall meeting na hindi lang top administrators. Kung may concern, lahat gina gather, from top to down, no? That's one thing, and we really strengthened our… we call that one as social media, FB Messenger, Chat group.* (It is on papers only, but one thing now with Father----- compared with previous administrations, we are now experiencing every now and then townhall meeting. So, face to face… so, that is one thing that we introduced in the last three years townhall meeting which involves not only the top administrators. When there are concerns, we gather everyone, from top to down, okay? That's one thing, and we really strengthened our… we call that one as social media, FB Messenger, Chat group.) (LAY2, online interview, April 12, 2025, number lines 134-139)

Leadership and governance. Effective leadership and governance are crucial in establishing both the structure and the culture for managing institutional risk, yet the current approach remains largely reactive, triggered primarily by the severity of an issue. While a Crisis Management Committee (or Risk Management Committee) exists, it is typically convened only when problems are too significant for lower levels to resolve, highlighting a dependency on the President's intervention for serious concerns. This centralization contrasts with existing pockets of proactive strategy, such as regular SWOT analyses and environmental scans conducted during planning sessions to anticipate threats. Furthermore, leadership uses systematic processes, including mid-year and year-end risk evaluations, and actively crafts recovery plans to address major concerns.

> We don't have a system yet, but normally, when problems reach the president, they are already considered serious because if the department or the office concerned can solve the problem at their level, they would just report to the president – this, Father happened – but if the problem is not solved at their level, that is the time the president would call for the committee, the risk management committee called the crisis management committee. (LAY1, online interview, April 9, 2025, number lines 95-99)

> During our planning, one of the things that I raised was to come up with a really formal process on how to do that. And the (network) is answering that by coming up with even a (network)-wide things like that. (LAY2, online interview, April 12, 2025, number lines 50-52)

Infrastructure Improvement. Qualitative findings show that higher education institutions treat infrastructure development as a critical strategy to combat enrollment declines,

mitigate safety hazards, and enhance overall competitiveness by upgrading facilities and seeking funds despite budget constraints (ISO, 2015; UNESCO, 2017). Furthermore, Cheng and Tam (2019) note that modern physical spaces directly improve operational efficiency, boost student satisfaction, and reinforce institutional reputation and financial stability.

> And then, of course, one thing that we also address is the physical facilities *kasi isa rin yan sa mga comment ng mga na exit interview na faculty* (because this is one of the comments of the faculty whom met during the exit interview) about physical activities… and all of that. So, we have a plan now, and we've already started converting the facilities. (LAY2, online interview, April 12, 2025, number lines 242-245)

> Outdated laboratories and equipment are to be changed to state-of-the-art facilities but they are too expensive… (LAY4, personal communication, May 2, 2025, number lines 106-107)

> *Kasi for me, the three pillars of of education, which we cannot really undermine and go hand in hand would be the human human resource, the human resource, and then we have the infrastructure infrastructure, and then the quality of education.* (Because for me, the three pillars of education, which we cannot really undermine and should go hand in hand would be the human resource, and then we have the infrastructure, and then the quality of education.) (REL1, online interview, April 13, 2025, number lines 190-192)

Emerging Framework

Figure 2 presents an emerging framework for institutional resilience in higher education institutions, specifically the selected Catholic higher education institutions involved in this study, which systematically connects four major risk categories to corresponding strategic management practices, all aimed at achieving organizational stability and sustainability. The framework begins with operational risks, which are addressed through operational risk management practices to prevent disruptions to core functions. Financial risks are mitigated through financial and enrollment management strategies, which are critical to securing tuition revenue and ensuring fiscal health. To counter talent attrition and maintain quality, human resources risks are linked to human resources and employee development strategies, focusing on retention and skill enhancement. Addressing overall efficiency and leadership effectiveness, operational and management risks require specific operational and management strategies to formalize systems and move away from reactive governance. Finally, other significant risks, including threats related to physical security or external competition, are addressed through infrastructure improvements to ensure a safe and modern institutional

environment. By executing these aligned strategies across all four domains, the institutions move toward greater resilience.



Figure 2. Resilience Framework for Higher Educational Institutions

Conclusion

The study concludes that selected Catholic higher educational institutions in the Philippines generally demonstrate a great extent of operational risk management practices alongside a high degree of resilience. Importantly, the analysis found no significant differences in ORM practices or resilience levels when institutions were grouped by student population, workforce size, budget, accreditation status, or institutional age. This consistency suggests that institutional profile variables do not determine the effectiveness of risk management or resilience outcomes.

Instead, the findings underscore that internal factors such as leadership commitment, organizational culture, and strategic focus drive strong operational risk management and resilience practices. These factors enable institutions of varying sizes and resources to maintain stability and navigate disruptive challenges successfully. Consequently, fostering proactive leadership, nurturing a culture of continuous improvement, and formalizing risk management frameworks are critical strategies to sustain institutional endurance regardless of external characteristics.

In sum, the intersection of operational risk management and resilience forms a foundational pillar for educational institutions aiming for long-term stability and quality, achievable through deliberate internal governance rather than depending solely on institutional scale or financial capacity.

Limitations of the Findings

The limitations of this study's findings include several key considerations. First, the reliance on self-reported data may introduce bias, as respondents might overestimate their institutions' resilience levels or provide socially desirable responses, potentially affecting the accuracy of the results. Second, the cross-sectional nature of the data limits the ability to establish causality or observe changes in resilience over time, restricting insights into how institutional practices evolve in response to crises. Third, the study's scope is confined to selected Catholic higher education institutions in the Philippines, which may limit the generalizability of findings to other contexts, such as secular or private institutions, or those in different geographical regions. Additionally, measuring resilience through specific areas—leadership involvement, continuous improvement, resource management, and process standardization—may not capture all facets of institutional resilience, such as community engagement or stakeholder participation, providing an incomplete picture. Lastly, variability in institutional size, resources, and student populations, while accounted for in some analyses, still makes direct comparisons across diverse institutions challenging and may affect the interpretability of the results. These limitations highlight the need to apply the findings cautiously and suggest avenues for future research to deepen understanding and strengthen empirical evidence.

Directions for Future Research

Based on these findings, future research should explore several key areas to deepen understanding and strengthen practical applications. One possible area of interest is longitudinal studies on institutional development to examine how institutional age, leadership involvement, and internal practices evolve and influence resilience and performance, particularly for emerging and younger institutions. Another could examine the impact of organizational culture and leadership styles by investigating which leadership behaviors, management practices, and organizational cultures most effectively foster resilience and continuous improvement, especially in resource-constrained settings. Future studies can examine the role of technology and innovation to see how adopting technological solutions and innovative strategies can complement traditional practices to accelerate resilience-building, especially in smaller or newer institutions. The research can be extended to different

geographic regions or types of higher education institutions to identify universal versus context-specific factors influencing resilience and quality improvement. Studies may empirically test specific low-cost or resource-efficient interventions (such as leadership training or process standardization) to determine their impact on resilience and continuous improvement outcomes. Research that incorporates feedback from students, faculty, and other stakeholders to understand how perceptions of resilience and quality management influence institutional practices and outcomes could also be worthwhile. Pursuing these areas will contribute to a more nuanced understanding of resilience in higher education and provide practical guidance for institutions aiming to enhance their adaptability and performance in dynamic environments.

References

Alhamad, B. (2021). Leadership and management of HEIs using strategic risk-based approach for sustainable academic excellence in higher education. *2021 Sustainable Leadership and Academic Excellence International Conference (SLAE), 1–8.* https://doi.org/10.1109/SLAE54202.2021.9788096

Almerez, Q., & Duping, A. (2022). Challenges and responses of higher education institutions (HEIs) towards academic resilience. *International Journal of Research and Innovation in Social Science*. https://doi.org/10.47772/ijriss.2022.61225

Amos, N. B., Dogo, E. B., Egwakhe, J. A., & Umukoro, J. E. (2022). Operational resilience and efficiency of private universities in Southwest Nigeria: The Covid-19 pandemic experience. *Journal of Business and Entrepreneurship, 10*(1), 1–14. https://doi.org/10.46273/job&e.v9i2.203

Campbell, H., Crippen, A., Hawkey, C., & Dalrymple, M. (2020). A roadmap for building climate resilience at higher education institutions: A case study of Arizona State University. *Journal of Green Building, 15*, 237–256. https://doi.org/10.3992/jgb.15.4.237

Cheng, Y. C., & Tam, W. M. (2019). *Quality assurance and management in education: Research and development in the Asia-Pacific*. Springer Nature.

Commission on Higher Education (CHED). (2022). CHED Memorandum Order No. 16, s. 2022: Updates on online learning in higher education. https://ched.gov.ph/wp-content/uploads/CMO-16-2022.pdf

Cotelnic, A. (2023). Quality assurance in higher education institutions through the risk management integration. *Journal of Social Sciences*. https://doi.org/10.52326/jss.utm.2023.06(1).06

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.).* SAGE Publications.

Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research (3rd ed.)*. SAGE Publications.

Curacubby Team. (January 3, 2023). Everything you need to know about risk management in schools. https://www.curacubby.com/resources/risk-management-in-schools

Dehdashti, A., Fatemi, F., Jannati, M., Asadi, F., & Kangarloo, M. (2020). Applying health, safety, and environmental risk assessment at academic settings. *BMC Public Health, 20*. https://doi.org/10.1186/s12889-020-09419-5

Delgado-Abad, J. (2022). Towards resilient educational system and governance: Measuring effectiveness and competitiveness of private HEIs. *Proceedings of the International Conference on Industrial Engineering and Operations Management*. https://doi.org/10.46254/an12.20220350

Deming, W. E. (2000). Out of the crisis. The MIT Press.

Drahein, A., Lima, E., & Costa, S. (2019). Sustainability assessment of the service operations at seven higher education institutions in Brazil. *Journal of Cleaner Production*. https://doi.org/10.1016/J.JCLEPRO.2018.11.293

Gamble, B., & Crouse, D. (2020). Strategies for supporting and building student resilience in Canadian secondary and post-secondary educational institutions. *SciMedicine Journal.* https://doi.org/10.28991/scimedj-2020-0202-4

Gim, C., Miller, C., & Hirt, P. (2019). The resilience work of institutions. *Environmental Science & Policy.* https://doi.org/10.1016/J.ENVSCI.2019.03.004

Goh, M. H. (2023). Benefits of operational resilience. https://blog.bcm-institute.org/operational-resilience/benefits-of-operational-resilience

Hina, S., Selvam, D. D. D. P., & Lowry, P. B. (2019). Institutional governance and protection motivation: Theoretical insights into shaping employees' security compliance behavior in higher education institutions in the developing world. *Computers & Security, 87*, 101594. https://doi.org/10.1016/J.COSE.2019.101594

Holtermann, R. S., Chaim, R. M., & Pinheiro, B. C. B. (2021). Evaluation, analysis, and treatment of educational risks in migration of presential teaching for remote. In *World Conference on Information Systems and Technologies (pp. 232–243)*. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-72660-7_23

Ichinose, T., & Oda, T. (2022). Risk management and resilience of schools in response to the COVID-19 pandemic. In *Pandemic Risk, Response, and Resilience* (pp. 445–456). Elsevier. https://doi.org/10.1016/B978-0-323-99277-0.00015-2

Indarbaev, S., & Kapustina, N. (2023). Features of operational risk management. *Russian journal of resources, conservation and recycling.* https://doi.org/10.15862/50ecor123

Institute of Risk Management (IRM). (2019). Survey report 2019: Risk management education courses in the Chinese university system.

https://www.theirm.org/news/survey-report-2019-risk-management-education-courses-in-the-chinese-university-system/

International Organization for Standardization. (2015). *Quality management systems — Requirements* (ISO Standard No. 9001:2015). https://www.iso.org/standard/62085.html

International Organization for Standardization (2023). ISO 31000:2018 Risk management guidelines. https://www.iso.org/standard/65694.html

James, B. W. (May 15, 2023). The essentials of operational risk management. https://www.noggin.io/blog/what-is-operational-risk-management-and-why-is-it-crucial-for-businesses

Johanson, J.-E., Johnsen, Å., Pekkola, E., & Reid, S. A. (2019). Strategic management in Finnish and Norwegian government agencies. *Administrative Sciences*, *9*(4), Article 80. https://doi.org/10.3390/admsci9040080

Kageyama, M. (2015). Integrated control systems and institutional size: A systematic approach to risk management. *Journal of Institutional Governance*, *12*(3), 45–62.

Karlsson, P., & Offord, M. (2023). Higher education during crisis: A case study on organic resilience. *Continuity & Resilience Review*. https://doi.org/10.1108/crr-10-2022-0030

Kenno, S., Lau, M., Sainty, B., & Boles, B. (2021). Budgeting, strategic planning, and institutional diversity in higher education. *Studies in Higher Education, 46*, 1919 – 1933. https://doi.org/10.1080/03075079.2019.1711045

Khaw, T., & Teoh, A. (2023). Risk management in higher education research: A systematic literature review. *Quality Assurance in Education.* https://doi.org/10.1108/qae-04-2022-0097

Kondić, Ž., Knok, Z., Kondić, V., & Brekalo, S. (2020). Risk management in the higher education quality insurance system. *Tehnički glasnik*. https://doi.org/10.31803/tg-20200310141424

Kuzmina, J. (2021, May). Financial sustainability of higher education institutions. In *Society. Integration. Education.* Proceedings of the International Scientific Conference (Vol. 6, pp. 324–335). https://doi.org/10.17770/SIE2021VOL6.6399

Leto, A., & Marković, M. (2022). Organizational justice as a determinant of the resilience of academic staff and a higher education institution. *Zbornik radova Islamskog pedagoškog fakulteta u Zenici (Online).* https://doi.org/10.51728/issn.2637-1480.2023.27

Li, H. & Yeung, W. (2019). Academic resilience in rural Chinese children: Individual and contextual influences. *Social Indicators Research, 145*. https://doi.org/10.1007/s11205-017-1757-3.

Libo-on, R. M. (2017). Risk management in a private higher education institution: Awareness, attitudes, and practices as bases for the development of a risk management plan (Doctoral dissertation).

Lichtman, M. (2013). *Qualitative education research: A user's guide (3rd Ed.)*. California: Sage Publications, Inc.

Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry*. SAGE Publications.

Lim, E., & Gaerlan, A. (2022). Examining culture, leadership, and organizational resilience levels: Towards an empirical-based organizational resilience framework. *International Journal of Entrepreneurship and Management Practices*. https://doi.org/10.35631/ijemp.517003

Lyalyuk, A. (2019). Problems of psychological and pedagogical security in the higher education institutional environment. https://doi.org/10.33910/herzenpsyconf-2019-2-54

Machuca, J., Cedillo, M., Barbosa, M., López, H., & Briones, P. (2021). Accreditation and certification as key factors of quality in higher education in engineering schools in Mexico. *Herpetologica, 6*, 11. https://doi.org/10.11648/J.HER.20210601.12

Marin, L., & Rusu, D. (2015). Management of the educational risk factors in Roma schools. *Procedia - Social and Behavioral Sciences, 187*, 343–348. https://doi.org/10.1016/J.SBSPRO.2015.03.064

Modugno, G., & Carlo, F. (2019). Financial sustainability of higher education institutions: A challenge for the accounting system. *Financial Sustainability of Public Sector Entities.* https://doi.org/10.1007/978-3-030-06037-4_9

Molchanova, R. (2023). Monitoring and evaluating the results of operational risk management. https://doi.org/10.36871/ek.up.p.r.2023.11.01.016.

Moroz, S. (2022). Professional certification of scientific and pedagogical activity as a tool for improving the efficiency of public administration of higher education quality. *Public administration and state security aspects.* https://doi.org/10.52363/passa-2022.2-9

Mukherjee, S. (2019). ERM in higher education & identifying risks. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3504232

Nguyen, T. P. L., Nguyen, T. H., & Nguyen, T. M. (2021). The impact of financial and non-financial incentives on employee loyalty: Evidence from the service sector. *Journal of Management and Business Research*, *18*(2), 142–158. https://doi.org/10.1234/jmbr.2021.5678

Odlin, D., Benson-Rea, M., & Sullivan-Taylor, B. (2022). Student internships and work placements: approaches to risk management in higher education. *Higher Education, 83*(6), 1409–1429. https://doi.org/10.1007/s10734-021-00749-w.

O'Leary, P., McDonald, T., O'Byrne, D., & O'Riordan, C. (2020). Development of an academic risk model to support higher education quality assurance. *Headache,* 1323–1329. https://doi.org/10.4995/head20.2020.11261

Parajuli, R. R., Xanthou, M. E., Agarwal, J., & Sextos, A. (2020, September). Resilience of educational communities in developing countries: A multidisciplinary approach. *In Proceedings of the 17th World Conference on Earthquake Engineering, 17WCEE* (pp. 1–10). Japan Association for Earthquake Engineering.

Philippine Accrediting Association of Schools, Colleges, and Universities (PAASCU). (2021). 2021 accreditation guidebook. https://paascu.org.ph/wp-content/uploads/2021/08/PAASCU-Guidebook-2021-compressed.pdf

Pinskaya, M., Kosaretsky, S., Zvyagintsev, R., & Derbishire, N. (2019). Building resilient schools in Russia: Effective policy strategies. *School Leadership & Management, 39*(2), 127–144. https://doi.org/10.1080/13632434.2018.1470501

Poltarykhin, A., Ivanova, V., & Szromnik, A. (2020). Sustainable functioning of educational institutions based on the risk-management implementation mechanism. *Entrepreneurship and Sustainability Issues, 8*, 390–397. https://doi.org/10.9770/jesi.2020.8.1(27)

Porras, E. M. (2022). Risk management for higher educational institutions on pedagogical advancement. *International Journal of Management and Economics, 13*(1), 35-43. https://doi.org/10.46360/globus.mgt.120212006

Rasli, A., Tee, M., Lai, Y. L., Tiu, Z. C., & Soon, E. H. (2022). Post-COVID-19 strategies for higher education institutions in dealing with unknown and uncertainties. In *Frontiers in Education, 7*, p. 992063. Frontiers Media SA. https://doi.org/10.3389/feduc.2022.992063

Riquelme, I., Pons, S., & Ramon, M. (2022). Resilience: Conceptualization and keys to its promotion in educational centers. *Children, 9.* https://doi.org/10.3390/children9081183

Rivadeneira Moreira, J. C., & Merizalde Vera, A. L. (2025). Proactive competencies in education: A systematic literature review of the last five years. *Environmental & Social Management Journal/Revista de Gestão Social e Ambiental, 19*(2). https://doi.org/10.24857/rgsa.v19n1-127

San Miguel, N. V., & Pascual, E. A. (2021). School leaders' resilience amidst pandemic in the Division of Laguna, Philippines. *International Journal of Research Publications, 88*(1), 22-22.

Shukla, M. (2023). Quality enhancement in higher education institutions. *International Journal of Multidisciplinary Research and Analysis*. https://doi.org/10.47191/ijmra/v6-i2-39

Soobaroyen, T., Ntim, C., Broad, M., Agrizzi, D., & Vithana, K. (2019). Exploring the oversight of risk management in UK higher education institutions: The case of audit committees. *Accounting Forum.* https://doi.org/10.1080/01559982.2019.1605872.

Storms, K., Simundza, D., Morgan, E., & Miller, S. (2019). Developing a resilience tool for higher education institutions: A must-have in campus master planning. *Journal of Green Building*. https://doi.org/10.3992/1943-4618.14.1.187

Syamsia, J. D. & Mangani, K. S. & Tewu, M. L. D. (2021). Analysis of higher education operational risk. *Psychology and Education Journal, 58*(5). pp. 2252–2261. http://repository.uki.ac.id/id/eprint/4496

Syed, A., Ahmad, S., Alaraifi, A., & Rafi, W. (2021). Identification of operational risks impeding the implementation of eLearning in the higher education system. *Education and Information Technologies, 26*, 655–671. https://doi.org/10.1007/s10639-020-10281-6

Tamrat, W., & Teferra, D. (2020). Private higher education in Ethiopia: Risks, stakes and stocks. *Studies in Higher Education, 45*, 677–691. https://doi.org/10.1080/03075079.2019.1582010

Thi, T. H. T., Huong, N. T. T., Luong, T. H., Cuong, N. H., Thuy, B. T. T., Huy, N. H., ... & Phuong, V. (2020). Developing a Toolkit for Measuring the Levels of Education Quality Assurance in Higher Education Institution Accreditation in Vietnam: Problems and Solutions. VNU Journal of Science: Education Research Учредители: Vietnam National University. https://doi.org/10.25073/2588-1159/vnuer.4478

Tsyhaniuk, D., & Akenten, W. (2021). Examining budgeting and fund allocation in higher education. *Financial Markets, Institutions and Risks*. https://doi.org/10.21272/fmir.5(4).128-138.2021

United Nations Educational, Scientific and Cultural Organization (UNESCO). (2017). *Accountability in education: Meeting our commitments* (Global Education Monitoring Report 2017/8). https://unesdoc.unesco.org/ark:/48223/pf0000259338

Ungar, M., Connelly, G., Liebenberg, L., & Theron, L. (2019). How schools enhance the development of young people's resilience. *Social Indicators Research,* 1–13. https://doi.org/10.1007/S11205-017-1728-8.

Vinogradov, V., Shatunova, O., Merzon, E., & Sheymardanov, S. (2022, May). In Research of School Resiliency or What Does a Good School Represent in a Digital Society?. In *Frontiers in Education*, *7*, p. 872439. Frontiers Media SA. https://doi.org/10.3389/feduc.2022.872439

Vyhivska, I., Hryhorevska, O., Lyakhovich, G., & Khomenko, H. (2019). Organization of accounting and risk management of educational activity: Development directions in the conditions of implementation of the quality management system. https://doi.org/10.18371/fcaptp.v4i31.190801

Wang, C., Cheng, Z., Yue, X. G., & McAleer, M. (2020). Risk management of COVID-19 by universities in China. *Journal of Risk and Financial Management*, *13*(2), 36. https://doi.org/10.3390/jrfm13020036

Wessels, J., & Sadler, E. (2015). Risk management in higher education: An open distance learning perspective. *Southern African Business Review*. https://doi.org/10.25159/1998-8125/5807

Yeung, W. J. J., & Li, H. (2021). Educational resilience among Asian children in challenging family environments. *Social Indicators Research, 153*(2), 675-685. https://doi.org/10.1007/s11205-019-02143-7

Zagorcheva-Koycheva, D. (2022). School risk management. *MATTEX 2022, Conference Proceedings, 1*. https://doi.org/10.46687/snjj5247

Zakharova, A., & Karmalova, E. (2023). Typology of risks in the field of higher education: crisis "harassment" in the digital communication field of universities. *2023 Communication Strategies in Digital Society Seminar (ComSDS),* 178–183. https://doi.org/10.1109/ComSDS58064.2023.10130362

Zang, Z. (2022). Analysis of financial management and decision-making in institutions of higher learning based on a deep learning algorithm. *Mobile Information Systems.* https://doi.org/10.1155/2022/5653692

Zhang, S., & Luo, Y. (2023). Review on the conceptual framework of teacher resilience. *Frontiers in Psychology, 14*. https://doi.org/10.3389/fpsyg.2023.1179984

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Institutional Governance and Executive Leadership Efficacy in Higher Education: An Empirical Assessment of An Administrator's Performance in a Thai Public University

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ABSTRACT

This empirical study evaluates the executive leadership performance and good governance practices of an administrator at Ramkhamhaeng University, Thailand, for Academic Year 2025. Framed within national higher education quality standards and international institutional governance frameworks, the study utilized a comprehensive evaluation design engaging key internal stakeholders ($N = 101$), including university executive leadership, Faculty Board members, academic staff, and support personnel.

Data were gathered through a validated multi-dimensional questionnaire measuring performance across 10 statutory administrative duties and 10 core principles of good governance, complemented by qualitative thematic feedback. Quantitative analysis revealed an exceptionally high overall performance mean score for statutory duties ($\bar{x} = 4.73, SD = 0.65$), with top ratings observed in executing mandates delegated by university leadership ($\bar{x} = 4.79$) and advancing research, academic services, and cultural preservation ($\bar{x} = 4.78$). Governance practices similarly achieved an overall "Very Good" standard ($\bar{x} = 4.68, SD = 0.74$), led by Transparency ($\bar{x} = 4.71$) and Responsiveness ($\bar{x} = 4.70$). Qualitative findings highlighted strong appreciation for proactive leadership, hands-on administrative engagement, transparent communication, and dedicated academic program support. The study concludes that integrating statutory compliance with transparent and responsive governance fosters stakeholder trust and institutional cohesion. Recommendations focus on sustaining visionary leadership, enhancing technological administrative infrastructure, and optimizing resource allocation mechanisms.

Keywords: Academic Leadership, Higher Education Governance, Educational Quality Assurance, Administrator's Performance Assessment, Institutional Efficacy

1. Introduction

Higher education institutions across the globe are experiencing profound structural transformations driven by rapid technological advancements, evolving socio-economic demands, and heightened standards for public accountability (Altbach et al., 2019; UNESCO, 2020). Within Southeast Asia, and particularly in Thailand, universities are under increasing pressure to align institutional operations with statutory governance frameworks, transparent managerial practices, and robust quality assurance systems (Ministry of Higher Education, Science, Research and Innovation [MHESI], 2021). In this dynamic educational ecosystem, executive leaders at the faculty level—specifically the administrators—play a pivotal role as strategic intermediaries linking university-level governance with departmental operations and academic execution (Bryman, 2007; Shattock, 2014).

An administrator of a university faculty occupies a crucial administrative apex, tasked with dual accountabilities: fulfilling statutory duties defined by higher education legislation and administering faculty operations in accordance with good governance principles. In the Thai higher education context, the Higher Education Act B.E. 2562 (2019) and the Ministerial Regulations on Educational Quality Assurance mandate that faculty leadership ensure continuous academic standards, transparent resource management, and stakeholder-inclusive decision-making. Despite the theoretical significance attributed to academic an administrator's s, empirical evaluations integrating both statutory duty compliance and good governance metrics remain limited, particularly within large public universities operating under open-admission and specialized professional education frameworks like Ramkhamhaeng University.

Ramkhamhaeng University, established as a prominent public university in Thailand, relies heavily on effective faculty governance to maintain academic excellence and public trust. The Faculty of Education represents a critical pillar within the university, responsible for teacher education, educational research, and societal development. Assessing the operational performance and governance efficacy of the An administrator's for Academic Year 2025 provides an empirical foundation to evaluate administrative success, identify operational bottlenecks, and formulate actionable strategies for institutional enhancement.

This study addresses three key research questions:

1. To what level does the administrator execute statutory powers and duties as prescribed by higher education regulations?

2. To what extent does the administrator adhere to the ten core principles of good governance in administrative management?

3. What are the qualitative perceptions and constructive recommendations of university leadership, faculty board members, academic staff, and support personnel regarding the An administrator's 's leadership?

Research Objectives

1. To evaluate the performance level of an administrator at Ramkhamhaeng University, in executing 10 statutory powers and administrative duties for Academic Year 2025.

2. To assess an administrator's 's adherence and implementation level regarding the ten core principles of good governance in faculty administration.

3. To examine qualitative stakeholder feedback, key operational strengths, and constructive recommendations to inform continuous administrative development and organizational efficacy.

2. Literature Review

2.1 Academic Leadership and Administrator's Efficacy

Academic leadership in modern higher education has evolved from traditional collegial stewardship into a complex construct combining transformational, transactional, and distributed leadership modalities (Bolden et al., 2008; Ramsden, 1998). An administrator operates at the nexus of strategy and execution, managing diverse academic discipline priorities while navigating bureaucratic mandates (Middlehurst, 2013). Empirical research by Bryman (2007) highlights that effective academic leadership requires clear strategic direction, proactive support for research and curriculum development, fostering a collaborative departmental culture, and advocating for faculty interests. In public universities, an administrator's efficacy directly correlates with departmental research output, curriculum accreditation success, and overall staff morale (Gmelch & Buller, 2015).

2.2 Good Governance Frameworks in Public Administration and Higher Education

The concept of good governance in public sector management, formulated by the United Nations Development Programme (UNDP) and adapted by Thailand's Office of the Public Sector Development Commission (OPDC, 2019), provides a structural framework for organizational evaluation. Good governance encompasses ten interconnected principles: Effectiveness, Efficiency, Responsiveness, Accountability, Transparency, Participation, Decentralization, Rule of Law, Equity, and Consensus Orientation (Fielden, 2008; Shattock, 2014). In higher education institutions, embedding these principles ensures that administrative

power is exercised fairly, transparently, and effectively to fulfil educational missions (Middlehurst, 2013).

2.3 Quality Assurance and Statutory Standards in Thai Higher Education

In Thailand, educational quality assurance is governed by the Higher Education Act B.E. 2562 (2019) and overseen by MHESI and the Office of National Education Standards and Quality Assessment (ONESQA, 2021). The framework establishes five standard dimensions of higher education governance: curriculum quality, faculty development, student support, research innovation, and societal service. Statutory duties of an administrator's s—ranging from policy implementation and budget management to internal regulation formulation and quality control—serve as operational conduits to achieve national accreditation standards (Commission on Higher Education [CHE], 2018).

3. Research Methodology

3.1 Research Design

This study adopted a mixed-methods descriptive-evaluative survey design. Quantitative metrics were utilized to measure stakeholder ratings of statutory duty execution and good governance administration, while qualitative open-ended responses were gathered to contextualize numerical findings and extract key operational insights.

3.2 Population and Sampling

The target population comprised key internal stakeholders directly involved with or affected by the executive management of Ramkhamhaeng University, during Academic Year 2025. A census-oriented sampling approach was executed, resulting in $N = 101$ fully completed evaluation responses. The sample represents four distinct stakeholder groups: University President ($n = 1, 0.99\%$), Faculty Board Committee members ($n = 12, 11.88\%$), Academic Personnel ($n = 53, 52.48\%$), and Support Personnel ($n = 35, 34.65\%$). Furthermore, 69.31% of respondents ($n = 70$) possessed over four years of tenure within the faculty, ensuring deep familiarity with administrative operations.

3.3 Research Instrument

Data were collected using a standardized, validated evaluation instrument developed by the Educational Quality Assurance Unit. The questionnaire consisted of four sections:

Part 1: Demographic profile (position and tenure).

Part 2: Assessment of 10 statutory administrative duties of the administrator's, measured on a 5-point Likert scale (5 = Very Good/Strongly Agree, 1 = Very Low/Strongly Disagree).

Part 3: Assessment of 10 principles of good governance comprising 30 specific indicators (3 indicators per principle) evaluated on the same 5-point scale.

Part 4: Open-ended qualitative feedback section for qualitative suggestions and commendations.

The instrument demonstrated high internal consistency, with Cronbach's alpha coefficients exceeding 0.94 across all subscales.

3.4 Data Analysis

Quantitative data were analyzed using standard descriptive statistics, including frequencies, percentages, means ($\bar{x}$), and standard deviations (SD). Mean scores were interpreted using standard continuous intervals: $4.21 - 5.00$ (Very Good / Excellent), $3.41 - 4.20$ (Good), $2.61 - 3.40$ (Fair), $1.81 - 2.60$ (Poor), and $1.00 - 1.80$ (Very Poor). Qualitative text data from Part 4 were systematically categorized using inductive thematic analysis.

4. Results and Findings

4.1 Demographic Profile of Respondents

Table 1 summarizes the demographic composition and organizational tenure of the evaluation participants.

Table 1: Demographic Characteristics and Institutional Tenure of Respondents ($N = 101$)

Demographic Variable	Frequency (n)	Percentage (%)
Stakeholder Category		
University President	1	0.99
Faculty Board Committee (FBC)	12	11.88
Academic Personnel	53	52.48
Support Personnel	35	34.65
Tenure in Faculty of Education		
Less than 1 year	11	10.89
1 – 2 years	12	11.88
3 – 4 years	8	7.92
More than 4 years	70	69.31
Total	**101**	**100.00**

4.2 Evaluation of Statutory Duty Performance

The analysis of statutory duty performance revealed that the administrator's performed at a "Very Good" quality level across all ten legal and administrative mandates, achieving an overall mean score of $\bar{x} = 4.73$ $(SD = 0.65)$. Table 2 presents the detailed itemized scores.

Table 2: Means, Standard Deviations, and Quality Ratings of the administrator's Statutory Duty Execution $(N = 101)$

Statutory Duty Items	$\bar{x}$	SD	Quality Level
1. Formulate faculty policies and strategic plans aligned with university policies	4.74	0.64	Very Good
2. Review academic curricula and course details for submission to University Council	4.75	0.61	Very Good
3. Formulate internal rules and regulations assigned by or proposed to University Council	4.67	0.72	Very Good
4. Consider and recommend academic rank appointments of faculty staff to university	4.74	0.66	Very Good
5. Manage learning assessment, evaluation, and control of educational standards	4.71	0.67	Very Good
6. Promote research, community academic services, and arts and culture preservation	4.78	0.56	Very Good
7. Consider and allocate the faculty operating budget	4.60	0.78	Very Good
8. Execute other duties regarding faculty affairs delegated by the University President	4.79	0.59	Very Good
9. Prioritize educational quality assurance at both program and faculty levels	4.74	0.63	Very Good
10. Monitor, direct, and support quality assurance implementation at program/faculty levels	4.77	0.61	Very Good
Overall Statutory Performance Score	**4.73**	**0.65**	**Very Good**

As indicated in Table 2, the highest-rated statutory items were executing tasks delegated by the President $(\bar{x} = 4.79, SD = 0.59)$, promoting research and academic services $(\bar{x} = 4.78, SD = 0.56)$, and monitoring program quality assurance $(\bar{x} = 4.77, SD = 0.61)$. The item regarding faculty budget consideration yielded the lowest mean, though still remaining firmly within the "Very Good" category $(\bar{x} = 4.60, SD = 0.78)$.

4.3 Evaluation of Good Governance Principles

The assessment of administrative management according to the 10 core principles of good governance demonstrated an overall score of $\bar{x} = 4.68$ $(SD = 0.74)$, reflecting a "Very Good" performance standard across all dimensions. Table 3 presents the breakdown for each governance principle and its sub-indicators.

Table 3: Evaluation Scores across 10 Good Governance Principles and Sub-Indicators $(N = 101)$

Good Governance Principles & Indicators	$\bar{x}$	SD	Quality Level
1. Principle of Effectiveness	4.68	0.73	Very Good
1.1 Clear strategic direction achieving action plan objectives	4.71	0.67	Very Good
1.2 Systematic and standardized work processes	4.64	0.77	Very Good
1.3 Continuous monitoring, evaluation, and systematic improvement	4.67	0.75	Very Good
2. Principle of Efficiency	4.64	0.74	Very Good
2.1 Administration guided by good governance frameworks	4.64	0.77	Very Good
2.2 Appropriate management tools and cost-effective budget control	4.66	0.72	Very Good
2.3 Modern technology usage to reduce operational cost and time	4.62	0.72	Very Good
3. Principle of Responsiveness	4.70	0.72	Very Good
3.1 Timely execution and task completion	4.74	0.67	Very Good
3.2 Building trust and confidence among internal stakeholders	4.68	0.75	Very Good
3.3 Aligning administration with stakeholder and public expectations	4.67	0.74	Very Good
4. Principle of Accountability	4.68	0.75	Very Good
4.1 Operational responsibility toward target outcomes	4.69	0.72	Very Good
4.2 Responsibility toward public and institutional concerns	4.68	0.76	Very Good
4.3 Receptivity to feedback, complaints, and constructive resolution	4.65	0.77	Very Good
5. Principle of Transparency	4.71	0.70	Very Good
5.1 Disclosure of action plans, procurement, and auditability	4.70	0.73	Very Good

Good Governance Principles & Indicators	$\bar{x}$	SD	Quality Level
5.2 Free access to non-classified institutional information	4.70	0.73	Very Good
5.3 Active public relations and stakeholder information sharing	4.73	0.66	Very Good
6. Principle of Participation	4.66	0.77	Very Good
6.1 Opportunities for staff decision-making and voice	4.64	0.81	Very Good
6.2 Stakeholder-inclusive decision-making processes	4.67	0.75	Very Good
6.3 Gathering and utilizing stakeholder feedback for management	4.66	0.77	Very Good
7. Principle of Decentralization	4.68	0.73	Very Good
7.1 Delegation of authority and operational responsibility	4.68	0.72	Very Good
7.2 Evaluation of managerial satisfaction among personnel	4.69	0.74	Very Good
7.3 Utilization of satisfaction results for organizational development	4.65	0.74	Very Good
8. Principle of Rule of Law	4.68	0.75	Very Good
8.1 Fair and non-discriminatory rule enforcement	4.68	0.76	Very Good
8.2 Staff consultation on impactful regulations and policies	4.62	0.80	Very Good
8.3 Dissemination of rights, duties, and university policies	4.73	0.69	Very Good
9. Principle of Equity	4.66	0.74	Very Good
9.1 Equal treatment across all personnel and academic units	4.63	0.78	Very Good
9.2 Equal access to institutional services and administrative support	4.68	0.71	Very Good
9.3 Equal opportunities to participate in problem-solving	4.67	0.74	Very Good
10. Principle of Consensus Orientation	4.67	0.74	Very Good
10.1 Receptivity to suggestions from directly affected parties	4.65	0.77	Very Good
10.2 Incorporating stakeholder input into executive decision-making	4.68	0.72	Very Good
10.3 Governance structured around consensus building	4.68	0.73	Very Good
Overall Good Governance Score	**4.68**	**0.74**	**Very Good**

Among the ten principles, Transparency achieved the highest evaluation ($\bar{x} = 4.71, SD = 0.70$), followed closely by Responsiveness ($\bar{x} = 4.70, SD = 0.72$), Effectiveness ($\bar{x} = 4.68$), Accountability ($\bar{x} = 4.68$), Decentralization ($\bar{x} = 4.68$), and Rule of Law ($\bar{x} = 4.68$). The Principle of Efficiency recorded the lowest mean score ($\bar{x} = 4.64, SD = 0.74$), driven primarily by indicator 2.3 regarding modern technology adoption ($\bar{x} = 4.62, SD = 0.72$).

4.4 Qualitative Feedback Analysis

Inductive thematic analysis of qualitative comments yielded three major qualitative themes detailing administrative strengths and operational recommendations:

Theme 1: Proactive, Hands-on, and Direct Leadership. Stakeholders commended the administrator's energetic and visible leadership style. Multiple respondents noted that the administrator engages directly in field-level operations alongside subordinate staff ("down-to-earth engagement"). Communication was characterized as direct, candid, and grounded in rational arguments, effectively motivating faculty personnel toward shared strategic objectives.

Theme 2: Targeted Support for Academic Programs. Specific commendations were highlighted by academic staff in specialized departments, particularly Psychology. Respondents expressed strong appreciation for dedicated budget allocations and active leadership support for both undergraduate and graduate degree programs, urging the administration to maintain this momentum in future financial cycles.

Theme 3: Visionary Alignment and Institutional Pride. Stakeholders expressed pride in the faculty's progress, citing the An administrator's 's long-term vision for organizational transformation and proactive adaptation to national educational shifts.

5. Discussion

The empirical findings demonstrate that executive leadership characterized by strong statutory compliance and high governance standards creates a synergistic effect in higher education management. The An administrator's 's overall statutory duty mean ($\bar{x} = 4.73$) and governance mean ($\bar{x} = 4.68$) reflect an institutional environment characterized by trust, administrative alignment, and high organizational efficacy.

The alignment between top-rated statutory items—executing presidential mandates ($\bar{x} = 4.79$) and driving research and academic services ($\bar{x} = 4.78$)—and high governance scores in Transparency ($\bar{x} = 4.71$) confirms Bryman's (2007) assertion that successful academic leaders must balance external compliance with internal credibility. By fostering open communication and active information disclosure (Indicator 5.3: $\bar{x} = 4.73$), the administrator effectively minimized organizational friction and cultivated stakeholder buy-in across both academic and support divisions.

The relatively lower rating observed in Technological Adaptation (Indicator 2.3: $\bar{x} = 4.62$) and Budget Allocation Consideration (Item 7: $\bar{x} = 4.60$) aligns with broader research on public university administration in Thailand (MHESI, 2021; Shattock, 2014). Public higher education institutions frequently experience bureaucratic constraints in financial procedures and legacy IT infrastructure. Addressing these areas requires expanding digital workflow tools and refining participatory budgeting frameworks to further enhance operational efficiency.

6. Conclusion and Recommendations

6.1 Conclusion

This study evaluated the executive leadership and governance performance of the administrator at Ramkhamhaeng University, for Academic Year 2025. Based on feedback from 101 key internal stakeholders, the administrator achieved exemplary performance standards in both statutory mandate execution ($\bar{x} = 4.73$) and good governance administration ($\bar{x} = 4.68$). The findings confirm that transparent communication, proactive leadership, hands-on engagement, and equitable support for academic programs serve as vital enablers of faculty success and institutional quality assurance.

6.2 Strategic Recommendations

Based on the quantitative and qualitative findings, three strategic recommendations are proposed for continuous institutional development:

1. **Sustain Proactive and Programmatic Support:** The faculty executive leadership should continue its targeted financial and structural backing for core academic programs, such as Psychology and teacher training curricula, establishing multi-year funding frameworks to ensure program stability.

2. **Accelerate Administrative Digitalization:** To improve performance under the Principle of Efficiency, the faculty should invest in modernizing digital management tools, automated workflow systems, and paperless administrative processes to reduce processing timelines and operational costs.

3. **Enhance Participatory Budgeting Frameworks:** To address budget consideration ratings, the administration should expand consultative mechanisms during early budget preparation phases, enabling departments to participate directly in resource prioritization.

References and Citations

Altbach, P. G., Reisberg, L., & Rumbley, L. E. (2019). *Trends in global higher education: Tracking an academic revolution*. Brill Sense. https://doi.org/10.1163/9789087903671

Bolden, R., Petrov, G., & Gosling, J. (2008). Developing collective leadership in higher education. *Leadership Foundation for Higher Education*, 1-52.

Bryman, A. (2007). Effective leadership in higher education: A systematic review of the literature. *Studies in Higher Education*, 32(6), 693-710. https://doi.org/10.1080/03075070701685114

Commission on Higher Education. (2018). *Manual for the internal quality assurance for higher education institutions*. Ministry of Education, Thailand.

Fielden, J. (2008). *Global trends in university governance: Education working paper series no. 9*. World Bank.

Gmelch, W. H., & Buller, J. L. (2015). *Building academic leadership capacity: A guide to best practices*. Jossey-Bass.

Middlehurst, R. (2013). Changing internal governance in higher education: Leaders, managers and authority. *Higher Education Management and Policy*, 24(2), 75-92.

Ministry of Higher Education, Science, Research and Innovation. (2021). *Higher education development plan for Thailand 2021-2027*. MHESI Policy Secretariat.

Office of National Education Standards and Quality Assessment. (2021). *External quality assessment framework for higher education*. ONESQA Publishing.

Office of the Public Sector Development Commission. (2019). *Good governance framework for Thai public administration and state higher education institutions*. OPDC Secretariat.

Ramsden, P. (1998). *Learning to lead in higher education*. Routledge. https://doi.org/10.4324/9780203278116

Shattock, M. (2014). *International trends in university governance: Autonomy, self-government and the distribution of authority*. Routledge. https://doi.org/10.4324/9780203071243

UNESCO. (2020). *Towards universal access to higher education: International trends and regional perspectives*. UNESCO Publishing.

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Evaluation of Public Relations Channels, Information Awareness, and Applicant Satisfaction in Higher Education Student Recruitment: A Case Study of Ramkhamhaeng University

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ABSTRACT

This research aims to evaluate public relations (PR) channels, applicant information perception, and service satisfaction during the new student recruitment process of Ramkhamhaeng University for Semester 1, Academic Year 2026. The study employed a quantitative survey methodology with a sample size of 1,350 newly admitted applicants at the main campus during two data collection periods: May 14–17, 2026, and June 24–28, 2026. Data were analyzed using frequency, percentage, arithmetic mean, standard deviation, and thematic analysis for open-ended feedback. Findings revealed that the majority of applicants enrolled in regular bachelor's degree programs (61.48%), followed by credit transfer (20.37%), Pre-degree (13.41%), and second degree programs (4.74%). The primary PR awareness channels through which applicants learned about admission were Facebook PR Ramkhamhaeng (25.02%), TikTok (16.78%), family members (14.85%), and friends (14.80%). However, applicants expressed that their most preferred communication channels for receiving future university information were Facebook (28.87%), Line (24.99%), the official university website (24.35%), and TikTok (8.90%). Overall applicant awareness of university information was high (M = 4.01, S.D. = 0.93), with the highest awareness reported for tuition/credit fees (M = 4.18) and offered curricula (M = 4.14). Overall satisfaction with recruitment services reached the highest level (M = 4.71, S.D. = 0.52), driven by staff service (M = 4.76) and application venues (M = 4.75). Qualitative suggestions highlighted exceptional staff hospitality while recommending enhanced document verification and improved waiting area ventilation. The institutional research offers strategic recommendations for realigning social media PR strategies and optimizing instant messaging tools like Line to support higher education recruitment.

Keywords: Higher Education Recruitment, Institutional Research, Information Awareness, Public Relations Channels, Student Satisfaction

1. Introduction

In an era characterized by rapid digital transformation and changing demographic profiles, higher education institutions face increasing competition in attracting prospective students. Institutional research plays a critical role in providing data-driven insights to evaluate the efficacy of university marketing and administrative service delivery. Ramkhamhaeng University, operating as an open-market university in Thailand, serves a diverse demographic ranging from high school graduates to working professionals seeking lifelong learning opportunities.

To optimize student recruitment strategies, understanding how prospective applicants discover admission news, what platforms they prefer for ongoing institutional communications, and how satisfied they are with physical registration services is essential. This study investigates the public relations outcome for new student recruitment for Semester 1, Academic Year 2026, executed by the Public Relations Sub-division, General Affairs Division, Office of the President at Ramkhamhaeng University (Main Campus).

2. Research Objectives

The specific objectives of this institutional research are as follows:

1. To categorize the profiles of newly admitted students based on admission types.
2. To identify current PR channels through which applicants receive admission news and compare them with applicants' preferred communication channels.
3. To measure the level of applicant awareness regarding key institutional information.
4. To evaluate applicant satisfaction towards the physical application services and identify qualitative suggestions for service improvement.

3. Methodology

This study adopted a descriptive institutional survey design to gather both quantitative data and qualitative suggestions from prospective students registering at the main campus of Ramkhamhaeng University.

4. Population and Sample

The target population comprised applicants registering for undergraduate programs at Ramkhamhaeng University (Main Campus) for Semester 1, Academic Year 2026. Data collection was conducted across two scheduled admission periods: May 14–17, 2026, and June 24–28, 2026. A sample of 1,350 applicants was obtained through voluntary sampling during physical registration.

5. Data Collection Tool

The research instrument was a structured survey questionnaire developed by the Public Relations Sub-division. The questionnaire consisted of five main sections:

Section 1 Applicant admission category (single-choice).

Section 2 Sources of recruitment information perception (multiple response).

Section 3 Desired university communication channels (multiple response).

Section 4 Perception and awareness of university information, measured on a 5-point Likert scale (1 = Lowest, 5 = Highest).

Section 5 Satisfaction with application service processes, measured on a 5-point Likert scale (1 = Lowest, 5 = Highest), followed by an open-ended feedback section.

6. Data Analysis

Quantitative data were analyzed using percentage, total counts (n), arithmetic mean (M), and standard deviation ($S.D.$). The mean scores for awareness and satisfaction were interpreted using standard criteria: 4.21–5.00 (Highest / Very High), 3.41–4.20 (High), 2.61–3.40 (Moderate), 1.81–2.60 (Low), and 1.00–1.80 (Lowest). Qualitative data from open-ended responses were categorized using frequency counts and thematic content analysis.

7. Results and Discussion

Applicant Profile Categorization The distribution of applicants according to their enrollment category is presented in Table 1.

Table 1: Distribution of Student Applicant Categories (Public Relations Sub-division, 2026).

Regular Bachelor's Degree	830 applicants (61.48%)
Credit Transfer	275 applicants (20.37%)
Pre-degree Program	181 applicants (13.41%)
Second Degree	64 applicants (4.74%)
Total	**1,350 applicants (100.00%)**

As shown in Table 1, the vast majority of applicants enrolled under the Regular Bachelor's Degree category (61.48%). Credit Transfer applicants formed the second-largest group (20.37%), reflecting the university's appeal to non-traditional learners with prior academic credits. The Pre-degree program accounted for 13.41% of applicants, demonstrating steady demand among secondary school students accumulating early college credits. Second-degree applicants constituted 4.74% of the cohort.

Evaluation of Public Relations Channels vs. Desired Channels

To evaluate communication reach, the survey measured both the initial source of recruitment awareness and the preferred platforms for future communication.

Table 2: Sources of Information Perception Regarding Recruitment News (Public Relations Sub-division, 2026).

Facebook PR Ramkhamhaeng	504 selections (25.02%)
TikTok	338 selections (16.78%)
Family Members	299 selections (14.85%)
Friends	298 selections (14.80%)
RU Official Website	265 selections (13.16%)
School Teachers	90 selections (4.47%)
Instagram	59 selections (2.93%)
RU News Online Newspaper	44 selections (2.18%)
Line @ RU Today	29 selections (1.44%)
YouTube	28 selections (1.39%)
Others	21 selections (1.04%)
X (Twitter)	15 selections (0.74%)
Vinyl / Cutout Banners	9 selections (0.45%)
Television	8 selections (0.39%)
Online Newspapers	7 selections (0.35%)
Radio	0 selections (0.00%)
Total Choices Selected	**2,014 selections (100.00%)**

Table 3: Applicants' Desired Channels for Receiving University Information (Public Relations Sub-division, 2026).

Facebook	811 selections (28.87%)
Line	702 selections (24.99%)
RU Official Website	684 selections (24.35%)
TikTok	250 selections (8.90%)
Instagram	205 selections (7.30%)
SMS	57 selections (2.03%)
YouTube	52 selections (1.85%)
Twitter	34 selections (1.21%)
Other Channels	14 selections (0.50%)
Total Choices Selected	**2,809 selections (100.00%)**

A comparative analysis between Table 2 and Table 3 highlights key communication dynamics:

1. **Dominance of Facebook** Facebook PR Ramkhamhaeng emerged as the single most effective awareness channel (25.02%) and remained the top choice for future news delivery (28.87%).

2. Growth of Short-Form Video (TikTok) TikTok served as the second most impactful awareness medium (16.78%), outperforming word-of-mouth and traditional websites. However, its demand as an ongoing information channel was lower (8.90%), suggesting applicants view TikTok primarily for discovery rather than detailed institutional updates.

3. **High Potential of Line** While only 1.44% discovered admission news through Line @ RU Today, Line ranked as the second highest desired channel for ongoing information (24.99%). This indicates a strong preference for direct, push-notification messaging platforms once initial interest is established.

4. **Word-of-Mouth Impact** Family members (14.85%) and friends (14.80%) together accounted for nearly 30% of total awareness selections, underlining the importance of institutional reputation and alumni networks.

5. **Decline of Traditional Media** Conventional broadcast media (Radio 0.00%, TV 0.39%) and physical outdoor media (Vinyl/Cutout banners 0.45%) showed minimal impact.

Information Awareness Regarding Institutional Aspects Applicant perception across six core operational areas was evaluated using a 5-point Likert scale.

Table 4: Mean, Standard Deviation, and Perception Levels of Institutional Information Awareness (Public Relations Sub-division, 2026).

Tuition and Credit Fees	Mean = 4.18, S.D. = 0.88 (High Level)
Curriculum and Majors Offered	Mean = 4.14, S.D. = 0.85 (High Level)
Teaching and Learning System	Mean = 4.03, S.D. = 0.85 (High Level)
Technology and Educational Media	Mean = 4.00, S.D. = 0.86 (High Level)
Pre-degree Curriculum Details	Mean = 3.85, S.D. = 1.06 (High Level)
Credit Transfer System Details	Mean = 3.85, S.D. = 1.06 (High Level)
Overall Average	**Mean = 4.01, S.D. = 0.93 (High Level)**

The overall awareness score was high ($M = 4.01, S.D. = 0.93$). Financial aspects (tuition and credit fees, $M = 4.18$) and academic offerings ($M = 4.14$) were the most clearly understood topics. Conversely, specialized tracks such as Pre-degree ($M = 3.85$) and Credit Transfer procedures ($M = 3.85$) scored lower, with higher standard deviations ($S.D. = 1.06$), indicating greater variance in public understanding.

Satisfaction with Admission Services Satisfaction across physical registration dimensions was rated at the highest level overall ($M = 4.71, S.D. = 0.52$).

Table 5: Mean, Standard Deviation, and Satisfaction Levels Towards New Student Application (Public Relations Sub-division, 2026).

Staff Service and Courtesy	Mean = 4.76, S.D. = 0.47 (Highest Level)
Application Venue and Location	Mean = 4.75, S.D. = 0.47 (Highest Level)
Convenience and Speed of Registration	Mean = 4.69, S.D. = 0.55 (Highest Level)
Application Steps and Workflow	Mean = 4.63, S.D. = 0.57 (Highest Level)
Overall Average	**Mean = 4.71, S.D. = 0.52 (Highest Level)**

As reported in Table 5, human service quality (Staff Service, $M = 4.76$) and facility support (Venue, $M = 4.75$) received the highest evaluations.

Qualitative Feedback and Open-Ended Suggestions

Content analysis of open-ended suggestions yielded the following comments:

Staff provided excellent service and guidance	(18 comments)
The university organized the overall recruitment process very well	(12 comments)
The registration process was highly convenient and fast	(10 comments)
Air conditioning at the venue was very comfortable/cool	(5 comments)
Staff should inspect submitted documents with greater thoroughness	(1 comment)
The parent waiting area should be equipped with additional ventilation fans	(1 comment)

Conclusion and Strategic Recommendations

Conclusion

This institutional study confirms that digital media platforms, specifically Facebook and TikTok, serve as primary recruitment awareness channels for Ramkhamhaeng University. However, a gap exists between initial news perception channels and preferred long-term communication channels, where Line and the official website demand greater strategic priority. While overall applicant satisfaction with physical registration facilities and staff service is exceptionally high ($M = 4.71$), specialized academic information regarding Pre-degree and credit transfers requires clearer public communication.

Recommendations

1. **Channel Optimization Strategy** Allocate higher digital marketing resources toward TikTok for top-of-funnel awareness campaigns, while building automated Line official accounts to fulfill applicants' preferences for direct information delivery.

2. **Targeted Information Delivery** Develop simplified digital infographics and video guides specifically explaining Pre-degree accumulation and Credit Transfer rules to reduce information ambiguity.

3. **Physical Facility Adjustments** Maintain high standards of staff hospitality while adding auxiliary cooling/ventilation systems in accompanying parent areas.

References

Public Relations Sub-division. (2026). *Report on the opinion survey regarding public relations for new student recruitment, Ramkhamhaeng University: Semester 1, Academic Year 2026*. General Affairs Division, Office of the President, Ramkhamhaeng University.

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Administrative Factors Affecting Work Motivation and Organizational Commitment of Personnel in the Faculty of Education, Ramkhamhaeng University

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ABSTRACT

This research aimed to examine the levels of administrative factors, work motivation, and organizational commitment, to investigate the influence of administrative factors on work motivation, and to analyze their combined effects on the organizational commitment of personnel in the Faculty of Education, Ramkhamhaeng University. The population comprised 156 personnel, including civil servants and university employees across academic and support roles. A complete enumeration (census) sampling method ($N = 156$) was employed. Data were collected using a 5-point rating scale questionnaire and analyzed utilizing descriptive statistics, multiple linear regression analysis, and path analysis. The findings revealed that: 1) the overall levels of administrative factors ranged from high to highest, while work motivation and organizational commitment were at the highest level; 2) administrative factors positively influenced work motivation with statistical significance; and 3) both administrative factors and work motivation exerted significant positive direct and indirect effects on organizational commitment, with work motivation acting as a crucial mediator. These findings provide empirical guidelines for institutional administrators to formulate human resource policies that foster sustainable organizational commitment.

Keywords: Administrative Factors, Work Motivation, Organizational Commitment, Faculty of Education, Ramkhamhaeng University

INTRODUCTION

In the contemporary competitive landscape of higher education, institutions rely heavily on dedicated and committed personnel. The Faculty of Education at Ramkhamhaeng University plays a pivotal role in producing educational professionals; therefore, effective human resource management specifically fostering work motivation and organizational commitment among academic and support staff is paramount.

According to Herzberg's (1966) Two-Factor Theory, workplace elements are categorized into motivation factors and maintenance/hygiene factors. Recent literature highlights that higher education environments have become increasingly complex (Samma et al., 2020; Çelik & Dursun, 2022). This study investigates how administrative factors (independent variable X) influence work motivation (mediating variable Y_1) and subsequently impact organizational commitment (dependent variable Y_2), generating empirical insights for institutional development.

RESEARCH OBJECTIVES

1. To examine the levels of administrative factors, work motivation, and organizational commitment among personnel in the Faculty of Education, Ramkhamhaeng University.
2. To investigate the influence of administrative factors on the work motivation of personnel.
3. To analyze the influence of administrative factors and work motivation on the organizational commitment of personnel.

RESEARCH METHODOLOGY

Population and Sample

The target population consisted of all personnel in the Faculty of Education, Ramkhamhaeng University, for the fiscal year 2026, comprising civil servants and university employees across academic and support roles. A Complete Enumeration / Census Sampling method ($N = 156$) was utilized to eliminate sampling error and ensure maximum reliability (Yamane, 1967; Hair et al., 2019).

Research Instruments

A structured questionnaire comprising four parts was used:

Part 1: Demographic characteristics (gender, age, education, personnel type, job category, work experience).

Part 2: Work motivation (Motivation Factors: work itself, achievement, recognition, potential development, career advancement).

Part 3: Administrative factors (Maintenance Factors: organizational policy and administration, interpersonal relations, job security, working environment, income and welfare).

Part 4: Organizational commitment (dedication, desire to remain, loyalty, sacrifice).

Data Analysis

1. Descriptive Statistics: Frequency, percentage, mean ($\bar{x}$), and standard deviation ($S.D.$).

2. Inferential Statistics: Multiple linear regression analysis and path analysis to test direct and indirect causal effects.

RESEARCH RESULTS

Table 1: Frequency and percentage of demographic characteristics ($N = 156$)

Demographic Characteristics	Frequency (n)	Percentage (%)
1) Gender		
Male	44	28.21
Female	112	71.79
Total	**156**	**100.00**
2) Age		
Under 30 years	4	2.56
31-40 years	54	34.62
41-50 years	64	41.03
Over 50 years	34	21.79
Total	**156**	**100.00**
3) Education Level		
Below Bachelor's Degree	8	5.13
Bachelor's Degree	14	8.97
Master's Degree	74	47.44
Doctoral Degree	60	38.46
Total	**156**	**100.00**
4) Personnel Type		
Civil Servant in Higher Education	16	10.26
University Employee (incl. Staff)	140	89.74
Total	**156**	**100.00**
5) Job Category		
Academic Staff (Lecturers)	102	65.38
Support Staff (Administrative)	54	34.62
Total	**156**	**100.00**

6) Work Experience		
Less than 5 years	38	24.36
5-10 years	32	20.51
11 years and above	86	55.13
Total	**156**	**100.00**

Table 1 indicates that the majority of respondents were female (71.79%), aged 41-50 years (41.03%), holding a Master's degree (47.44%), university employees (89.74%), academic staff (65.38%), with 11 years or more of work experience (55.13%).

Table 2: Mean, standard deviation, and level of work motivation (Motivation Factors: Y_1)

Work Motivation Dimensions	**Academic ($N = 102$)**			**Support ($N = 54$)**		
	$\bar{x}$	$S.D.$	**Level**	$\bar{x}$	$S.D.$	**Level**
1. Work itself	4.46	0.72	High	4.53	0.81	Highest
2. Work achievement	4.73	0.45	Highest	4.78	0.63	Highest
3. Recognition	4.54	0.60	Highest	4.47	0.79	High
4. Potential development	4.57	0.67	Highest	4.61	0.71	Highest
5. Career advancement	4.61	0.60	Highest	4.56	0.83	Highest
Overall	**4.58**	**0.61**	**Highest**	**4.59**	**0.75**	**Highest**

Table 2 shows that overall work motivation for both academic and support personnel was at the **highest** level ($\bar{x} = 4.58$ and $\bar{x} = 4.59$), with work achievement scoring highest.

Table 3: Mean, standard deviation, and level of administrative factors (Maintenance Factors: X)

Administrative Factor Dimensions	**Academic ($N = 102$)**			**Support ($N = 54$)**		
	$\bar{x}$	$S.D.$	**Level**	$\bar{x}$	$S.D.$	**Level**
1. Policy and administration	4.43	0.76	High	4.58	0.77	Highest
2. Interpersonal relations	4.46	0.73	High	4.64	0.76	Highest
3. Job security	4.57	0.65	Highest	4.65	0.75	Highest
4. Working environment	4.44	0.71	High	4.57	0.77	Highest
5. Income and welfare	4.24	0.89	High	4.30	1.03	High
Overall	**4.43**	**0.75**	**High**	**4.55**	**0.82**	**Highest**

Table 4: Mean, standard deviation, and level of organizational commitment (Y_2)

Organizational Commitment Dimensions	**Academic ($N = 102$)**			**Support ($N = 54$)**		
	$\bar{x}$	$S.D.$	**Level**	$\bar{x}$	$S.D.$	**Level**
1. Dedication to work	4.77	0.44	Highest	4.77	0.64	Highest
2. Desire to remain a member	4.71	0.54	Highest	4.70	0.74	Highest
3. Organizational loyalty	4.73	0.47	Highest	4.77	0.66	Highest
4. Sacrifice for the organization	4.57	0.63	Highest	4.67	0.67	Highest
Overall	**4.69**	**0.52**	**Highest**	**4.73**	**0.68**	**Highest**

Inferential Statistics Results

To examine the causal relationships and hypotheses, Multiple Linear Regression Analysis and Path Analysis were conducted to test the direct and indirect effects of administrative factors (X - maintenance factors) on work motivation (Y_1 - motivation factors) and organizational commitment (Y_2).

Table 5: Multiple regression analysis of administrative factors predicting work motivation (Y_1)

Independent Variables (Administrative Factors: X)	**Unstandardized Coefficients (B)**	**Standard Error (SE_B)**	**Standardized Coefficients (β)**	***t*-value**	***p*-value**
(Constant)	0.814	0.215	-	3.786	0.000**
1. Policy and administration (X_1)	0.245	0.062	0.281	3.951	0.000**
2. Interpersonal relations (X_2)	0.112	0.054	0.134	2.074	0.039*
3. Job security (X_3)	0.318	0.068	0.345	4.676	0.000**
4. Working environment (X_4)	0.105	0.105	0.118	1.810	0.072
5. Income and welfare (X_5)	0.089	0.045	0.102	1.977	0.049*

Note: * $p < 0.05$, $p < 0.01$

Table 5 indicates that the five dimensions of administrative factors significantly predicted work motivation (Y_1) ($p < 0.01$), yielding a multiple correlation coefficient (R) of 0.784 and a coefficient of determination (R^2) of 0.615. This demonstrates that administrative factors accounted for 61.50% of the variance in work motivation, with job security ($\beta = 0.345$) and policy and administration ($\beta = 0.281$) emerging as the strongest predictors.

Table 6: Path analysis results showing direct, indirect, and total effects on organizational commitment (Y_2)

Causal Variables / Mediator	**Effects on Organizational Commitment (Y_2)**		
	Direct Effect (DE)	**Indirect Effect (IE)**	**Total Effect (TE)**
1. Administrative Factors (X)	0.412**	0.285**	0.697**
2. Work Motivation (Y_1)	0.458**	-	0.458**
Model Fit Statistics	$R^2 = 0.724$,	$F = 201.450$,	$p = 0.000^{**}$

Note: p < 0.01

As shown in Table 6, the path analysis evaluating the conceptual framework ($X \rightarrow Y_1 \rightarrow Y_2$) revealed:

1. **Direct Effects:** Administrative factors (X) exerted a significant positive direct effect on organizational commitment (Y_2) ($\beta = 0.412, p < 0.01$). Similarly, work motivation (Y_1) had a significant positive direct effect on organizational commitment ($\beta = 0.458, p < 0.01$).

2. **Indirect Effects:** Administrative factors (X) indirectly influenced organizational commitment (Y_2) through work motivation (Y_1) with an indirect effect coefficient of 0.285 ($p < 0.01$). This confirms that work motivation functions as a vital mediating variable bridging administrative practices and organizational commitment.

3. **Total Effects:** The total effect of administrative factors (X) on organizational commitment (Y_2) was 0.697, with the hypothesized model explaining 72.40% of the total variance in organizational commitment ($R^2 = 0.724$).

DISCUSSION

The findings indicated high levels of perceived administrative factors, work motivation, and organizational commitment among personnel. The discussion is structured as follows:

1. **Alignment and Comparison with Prior Studies:** The results align with Herzberg's (1966) Two-Factor Theory and corroborate findings by Samma et al. (2020) and Shah et al. (2021), which established that maintenance administrative factors serve as a vital baseline preventing job dissatisfaction, whereas motivation factors drive achievement and long-term organizational commitment.

2. **Contextual Differences Between Academic and Support Staff:** The empirical data demonstrated that academic staff prioritized work achievement and autonomy, whereas support

staff placed higher emphasis on interpersonal relations and job security. This reflects the unique structural dynamics of Thai higher education human resource management, where different job categories possess distinct psychological needs and motivational drivers (Ahmad & Oranya, 2019; Çelik & Dursun, 2022).

3. **Mediating Role of Work Motivation:** Path analysis confirmed that work motivation acts as a critical mediator. Institutional administrative policies alone cannot fully foster organizational commitment unless they effectively stimulate internal work motivation among staff members (Mowday et al., 1979; İnce, 2020).

RECOMMENDATIONS

Policy and Practical Recommendations:

1. **Development of Performance Management Systems:** The faculty should establish clear, transparent, and fair key performance indicators (KPIs) linked directly to reward and recognition systems.

2. **Establishment of Clear Career Pathing:** Structured career advancement pathways should be designed for both academic staff (streamlined academic ranking processes) and support staff (specialized and managerial tracks) to mitigate stagnation concerns.

3. **Implementation of Tailored Welfare and Flexible Benefits:** Flexible welfare systems—such as customized healthcare packages, educational support for dependents, and provident funds—should be introduced to accommodate diverse demographic needs across staff cohorts.

References

Ahmad, A. R., & Oranya, S. (2019). Job satisfaction and organizational commitment among academic staff in public universities. *Journal of Human Resources in Hospitality & Tourism*, 18(3), 312-330.

Çelik, M., & Dursun, M. (2022). Evaluation of work motivation and commitment among university staff in higher education. *Educational Policy Analysis and Strategic Research*, 17(2), 145-168.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.

Herzberg, F. (1966). *Work and the nature of man*. World Publishing Company.

İnce, F. (2020). The effect of leadership styles on organizational commitment and job motivation in higher education. *Journal of Higher Education Science*, 10(1), 45-58.

Mowday, R. T., Steers, R. M., & Porter, L. W. (1979). The measurement of organizational commitment. *Journal of Vocational Behavior*, 14(2), 224-247.

Samma, M., et al. (2020). The influence of work motivation on organizational commitment: Evidence from higher education. *International Journal of Higher Education*, 9(4), 112-124.

Shah, S. M. M., et al. (2021). Impact of organizational culture and leadership on organizational commitment in higher education. *Frontiers in Psychology*, 12, 642890.

Yamane, T. (1967). *Statistics: An introductory analysis* (2nd ed.). Harper & Row.

Sub-Theme III

Building Institutional Readiness and Capabilities of AI in Teaching, Learning & Research

P26002

Evaluating the DRIVE Model: A Structured Transfer-and-Implementation Framework for Faculty Technology Integration

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ABSTRACT

Despite continued faculty development initiatives, the transfer of digital-technology learning into sustained classroom practice remains inconsistent in higher education. This study evaluated changes associated with participation in the DRIVE Model, a five-stage transfer-and-implementation process comprising Diagnostic Needs Analysis, Responsive Planning, Instructional Validation, Verification, and Evaluation. Using a convergent mixed-methods descriptive, single-group pre-post design, data were gathered from 35 undergraduate instructors who participated in blended professional development over one academic semester. Quantitative self-assessments were triangulated with focus group discussions, instructional artifacts, and reflective narratives. Faculty reported gains in digital competence (16.67%), frequency of technology use (16.70%), and instructional confidence (8.97%), while artifact evidence documented the use of formative feedback tools (82.86%), multimedia strategies (80.00%), digital assessments (68.57%), flipped instruction (57.14%), and collaborative technologies (51.43%). Tool complexity (97.14%) and time constraints (85.71%) remained substantial barriers. Paired-samples analyses showed statistically significant pre-post increases in all three self-reported outcomes, with large standardized within-participant effects; however, the highly discrete difference-score distributions departed from normality. Wilcoxon sensitivity analyses likewise indicated significant pre-post differences. Given the single-site design and absence of a comparison group, the findings are interpreted as preliminary associations rather than causal effects. DRIVE is therefore positioned not as a new theory of technology integration, but as a procedural transfer-and-implementation framework that complements competence-oriented models by linking professional learning to classroom enactment through staged planning, peer validation, artifact-based verification, and reflective evaluation. The study highlights the value of implementation accountability while identifying the need for multi-institutional, controlled, and longitudinal validation.

Keywords: Professional Development Transfer, Technology-Enhanced Learning, Instructional Implementation, Higher Education, Faculty Development, Pedagogical Innovation

1. Introduction

The rapid expansion of digital technologies in higher education has transformed expectations for teaching and learning, yet effective classroom integration remains inconsistent across institutional contexts (Bond et al., 2021; Mercader & Gairin, 2020; Philipsen et al., 2019; Scherer et al., 2019). Universities may provide infrastructure and professional development, but participation in training does not automatically produce sustained pedagogical enactment (Akram et al., 2022; Scherer et al., 2021; Falloon, 2020; Timotheou et al., 2023). The central problem addressed in this study is therefore an implementation gap: faculty may develop digital knowledge, confidence, or favorable attitudes without consistently translating these gains into observable changes in course design, assessment, feedback, and classroom interaction. This gap points to the need for implementation processes that connect professional learning to planned enactment, verification, and reflection rather than treating competence development as an endpoint.

Competency-oriented frameworks such as TPACK and DigCompEdu are valuable for specifying what educators need to know and be able to do, while SELFIE supports institutional reflection on digital capacity (Redecker & Punie, 2017; Mishra & Koehler, 2006; Costa et al., 2021; Kampylis et al., 2015). However, these frameworks do not by themselves prescribe a faculty-development transfer pathway that moves an identified instructional need through planning, pedagogical review, classroom enactment, verification, and evaluation. Conversely, instructional-design and implementation-science traditions provide staged processes but are not specifically organized around the transfer of faculty digital learning into verified classroom practice. The scholarly gap addressed here is thus not the absence of digital competence frameworks, but the limited operational linkage between competence development and evidence of classroom implementation.

Grounded in implementation science, design-based implementation research, instructional design, and professional development transfer, this study evaluates the DRIVE Model as a procedural transfer-and-implementation framework. Its proposed contribution is deliberately modest and operational rather than theoretical: DRIVE integrates diagnostic analysis, responsive planning, peer-supported instructional validation, artifact-based verification, and reflective evaluation into one accountable sequence. The model is intended to complement—not replace—TPACK, DigCompEdu, SELFIE, ADDIE, or related approaches by providing a structured bridge from professional learning to observable instructional enactment.

1.1. *Theoretical Positioning and Comparative Contribution of the DRIVE Framework*

The DRIVE framework is conceptually grounded in implementation science, design-based implementation research, instructional design, and professional development transfer theory. Implementation science emphasizes the systematic movement of innovations from adoption to sustained use under real-world conditions, with attention to context, fidelity, adaptation, and

feedback. Design-based implementation research similarly emphasizes iterative design, enactment, analysis, and refinement in authentic settings. Professional development transfer theory focuses on the conditions under which learning acquired during training is applied and maintained in work practice. Within DRIVE, these perspectives converge on one mechanism: sequencing reduces the distance between learning and enactment by requiring each stage to produce evidence that becomes the input for the next stage.

The model's distinctive mechanism is the combination of procedural sequencing and verification checkpoints. Diagnostic Needs Analysis anchors technology choices in an instructional problem; Responsive Planning converts the diagnosis into an implementation plan; Instructional Validation introduces a pedagogical quality check before use; Verification requires evidence of actual classroom enactment; and Evaluation returns evidence and reflection to the next cycle. Verification is theoretically important because it shifts evaluation away from intention or confidence alone toward observable implementation evidence. In transfer terms, this checkpoint creates accountability for enactment and makes nonimplementation visible, while reflective evaluation supports adaptation rather than one-time adoption.

Table 1: Comparative Positioning of DRIVE and Related Frameworks

Framework	Primary Focus	Typical Unit of Analysis	Implementation/Transfer Mechanism	How DRIVE Differs or Complements It
TPACK (Mishra & Koehler, 2006)	Integration of technology, pedagogy, and content knowledge	Teacher knowledge	Conceptual knowledge domains; no required staged enactment evidence	Operationalizes TPACK-informed decisions through planning, validation, classroom verification, and evaluation.
DigCompEdu (Redecker & Punie, 2017)	Educator digital competence	Individual educator competence	Competence descriptors and proficiency development	Treats competence as an input and adds a transfer sequence leading to verified classroom use.
SELFIE / digitally competent organizations (Costa et al., 2021; Kampylis et al., 2015)	Digital capacity and organizational self-reflection	School/organization	Diagnostic reflection and capacity review	Begins with diagnosis but extends through implementation, artifact verification, and reflective follow-through.
ADDIE (Branch, 2009)	Systematic instructional design	Instructional product/program	Analysis, Design, Development, Implementation, Evaluation	Narrower purpose: faculty-development transfer; adds peer validation and explicit classroom-evidence checkpoints.
Implementation science / DBIR (Fixsen et al., 2005; Penuel et al., 2011)	Adoption, enactment, adaptation, and sustainability of innovations	Program/system in context	Staged implementation, feedback, adaptation, iterative refinement	Translates these principles into a compact faculty-development workflow centered on pedagogical alignment and verified enactment.

Guided by this positioning, the study addressed four questions: (1) what changes in faculty digital competence, instructional confidence, and technology-use frequency are observed across the implementation period; (2) what technology-supported instructional practices are enacted; (3) how do faculty describe changes in engagement, assessment, and instructional

organization, and how are these accounts corroborated by artifacts; and (4) what barriers emerge during implementation? Because the study used a single-group pre-post descriptive design, these questions concern change and implementation patterns associated with participation rather than causal effectiveness relative to alternative models.

2. Method

2.1. Research Design

This study employed a convergent mixed-methods descriptive, single-group pre-post design to examine changes and implementation patterns associated with a structured faculty development process. Quantitative and qualitative strands were collected within the same implementation period and integrated through triangulation. The design was appropriate for documenting change over time and examining implementation evidence, but it was not designed to establish that the DRIVE Model caused the observed changes because no comparison or control group was included.

Combining survey indicators with focus group data, reflective narratives, and instructional artifacts enabled cross-validation between participant perceptions and observable evidence of instructional modification. This triangulation reduced—but did not eliminate—the limitations of self-report. Alternative explanations such as participant motivation, institutional support, prior technology readiness, disciplinary culture, trainer quality, maturation, and reactivity to being observed remain plausible and are considered in the interpretation of findings.

2.2. Participants and Context

Participants included 35 undergraduate instructors from a higher education institution who voluntarily enrolled in blended faculty development activities focused on technology-enhanced instruction. Faculty represented multiple disciplinary backgrounds.

Research consistently shows that faculty digital competence varies across disciplines and institutional contexts (Bond et al., 2021; Falloon, 2020; Mishra & Koehler, 2006). Therefore, a multi-disciplinary participant group allowed examination of implementation across varied instructional environments.

The implementation period spanned one academic semester, consistent with recommendations that sustained professional development cycles are necessary for meaningful pedagogical change (Voogt et al., 2013; Pettersson, 2021).

2.3. Implementation Procedure: the Five-Stage Framework

The structured framework was operationalized through five sequential stages aligned with principles of design-based implementation research and structured professional development cycles (Chiu, 2023; Clipa et al., 2023).

Stage 1: Diagnostic Needs Analysis

Faculty completed a structured needs assessment examining current technology use, pedagogical challenges, and digital competence levels. Establishing baseline instructional practices aligns with recommendations for competence-based faculty development (Bond et al., 2021; Falloon, 2020).

Stage 2: Responsive Planning

Participants developed integration plans aligning digital tools with course learning outcomes. Pedagogical alignment is central to technological pedagogical content knowledge theory (Akram et al., 2022; Hillmayr et al., 2020).

Stage 3: Instructional Validation

Proposed strategies were peer-reviewed to ensure feasibility and pedagogical coherence. Collaborative validation processes are associated with higher professional development effectiveness (Voogt et al., 2013).

Stage 4: Verification

Faculty implemented planned strategies in live courses. Instructional artifacts were collected to verify classroom application, addressing concerns that faculty training often fails to translate into observable practice (Haleem et al., 2022).

Stage 5: Evaluation

Participants engaged in structured reflection and group discussion to assess instructional effectiveness. Reflective evaluation aligns with iterative improvement models in design-based research (Kampylis et al., 2015; Clipa et al., 2023).

Each stage informed the subsequent phase, ensuring structured progression rather than isolated technology adoption.

2.4. Instruments and Data Collection

Multiple instruments were employed to enhance methodological rigor and ensure triangulation across data sources.

Structured Survey Instrument.

A structured questionnaire using a five-point Likert scale was administered before and after the implementation period to measure three constructs: perceived digital competence, instructional confidence, and frequency of technology integration. Items were aligned with established dimensions of educator digital competence and instructional integration (Bond et al., 2021; Falloon, 2020). Examples of the measured domains included selecting digital tools for

instructional purposes, confidence in integrating technology with pedagogy, and the regularity with which digital strategies were used in teaching. Prior to deployment, the instrument underwent content review by two educational technology experts for clarity, relevance, and alignment with the intended constructs.

Instrument Validation and Scale Reporting. The structured survey instrument underwent expert content review by two educational technology and instructional design specialists prior to deployment to ensure construct clarity, pedagogical relevance, and alignment with established digital competence dimensions. In the primary data collection, survey indicators were logged as domain composite scores across perceived digital competence, instructional confidence, and frequency of technology integration. Because item-level responses were not recorded separately, internal-consistency reliability coefficients such as Cronbach's alpha or McDonald's omega could not be computed post hoc without inappropriate reconstruction or imputation of item-level data. Accordingly, the present study reports the instrument's expert-based content validation while acknowledging the absence of internal-consistency estimates as a methodological limitation. Future multi-site applications of the DRIVE framework will retain item-level responses to permit full reliability analysis across all subscales.

Focus Group Discussions.

Semi-structured focus group sessions were conducted to gather in-depth insights into faculty experiences during implementation. Guiding questions explored instructional alignment, student engagement, assessment adaptation, and encountered challenges. Qualitative inquiry has been shown to provide contextual understanding of technology integration processes and institutional barriers (Timotheou et al., 2023; Redecker & Punie, 2017).

Instructional Artifacts.

To verify classroom application, participants submitted instructional materials including revised lesson plans, digital assessments, multimedia instructional resources, and course integration plans. Artifact analysis served as an objective indicator of instructional modification and helped mitigate self-report bias commonly associated with professional development research (Voogt et al., 2013; Haleem et al., 2022).

Reflective Narratives.

Participants were asked to submit structured reflective accounts documenting instructional adjustments, student responses, and implementation challenges. Reflective documentation is recommended in implementation-focused studies to capture practitioner insight and iterative adaptation (Kampylis et al., 2015; Clipa et al., 2023).

Data collection occurred over one academic semester, allowing sufficient time for planning, classroom application, and reflective evaluation.

2.5. Data Analysis Procedures

Quantitative data were summarized using means, standard deviations, frequencies, percentages, and pre-post mean differences. Paired-samples t tests were used to examine within-participant change because the same instructors contributed pre- and post-measures. Cohen's dz was calculated by dividing the mean paired difference by the standard deviation of the paired differences, and 95% confidence intervals were reported for the mean differences. Difference-score distributions were examined using the Shapiro-Wilk test and standardized scores to identify extreme observations. Because the paired differences were highly discrete and departed from normality, Wilcoxon signed-rank tests were also examined as a nonparametric sensitivity analysis.

Assumption checks indicated statistically significant departures from normality for the paired difference scores: digital competence, $W = .758$, $p < .001$; instructional confidence, $W = .779$, $p < .001$; and frequency of technology use, $W = .758$, $p < .001$. No difference score exceeded three standard deviations from its outcome-specific mean. The sensitivity analyses yielded the same directional conclusion as the paired t tests (Wilcoxon signed-rank tests, all $p < .001$). Accordingly, the t-test results are reported with effect sizes and confidence intervals, while the non-normality of the highly concentrated difference scores is acknowledged when interpreting magnitude.

Qualitative data from focus group discussions and reflective narratives were analyzed thematically through open coding, category clustering, and constant comparison across qualitative sources. Coding decisions and theme definitions were documented in the study audit trail, and themes were compared across sources before being checked against instructional artifacts. Qualitative data were retained in synthesized thematic form rather than as verbatim transcripts for reporting. This source-to-source comparison was used to strengthen credibility and to identify both convergent and divergent evidence rather than treating participant accounts as self-validating.

Triangulation was conducted by cross-validating survey results, qualitative themes, and instructional artifacts, strengthening credibility and reducing mono-method bias (Chiu, 2023).

2.6. Validity and Trustworthiness

Several strategies were implemented to enhance the validity and credibility of the study. Methodological Triangulation.

Data were collected from multiple sources, including surveys, focus group discussions, instructional artifacts, and reflective narratives. Triangulation across quantitative and qualitative strands strengthened credibility by verifying consistency across independent data sources (Chiu, 2023; Clipa et al., 2023).

Content Validation of Instruments.

The survey instrument underwent expert review by specialists in educational technology and instructional design to ensure alignment with digital competence and instructional integration constructs (Bond et al., 2021; Falloon, 2020). Revisions were made based on expert feedback prior to administration.

Artifact-Based Verification.

To reduce reliance on self-reported data, instructional artifacts were analyzed to corroborate reported changes in classroom practice. Artifact triangulation has been recommended in professional development evaluation studies to enhance confirmability (Voogt et al., 2013; Haleem et al., 2022).

Audit Trail and Procedural Transparency.

Documentation was maintained throughout each stage of implementation, including needs assessment results, planning documents, workshop feedback, and evaluation summaries. Maintaining an audit trail strengthens dependability in implementation-oriented research (Kampylis et al., 2015; Clipa et al., 2023).

Reflexive Reporting of Challenges.

Participants were encouraged to document not only successful outcomes but also barriers and implementation difficulties. Explicit acknowledgment of challenges enhances confirmability and reduces positive-reporting bias (Timotheou et al., 2023; Redecker & Punie, 2017).

Together, these measures support the credibility, dependability, and confirmability of the findings within the institutional context examined.

3. Results and Discussion

3.1. Measurable Changes in Faculty Digital Integration

Table 2 presents the pre- and post-implementation self-assessment scores for participating faculty (n = 35). Digital competence increased from M = 30.00 to M = 35.00 (16.67%), frequency of technology use increased from M = 29.94 to M = 34.94 (16.70%), and instructional confidence increased from M = 32.17 to M = 35.06 (8.97%). Table 2: Pre- and Post-Implementation Self-Assessment Scores and Paired-Samples Tests (n = 35)

Variable	Pre M (SD)	Post M (SD)	Mean Difference [95% CI]	Paired test / effect size
Digital Competence	30.00 (2.47)	35.00 (2.00)	5.00 [4.80, 5.20]	t(34) = 49.79, p < .001; dz = 8.42
Instructional Confidence	32.17 (2.27)	35.06 (1.86)	2.89 [2.67, 3.10]	t(34) = 27.05, p < .001; dz = 4.57
Frequency of Technology Use	29.94 (2.27)	34.94 (1.86)	5.00 [4.80, 5.20]	t(34) = 49.79, p < .001; dz = 8.42

The descriptive changes in Table 2 indicate that participation in the implementation cycle was associated with higher post-implementation self-assessment scores. Digital competence increased by 5.00 points (16.67%), instructional confidence by 2.89 points (8.97%), and frequency of technology use by 5.00 points (16.70%). These changes are directionally consistent with research showing that sustained and contextually aligned professional learning can accompany improvements in digital teaching practice (Timotheou et al., 2023; Cam & Erdemir, 2024). However, percentage gains and statistically significant within-participant changes do not establish that DRIVE alone produced the improvements; the absence of a comparison group prevents unique causal attribution.

Paired-samples t tests showed higher post-implementation scores for digital competence, $t(34) = 49.79$, $p < .001$, Cohen's $dz = 8.42$, mean-difference 95% CI [4.80, 5.20]; instructional confidence, $t(34) = 27.05$, $p < .001$, $dz = 4.57$, 95% CI [2.67, 3.10]; and frequency of technology use, $t(34) = 49.79$, $p < .001$, $dz = 8.42$, 95% CI [4.80, 5.20]. The unusually large standardized effects reflect the very small variability of the paired difference scores in this sample and should therefore be interpreted cautiously alongside the design limitations and the non-normal, highly concentrated difference distributions.

The parallel descriptive increase in competence and use is consistent with behavioral transfer, but it should not be treated as proof that the framework produced that transfer. The pattern may reflect the combined influence of the structured implementation process, participant motivation, institutional support, prior readiness, disciplinary context, or other time-related influences. Accordingly, the results are interpreted as implementation-associated changes that warrant controlled comparative testing.

3.2. Adoption of Technology-Supported Instructional Practices

As shown in Table 3, formative feedback tools (82.86%) and multimedia-supported instruction (80.00%) were the most frequently implemented instructional practices following participation in the structured faculty development framework. Digital assessments were adopted by 68.57% of participants, while flipped instructional strategies were implemented by 57.14%. Collaborative tools demonstrated the lowest adoption rate (51.43%), though still reflecting majority uptake.

Table 3: Adoption of Technology-Supported Instructional Practices

Practice Category	Frequency (n)	Percentage (%)
Formative Feedback Tools	29	82.86
Multimedia Integration	28	80.00

Digital Assessments	24	68.57
Flipped Instruction	20	57.14
Collaborative Tools	18	51.43

These findings indicate that faculty prioritized engagement-oriented and feedback-driven technologies over more structurally demanding pedagogical redesign approaches. The strong adoption of formative feedback tools is particularly noteworthy, as digital feedback systems have been associated with improved learner engagement, responsiveness, and instructional adjustment when systematically embedded within course design (Creswell & Creswell, 2018; Mayer, 2021). Similarly, multimedia-supported instruction has been shown to enhance conceptual clarity and student motivation when aligned with learning objectives (Meyer et al., 2023).

The adoption pattern suggests that participants more readily enacted technologies that could be integrated into existing instructional routines than approaches requiring more extensive course redesign. Rather than claiming that these rates exceed those of other professional-development models, the present data are treated as within-study implementation indicators. The sequence from Diagnostic Needs Analysis to Responsive Planning provides a plausible mechanism for intentional tool selection because participants were required to connect a technology choice to an identified instructional need before classroom use; whether this mechanism performs better than alternative approaches remains an empirical question for comparative research.

3.3. Triangulated Classroom Effects

Faculty accounts converged on four perceived enactment domains: enhanced student responsiveness during live instruction, streamlined lesson organization, improved assessment efficiency, and increased confidence in peer-validated course designs. These self-reported reflections were corroborated through instructional artifacts, including verified lesson plans showing flipped-learning structures, digital assessment materials, learning-management-system structures, and interactive multimedia resources. This convergence strengthens confidence that at least some reported changes reflected enacted instructional modifications rather than perception alone.

Triangulation nevertheless does not remove self-report bias. Social desirability, recall effects, and heightened attention associated with participation in a development initiative may have influenced the qualitative accounts. The artifact strand was therefore used as corroborating evidence of enactment, not as proof of student-level effectiveness.

The verification checkpoint is the most operationally distinctive feature of DRIVE relative to competence-oriented frameworks: it requires evidence that a planned practice was enacted. This distinction concerns the type of evidence collected rather than the superiority of the model.

Because verbatim qualitative transcripts were not retained for reporting, direct participant quotations could not be reproduced without reconstructing statements from thematic summaries. The study therefore reports synthesized themes only and acknowledges the absence of verbatim quotations as a limitation of the qualitative evidence.

3.4. Implementation Challenges and Structural Barriers

Despite positive outcomes, faculty reported significant implementation barriers. Tool complexity (97.14%) and time constraints (85.71%) were the most frequently cited challenges. Student access issues (57.14%) and alignment difficulties (42.86%) were also reported.

Table 4: Implementation Challenges in Classroom Technology Integration

Challenge Category	Frequency (n)	Percentage (%)
Tool Complexity	34	97.14
Time Constraints	30	85.71
Student Access Issues	20	57.14
Instructional Alignment Difficulties	15	42.86

The challenge profile is substantial and should be interpreted as a limitation of implementation, not as evidence that staging overcame resistance. Tool complexity was reported by 97.14% of participants and time constraints by 85.71%, while student access issues (57.14%) and instructional-alignment difficulties (42.86%) were also common. These rates show that the framework operated in the presence of persistent structural and workload barriers and may not have been sufficient to resolve them.

The coexistence of substantial barriers and documented enactment suggests a more cautious interpretation: some participants continued to implement technology-supported practices despite difficulty. Future comparative work should test whether DRIVE reduces abandonment, implementation burden, or time-to-enactment relative to other professional-development approaches rather than inferring this effect from the present descriptive data.

Procedural Contribution and Theoretical Propositions

The primary contribution of DRIVE is procedural rather than theoretical. TPACK and DigCompEdu specify important knowledge and competence domains, SELFIE supports diagnosis and organizational reflection, ADDIE provides a broad instructional-design sequence, and implementation-science/DBIR traditions emphasize enactment and iterative refinement. DRIVE combines selected elements of these traditions for a narrower problem: transferring faculty professional learning into verified classroom technology use.

Three testable propositions follow from this synthesis. First, instructional technologies selected after diagnosis and explicit pedagogical planning should show stronger alignment with course outcomes than technologies selected primarily through tool exposure. Second, peer-supported instructional validation should identify feasibility or alignment problems before classroom enactment. Third, artifact-based verification should increase the visibility of transfer by distinguishing intended use from documented implementation. These propositions are not confirmed by the present single-group study; they articulate mechanisms that can be tested in future comparative and multi-institutional research.

4. The DRIVE Model as a Transfer-and-Implementation Framework

Figure 1 summarizes DRIVE as an iterative transfer pathway rather than a stand-alone theory of technology integration. Its function is to connect needs diagnosis, pedagogical planning, quality review, classroom enactment, and reflection in a sequence that makes implementation evidence visible. The framework can therefore sit alongside competence models such as TPACK or DigCompEdu and within broader instructional-design or implementation-science approaches.

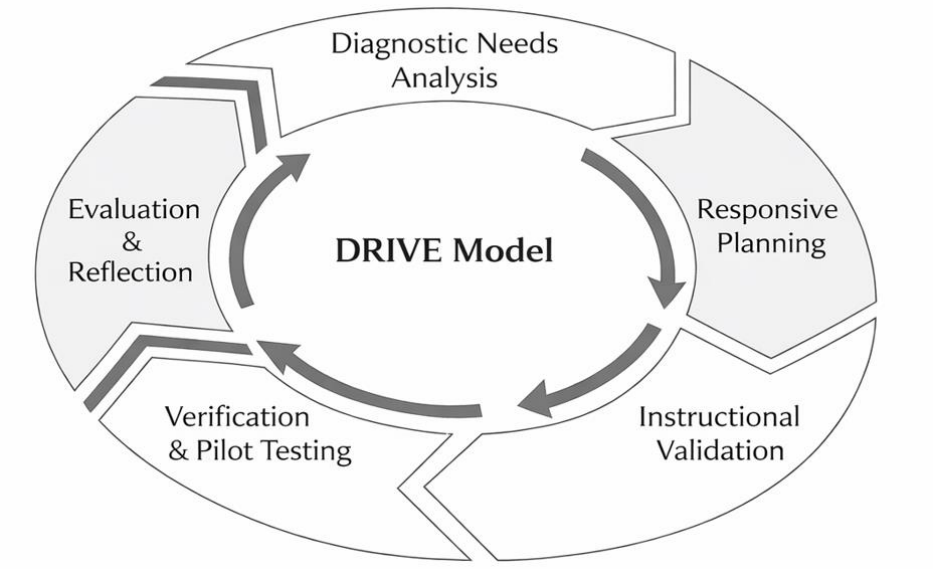


Figure 1: The DRIVE Model: A Cyclical Framework for Classroom Technology Integration

The DRIVE Model illustrates a five-stage transfer-and-implementation process linking diagnostic analysis, planning, validation, classroom verification, and reflective evaluation.

Each stage produces information or evidence used in the next stage, while Evaluation feeds back into the next Diagnostic Needs Analysis cycle.

4.1. Diagnostic Needs Analysis

Diagnostic Needs Analysis identifies the instructional problem, classroom context, learner constraints, and desired pedagogical outcome before a technology is selected. This stage prevents technical-skill deficits from becoming the sole basis for training decisions and establishes the implementation baseline.

4.2. Responsive Planning

Responsive Planning converts the diagnosis into an actionable integration plan by aligning selected digital tools with course outcomes, assessment needs, learner access, available time, and instructor readiness. The emphasis is on fit and feasibility rather than tool novelty.

4.3. Instructional Validation

Instructional Validation provides a pre-enactment pedagogical checkpoint through peer feedback, guided reflection, and design review. Its purpose is to identify alignment, feasibility, accessibility, or workload problems before classroom implementation.

4.4. Verification

Verification is the classroom-enactment checkpoint. Faculty implement the planned strategy and submit observable evidence such as revised lesson plans, digital assessments, learning-management-system structures, or other instructional artifacts. Verification documents whether planned transfer occurred; it does not by itself establish student-learning effects.

4.5. Evaluation

Evaluation combines reflection, available learner feedback, implementation evidence, and identified barriers to judge what should be sustained, adapted, or discontinued. The output of Evaluation becomes input for the next diagnostic cycle, reinforcing iterative improvement rather than one-time adoption.

For institutional use, DRIVE requires at minimum: protected faculty planning time; access to appropriate digital platforms and technical support; a facilitator or peer-review mechanism for validation; a simple repository for implementation artifacts; and a structured reflection process. Institutions with limited resources may shorten workshops or use existing learning-management systems, but the diagnostic, validation, verification, and evaluation functions should remain visible if the transfer logic of the model is to be preserved.

5. Limitations, Implementation Implications, and Future Research

Several limitations constrain interpretation. First, the sample was small (n = 35) and drawn from one higher education institution, limiting statistical power and external validity. Second, this evaluation utilized a single-group pre-post design without a concurrent comparison group. Consequently, observed improvements in digital competence, instructional confidence, and technology use represent preliminary associations rather than causal effects; maturation, institutional initiatives, participant motivation, prior readiness, disciplinary culture, trainer quality, and Hawthorne-type reactivity cannot be ruled out as alternative explanations. Because a comparison group cannot be retrofitted post hoc into a completed evaluation, establishing comparative efficacy—for example, by evaluating DRIVE against traditional workshop models or alternative implementation frameworks—is designated as a primary direction for future research. Third, key quantitative outcomes relied on faculty self-assessment and are vulnerable to social-desirability and recall bias. The archived survey data consisted of domain composite scores rather than item-level responses, preventing post-hoc estimation of internal-consistency reliability; expert content validation is therefore reported separately from reliability. Fourth, artifact verification strengthens evidence of enactment but does not establish the quality of implementation or its effect on student learning. Fifth, qualitative findings were retained as synthesized themes rather than verbatim transcripts, limiting the use of direct participant quotations. The study also did not include direct student-learning measures or longitudinal follow-up, so persistence and downstream educational effects remain unknown. Finally, the high rates of tool complexity and time constraints indicate that the framework did not remove major structural barriers and may require stronger technical, workload, and access supports in other settings.

These limitations also shape institutional use. DRIVE should be treated as a context-sensitive implementation scaffold rather than a universally replicable package. Before adoption, institutions should assess faculty workload, technical infrastructure, learner access, disciplinary needs, and the availability of peer-review and follow-up support. The model may be adapted in duration and delivery mode, but institutions should preserve the core transfer functions of diagnosis, planning, validation, verification, and evaluation so that adaptation does not reduce the process to another stand-alone training event.

Future research should test the propositions of DRIVE using larger, multi-institutional samples and explicit comparison conditions, such as traditional workshop-only professional development, competence-focused training without verification, or an alternative implementation framework. A priori power analysis should guide sample-size targets. Studies should report scale reliability and validity evidence, paired or between-group effect sizes with confidence intervals, and direct student outcomes where appropriate. Longitudinal follow-up at multiple points after training is needed to examine persistence, while implementation research should also compare resource requirements, fidelity/adaptation patterns, and outcomes across disciplines and institutions with different levels of digital capacity.

6. Conclusion

This study evaluated the DRIVE Model as a structured transfer-and-implementation framework for faculty technology integration. Across one academic semester, 35 instructors reported higher post-implementation scores in digital competence, instructional confidence, and technology-use frequency, and artifact evidence documented the enactment of several technology-supported practices. Participants also reported substantial implementation barriers, especially tool complexity and time constraints.

The study's contribution is best understood as procedural: DRIVE integrates diagnosis, responsive planning, peer-supported instructional validation, artifact-based verification, and reflective evaluation into a single faculty-development transfer cycle. In doing so, it offers a practical way to operationalize competencies described by frameworks such as TPACK and DigCompEdu while making classroom enactment an explicit checkpoint. The present evidence does not establish that DRIVE is superior to existing models or that it caused the observed changes; rather, it provides preliminary single-site evidence that the process is feasible and can generate observable implementation records.

Accordingly, DRIVE should be viewed as a candidate implementation scaffold requiring further validation. Its strongest next test is comparative: whether the staged sequence, particularly instructional validation and artifact-based verification, produces stronger or more durable transfer than less structured professional-development approaches under comparable conditions. Multi-institutional, longitudinal, and student-outcome studies are needed before broad claims of generalizability, scalability, or effectiveness are warranted.

Acknowledgments

The author extends her sincere appreciation to the CITL leadership, coordinators, and trainers for their support and active involvement throughout the conduct of this study. Their insights and cooperation greatly enriched the evaluation process and strengthened the development of the enhanced training model. The researcher also acknowledges the valuable contributions of faculty and student participants whose perspectives provided essential context to the findings. Their willingness to share experiences made this work possible.

Funding Information

The author acknowledges the University of Science and Technology of Southern Philippines for providing institutional support for the original research from which this manuscript was derived. This paper synthesizes key insights and findings from that study to articulate the DRIVE Model as an evidence-informed framework supporting instructional innovation and

program development. No external funding was received beyond institutional support. All interpretations and conclusions presented herein are solely those of the author.

Author Contributions

The author conducted the conceptualization, methodological development, data analysis, interpretation of results, and manuscript preparation for this paper. The study draws on data generated from earlier collaborative research; however, the extraction, reanalysis, interpretation, and writing presented here were undertaken solely by the author. The author approved the final version of the manuscript.

Conflict of Interest Statement

The author declares that she has no known financial, professional, or personal conflicts of interest that could have influenced the outcomes of this research. All procedures, analyses, and interpretations were conducted objectively and independently. The study's findings and conclusions reflect the genuine results of the evaluation process.

Informed Consent

All participants involved in the study were fully informed about the purpose, procedures, and voluntary nature of their participation prior to data collection. Written informed consent was obtained from every respondent, ensuring adherence to ethical standards. Participants were assured that their information would remain confidential and used solely for academic and program-improvement purposes.

Ethical Approval

This study underwent formal ethical review and received approval from the Institutional Research Ethics Review Board of the University of Science and Technology of Southern Philippines. All research activities were conducted in accordance with institutional guidelines and national ethical standards for studies involving human participants. Careful attention was given to confidentiality, informed consent, and respect for participant autonomy.

Data Availability

The data supporting the findings of this research are available from the corresponding author upon reasonable request. Access may be granted for academic, non-commercial purposes while ensuring participant confidentiality. Additional documentation or supplementary materials used during analysis can likewise be provided as permitted by institutional policies.

References

Abaci, S., Robertson, J., Linklater, A., McNeill, A., Brown, J. M., & Aydin, R. A. M. (2021). Supporting school teachers' rapid engagement with online education. Education and Information Technologies, 26, 3899–3925. https://doi.org/10.1007/s10639-020-10367-1

Akram, H., Abdelrady, A. H., Al-Adwan, A. S., & Ramzan, M. (2022). Teachers' perceptions of technology integration in teaching-learning practices: A systematic review. Frontiers in Psychology, 13, Article 920317. https://doi.org/10.3389/fpsyg.2022.920317

Baldwin, T. T., & Ford, J. K. (1988). Transfer of training: A review and directions for future research. Personnel Psychology, 41(1), 63–105. https://doi.org/10.1111/j.1744-6570.1988.tb00632.x

Bond, A., Bedenlier, O., Marin, P., & Handel, J. (2021). Emergency remote teaching in higher education: Mapping the first global online semester. International Journal of Educational Technology in Higher Education, 18, Article 50. https://doi.org/10.1186/s41239-021-00282-x

Branch, R. M. (2009). Instructional design: The ADDIE approach. Springer. https://doi.org/10.1007/978-0-387-09506-6

Cam, Ş. S., & Erdemir, N. (2024). Professional development program to develop teacher educators' technological pedagogical content knowledge (TPACK). SAGE Open, 14(2). https://doi.org/10.1177/21582440241242841

Carless, D., & Boud, D. (2018). The development of student feedback literacy: Enabling uptake of feedback. Assessment & Evaluation in Higher Education, 43(8), 1315–1325. https://doi.org/10.1080/02602938.2018.1463354

Chiu, T. K. F. (2023). A systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. Computers and Education: Artificial Intelligence, 4, Article 100118. https://doi.org/10.1016/j.caeai.2022.100118

Clipa, O., Delibas, C.-S., & Mata, L. (2023). Teachers' self-efficacy and attitudes towards the use of information technology in classrooms. Education Sciences, 13(10), Article 1001. https://doi.org/10.3390/educsci13101001

Coban, M., Bolat, Y. I., & Goksu, I. (2022). The potential of immersive virtual reality to enhance learning: A meta-analysis. Educational Research Review, 36, Article 100452. https://doi.org/10.1016/j.edurev.2022.100452

Costa, P., Castano-Munoz, J., & Kampylis, P. (2021). Capturing schools' digital capacity: Psychometric analyses of the SELFIE self-reflection tool. Computers & Education, 162, Article 104080. https://doi.org/10.1016/j.compedu.2020.104080

Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE.

Delcker, J., & Ifenthaler, D. (2021). Teachers' perspective on school development at German vocational schools during the COVID-19 pandemic. Technology, Pedagogy and Education, 30(1), 125–139. https://doi.org/10.1080/1475939X.2020.1857826

Di Pietro, M. J., Biagi, F., Costa, P., Karpinski, Z., & Mazza, J. (2020). The likely impact of COVID-19 on education: Reflections based on the existing literature and recent international datasets. Publications Office of the European Union.

Falloon, G. (2020). From digital literacy to digital competence: The teacher digital competency (TDC) framework. Educational Technology Research and Development, 68(5), 2449–2472. https://doi.org/10.1007/s11423-020-09767-4

Fetters, M. D., Curry, L. A., & Creswell, J. W. (2013). Achieving integration in mixed methods designs—Principles and practices. Health Services Research, 48(6 Pt 2), 2134–2156. https://doi.org/10.1111/1475-6773.12117

Fixsen, D. L., Naoom, S. F., Blase, K. A., Friedman, R. M., & Wallace, F. (2005). Implementation research: A synthesis of the literature. University of South Florida, Louis de la Parte Florida Mental Health Institute.

Haleem, S., Javaid, M., Qadri, M. A., & Suman, R. (2022). Understanding the role of digital technologies in education: A review. Sustainable Operations and Computers, 3, 275–285. https://doi.org/10.1016/j.susoc.2022.05.004

Hillmayr, K., Ziernwald, L., Reinhold, F., Hofer, S. I., & Reiss, K. M. (2020). The potential of digital tools to enhance mathematics and science learning in secondary schools: A

context-specific meta-analysis. Computers & Education, 153, Article 103897. https://doi.org/10.1016/j.compedu.2020.103897

Hodges, T., Moore, S., Lockee, B., Trust, T., & Bond, A. (2020). The difference between emergency remote teaching and online learning. EDUCAUSE Review.

Kampylis, A., Punie, Y., & Devine, J. (2015). Promoting effective digital-age learning: A European framework for digitally-competent educational organisations. Publications Office of the European Union. https://doi.org/10.2791/54070

König, J., Jäger-Biela, D., & Glutsch, N. (2020). Adapting to online teaching during COVID-19 school closure: Teacher education and teacher competence effects among early career teachers in Germany. European Journal of Teacher Education, 43(4), 608–622. https://doi.org/10.1080/02619768.2020.1809650

Lei, H., Wang, C., Chiu, M. M., & Chen, S. (2022). Do educational games affect students' achievement emotions? Evidence from a meta-analysis. Journal of Computer Assisted Learning, 38(4), 946–959. https://doi.org/10.1111/jcal.12664

Liu, M., Pang, W., Guo, J., & Zhang, Y. (2022). A meta-analysis of the effect of multimedia technology on creative performance. Education and Information Technologies. https://doi.org/10.1007/s10639-022-10981-1

Mayer, R. E. (2021). The Cambridge handbook of multimedia learning (3rd ed.). Cambridge University Press.

Mercader, C., & Gairin, J. (2020). University teachers' perception of barriers to the use of digital technologies: The importance of the academic discipline. International Journal of Educational Technology in Higher Education, 17, Article 4. https://doi.org/10.1186/s41239-020-0182-x

Meyer, A., Kleinknecht, M., & Richter, D. (2023). What makes online professional development effective? The effect of quality characteristics on teachers' satisfaction and changes in their professional practices. Computers & Education, 200, Article 104805. https://doi.org/10.1016/j.compedu.2023.104805

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. Teachers College Record, 108(6), 1017–1054.

OECD. (2021). OECD digital education outlook 2021: Pushing the frontiers with artificial intelligence, blockchain and robots. OECD Publishing.

Penuel, W. R., Fishman, B. J., Cheng, B. H., & Sabelli, N. (2011). Organizing research and development at the intersection of learning, implementation, and design. Educational Researcher, 40(7), 331–337. https://doi.org/10.3102/0013189X11421826

Pettersson, F. (2021). Understanding digitalization and educational change in school by means of activity theory and the levels of learning concept. Education and Information Technologies, 26(1), 187–204. https://doi.org/10.1007/s10639-020-10239-8

Philipsen, B., Tondeur, J., Pareja Roblin, N., Vanslambrouck, S., & Zhu, C. (2019). Improving teacher professional development for online and blended learning: A systematic meta-aggregative review. Educational Technology Research and Development, 67(5), 1145–1174. https://doi.org/10.1007/s11423-019-09645-8

Redecker, S., & Punie, Y. (2017). European framework for the digital competence of educators: DigCompEdu. Publications Office of the European Union. https://doi.org/10.2760/159770

Scherer, R., Howard, S. K., Tondeur, J., & Siddiq, F. (2021). Profiling teachers' readiness for online teaching and learning in higher education: Who's ready? Computers in Human Behavior, 118, Article 106675. https://doi.org/10.1016/j.chb.2020.106675

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. Computers & Education, 128, 13–35. https://doi.org/10.1016/j.compedu.2018.09.009

Timotheou, S., Miliou, O., Dimitriadis, Y., Sobrino, S. V., Giannoutsou, N., Cachia, R., & Gilleran, M. (2023). Impacts of digital technologies on education and factors influencing schools' digital capacity and transformation: A literature review. Education and Information Technologies, 28, 6695–6726. https://doi.org/10.1007/s10639-022-11431-8

Trust, T., Carpenter, J. P., & Krutka, D. G. (2017). Moving beyond silos: Professional learning networks in higher education. The Internet and Higher Education, 35, 1–11. https://doi.org/10.1016/j.iheduc.2017.06.001

Voogt, J., Fisser, P., Pareja Roblin, N., Tondeur, J., & van Braak, J. (2013). Technological pedagogical content knowledge—A review of the literature. Journal of Computer Assisted Learning, 29(2), 109–121. https://doi.org/10.1111/j.1365-2729.2012.00487.x

Wen, L., & Walters, S. M. (2022). The impact of technology on students' writing performances in elementary classrooms: A meta-analysis. Computers and Education Open, 3, Article 100082. https://doi.org/10.1016/j.caeo.2022.100082

P26012

Faculty Perceptions of AI Use Across ADDIE Instructional Design Phases at DWCL

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Abstract

This study utilized the ADDIE Model to examine the uses and perceived effectiveness of AI across the instructional phases. Using a descriptive research approach, the study determined the extent of teachers' AI use across the ADDIE instructional phases, its perceived effectiveness, the challenges encountered, and the recommendations provided by the respondents. A self-developed questionnaire was distributed to 168 DWCL faculty members at the tertiary level during SY 2025–2026. The results revealed that AI is widely used and perceived as effectively integrated across the phases of the ADDIE Model. The prime uses of AI include generating diagnostic tests and quizzes, suggesting teaching strategies, creating multimedia content, serving as a teaching assistant, and generating rubrics and scoring guides. The integration of AI in each phase of instructional preparation and teaching strategies offers significant help, particularly in the Design phase, which emphasizes lesson planning and instructional design.

Keywords: Teaching, Artificial Intelligence, ADDIE, DWCL

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Teaching involves cultivating understanding, transferring ideas, and nurturing growth through shared learning experiences. It is both a process of preparation and an act of execution designed to help learners comprehend, analyze, and apply what they learn. Teaching also means assessing learners' competencies through examination and evaluation. Various countries use diverse approaches to teacher education shaped by their social, economic, and political contexts, with differences in governance, curricula, and reforms reflecting each country's development and policy priorities (Morris & Williamson, 1998). In the Philippines, teachers pursue teaching out of genuine passion to make a difference in students' lives (Trinidad, 2018). Rajagopalan (2019) shared that effective teaching is well-planned, student-centered, promoting guidance and participation in classroom activities. It requires empathy and emotional stability to address learners' needs and provide remedial support.

In today's generation, the evolution of teaching and learning through technology integration is evident. It has transformed classroom practices. No longer is the classroom confined to four walls where the teacher relies solely on direct instruction (Adcock, 2008). It is not only a shift in the position of students within the classroom but also their transformation into active participants in the learning process. Moreover, the use of various technologies aims to make learning more accessible to students while responding to the demands of the modern age (Muratai & Ceka, 2017).

Historically, education has evolved in form and delivery, which became significant by the end of the 15th century. Chalkboards became widely used in the 18th century, while more advanced technologies continue to play a vital role in teaching and learning in the 21st century. Technology has brought significant changes at all levels of education. From a pedagogical perspective, technology has improved management, administration, and the delivery of learning activities. Teaching evolves especially with digital integration (Jamil & Shah, 2011).

Artificial Intelligence (AI) has become increasingly prevalent across multiple domains, including education. AI is transforming various aspects of life through capabilities such as problem-solving, creativity, and perception, while also supporting inclusivity, reducing inequalities, and accelerating the achievement of the Sustainable Development Goals (UN, n.d.). AI can perform tasks such as grading and providing feedback on students' performance, or even as a substitute for teaching, as it can be programmed to deliver content and retrieve information for basic course materials (Fahimirad & Kotamjani, 2018). AI also offers opportunities for creating intelligent content and improving student engagement (Tang, 2024).

Artificial Intelligence in Teaching

The integration of AI ushers in a new era of teaching and learning, offering significant learning and instructional support opportunities (Slade et al., 2024). This demonstrates how AI is increasingly being used as a helpful tool to enhance various phases of the teaching and learning process. This integration can be better understood through the lens of the ADDIE Model, a 5-phase framework for training and instruction: Analysis, Design, Development, Implementation, and Evaluation (ADDIE). (1) Analysis. AI-powered systems can analyze pre-assessment data, historical performance metrics, and behavioral indicators to identify patterns in learners' understanding, cognitive readiness, and engagement levels (Holmes et al., 2019). Through machine learning, AI can classify learners into distinct groups based on their learning styles, preferences, and cognitive traits, enabling more effective differentiated instruction (Essa et al., 2023). By enabling educators to better understand students' needs and offer more individualized learning experiences, these applications collectively show how AI can support

data-driven decision-making. (2) Design. AI tools enhance instructional planning, generating lesson outlines by analyzing curriculum standards and previous instructional designs, reducing teachers' workload while ensuring alignment with educational goals (Alshammari & Al-Enezi, 2024). It can automate aspects of instructional development, allowing educators to focus more on pedagogical quality and learner individualization (Edutopia, 2023; University of Cincinnati Online, 2023). Hongli and Leong (2024) mentioned that AI-driven personalization tools help remove systemic barriers by addressing the needs of learners and promoting inclusive learning in low-resource settings. According to Dhakal and Devkota (2024), AI tools are transforming traditional teaching methods. These results show that AI supports inclusive and learner-centered approaches in education in addition to increasing instructional efficiency. (3) Development. AI-driven curriculum tools assist educators in formulating measurable objectives across cognitive levels, from remembering to creating (AlAfnan, 2024). Although AI is not a new concept, its increasing integration into education raises important questions regarding its impact on teachers' planning time and classroom instruction. This implies that although AI offers chances to enhance instructional development, its application should take educators' evolving roles and responsibilities into account. (4) Implementation. AI systems function as virtual teaching assistants by answering questions, guiding students through learning tasks, and promoting self-regulated learning (Roll & Wylie, 2016). AI-enabled intelligent tutoring systems also adapt to students' real-time progress, providing immediate and targeted support (Lin et al., 2023). Additionally, learning analytics dashboards powered by machine learning offer timely insights that allow instructors to monitor student engagement, mastery, and interaction (Chen et al., 2020; Zawacki-Richter et al., 2019). These applications demonstrate how AI can improve classroom support by giving teachers quick feedback and enabling them to better respond to students' learning progress. (5) Evaluation. AI continues to act as virtual teaching assistants by responding to students' real-time progress and delivering targeted interventions when needed. In several applications of AI in education, teachers can integrate AI lessons as supplementary materials to assist struggling students and provide hands-on learning experiences (Fahimirad & Kotamjani, 2018). Overall, research indicates that integrating AI throughout the ADDIE Model can improve teaching methods; however, its efficacy is contingent upon its responsible application, teacher participation, and ethical and educational considerations.

ADDIE Model in Teaching Strategy

The ADDIE model, introduced by Rosset (1987), is a 5-phase (Analysis, Design, Development, Implementation, and Evaluation) framework for training and instructional design that provides essential guidelines for creating teaching and learning materials. It also assists other factors that contribute to the development of effective instructional strategies (Jalil & Shahri, 2021).

Through the ADDIE model, teachers can systematically analyze the learning needs of the students (Yeh and Tseng, 2019).

In the Analysis phase, educators examine learners and other factors that may influence instruction. The Design phase focuses on creating a blueprint for instructional materials and activities, including planning content, instructional strategies, and assessment methods. By considering learning objectives, learning styles, and multimedia integration, teachers can design engaging learning experiences (Handrianto et al., 2021). The Development phase involves the actual creation of instructional materials where technology plays a key role, enabling the production of interactive learning resources. In the Implementation phase, teachers execute the instructional plan, manage classrooms effectively, and actively involve students in learning activities (Handrianto et al., 2021; Sial et al., 2024). This phase allows for real-time feedback and adjustments to meet learners' needs, while the Evaluation phase assesses the effectiveness of the instructional design and its impact on the learners. Through feedback collection and measurement of learning outcomes, educators can identify areas for improvement (Handrianto et al., 2021).

Traditional education systems, however, have often been criticized for not keeping pace with the evolving needs of learners and the demands of the 21st-century workforce (Adeoye et al., 2024). Technological integration is also highlighted as essential for increasing student engagement and personalization of instructional strategies (Maqsood et al., 2025). The widespread use of the ADDIE model in educational resource creation demonstrates its effectiveness in improving teachers' instructional practices (Almelhi, 2021; Chalifah, Leksono, & Karyono, 2020; Ebru, 2020; Adelowo et al., 2024). As AI becomes part of society in many ways, education must be knowledgeable about its ethics and user privacy when integrating it within academic institutions. Siau and Wang (2020) defined AI ethics as the field related to the study of ethical issues in AI. It focuses on ethical principles, rules, guidelines, policies, and regulations necessary to address potential ethical and moral issues caused by AI. Ethical AI refers to AI systems that perform and behave ethically. Similarly, Kakarala and Rongali (2025) emphasized the importance of AI cybersecurity, decentralized data storage, anonymization techniques, and strong ethical AI governance structures in ensuring responsible AI development. Therefore, as institutions explore the potential of AI in higher education, it is essential to embrace innovation responsibly while ensuring that education remains relevant, high-quality, and accessible in a rapidly changing world (Mishra & Srivastava, 2024).

Theoretical Framework

Constructivist theory suggests that learners build knowledge through their own experiences. While this theory explains how students learn, the ADDIE model provides the blueprint for how to teach them. These learning theories guide teachers in understanding the factors that influence students' learning processes.

In the Analysis phase of the ADDIE Model, AI can help teachers understand learners' prior knowledge, identify gaps, and analyze learning styles, aligning with constructivist principles that emphasize understanding learners' needs. As learners encounter new information, they reconcile it with prior knowledge, either modifying their existing beliefs or discarding irrelevant information (Beda & Olusegun, 2015). In the Design phase, AI assists teachers in planning learner-centered and interactive activities. Constructivism has roots in philosophy, psychology, sociology, and education, and understanding its implications is essential for teaching and professional development (Tam, 2000). Its central idea is that learners build new knowledge upon prior experiences, in contrast to passive models of learning where information is simply transmitted from teacher to student (Beda & Olusegun, 2015). In the Development phase, AI contributes to the creation of meaningful learning materials, supporting students in constructing knowledge through experience. During the Implementation phase, AI facilitates active learning and student engagement by supporting discussions and collaborative learning opportunities. Constructivist learning theory explains that learners produce knowledge and form meaning based on their experiences. Two key processes shape this construction of new knowledge: Assimilation, which allows individuals to incorporate new experiences into existing frameworks, while Accommodation involves re-framing new experiences within existing mental structures, altering perceptions and understanding (Beda & Olusegun, 2015). In the Evaluation phase, AI provides formative assessment, enabling continuous improvement. This aligns with the constructivist focus on meaningful, learner-centered instruction. Learning must occur in environments that promote active engagement, as active participation is a central tenet of the theory (Tam, 2000).

From these perspectives, it is crucial to examine the application of the ADDIE Model and AI in the instruction of faculty members at Divine Word College of Legazpi (DWCL) to determine effective approaches for integrating AI into academic operations. The institution continues to serve the needs of the community. In 2024, the institution launched its AI Policy, yet no studies have been conducted on AI integration into teaching strategies within the institution. This gap highlights the need for a systematic evaluation of how teachers currently use AI in teaching and learning. The findings of this study may serve as a basis for enhancing policies or guidelines, particularly in the area of teaching and learning.

Conceptual Framework

This study highlights the five phases of the ADDIE Model and analyzes the integration of AI in each phase. Specifically, the study considers the apparent effectiveness of AI use in the Analysis phase, particularly in identifying learner needs and learning gaps. The Design phase centers on AI-assisted lesson planning and instructional design. The Development phase examines the use of AI in teaching materials and content creation. The Implementation phase looks into AI-supported lesson delivery and classroom management, while the Evaluation phase centers on assessment, grading, and feedback. All major elements of the ADDIE Model are utilized in this study to determine the efficiency of AI integration across these phases among faculty members of DWCL. Once the level of effectiveness is identified, the study further investigates the challenges encountered by faculty members in using AI. It proposes possible recommendations to enhance the effective integration of AI in teaching and learning.

Statement of the Problem

This study sought answers to the following questions:

1. What evidence of the application of AI use by teachers is reflective of the ADDIE model in the following instructional phases:
    a. Analysis
    b. Design
    c. Development
    d. Implementation
    e. Evaluation
2. Which specific aspects of AI integration are perceived as most effective in those phases?
3. What challenges do teachers encounter in using AI in their teaching strategies?
4. What strategies may be proposed to maximize the efficiency of AI integration in teaching and learning?

Research Instrument

A self-developed, semi-structured survey questionnaire was utilized as the primary research instrument. The questionnaire consisted of four parts. The first part focuses on identifying how faculty members use AI tools in each phase of the ADDIE Model. The second part measures the perceived effectiveness of AI integration across the ADDIE phases using a 5-point Likert scale. The third part identifies the challenges encountered by faculty members in using AI across these phases, while the fourth part gathers recommendations from faculty members to enhance the effective and efficient integration of artificial intelligence in teaching and learning.

The research instrument underwent content validation by the Research Office, which checked the alignment of the questionnaire with the statement of the problem, and was pilot-tested among faculty members of the Senior High School Department of DWCL before its full administration.

Respondents of the Study

The respondents of the study were the full-time and part-time faculty members of DWCL, both tenured and non-tenured in the tertiary level. Through total enumeration, the study included 168 faculty members employed during the second semester of the SY 2025–2026, of which 84 survey questionnaires were retrieved, recording a 50% retrieval rate.

Data-Gathering Procedure

A letter to allow the conduct of the survey, duly approved by the Office of the President and the Office of the Vice President for Academic Affairs, was submitted to the college dean, along with the research tool. Upon approval, the questionnaire was converted into a Google Form and distributed to the respondents through the official group chats and was collected within 3 weeks.

Data Analysis

The collected data were analyzed using descriptive statistical techniques such as frequency, weighted mean, and percentage. Thematic analysis was applied to open-ended responses to identify themes. AI tools such as Grammarly and ChatGPT were used for grammar checking.

Ethical Considerations

Ethical standards were observed in this study by maintaining the confidentiality of the data. Related literature was properly cited in the use of their ideas throughout the study. Similarly, AI was utilized mainly for grammar checking to adhere to academic standards while the ideas and content of the study remained original and were developed by the researchers.

Results and Discussion

This sub-section presents the findings on the use and effectiveness of each phase of the ADDIE model in the teaching strategies, as employed by faculty members of DWCL.

I. AI Application by Teachers Reflective of the ADDIE Model

This section presents evidence of the application of AI in the teaching strategies across the instructional phases of the ADDIE Model: Analysis, Design, Development, Implementation, and Evaluation. Table 1 presents the uses of AI in the analysis phase. Among the 64 respondents (76%), the top-ranked use of AI was diagnostic tests and quizzes. These findings suggest that AI assists teachers in identifying learner needs and learning gaps, particularly in preparing diagnostic tests and understanding students' learning performance. The frequent use of AI for assessment tests and quizzes may be based on a teacher's fast assessment of the students' strengths and weaknesses to improve class performance.

Table 1: Identifying Learner Needs and Gaps *(N=84)

Indicators	Frequency	Percentage
for diagnostic tests and quizzes	64	76
analyze student performance data	37	44
identify learning styles or personalized needs	47	56
predict at-risk students	12	14
gather and analyze feedback from students	18	21

*Multiple Responses

The study by Holmes et al. (2019) found that AI-powered systems can analyze pre-assessment data, historical performance metrics, and behavioral indicators to recognize patterns in learners' understanding, cognitive readiness, and engagement levels. The results of this study indicate that AI is an important tool for teachers to find out what needs and gaps they have before designing instructional materials. By enabling faculty members to design more targeted interventions and personalized learning strategies for students, the integration of AI in teaching can enhance instructional decision-making.

The Design phase refers to the lesson planning and instructional design using AI. Table 2 presents the use of AI in this phase. Through multiple selection, 63 of the respondents (75%) identified “suggesting teaching strategies and activities” as the top use of AI in providing suggestions for teaching strategies and classroom activities. This common use of AI for suggesting teaching strategies and activities suggests that faculty members of DWCL utilize AI to explore different approaches that may address diverse learning styles, student attitudes, and classroom needs. Through AI-generated suggestions, teachers may develop more engaging and appropriate learning activities that support effective instruction.

Though “generating lesson plans” got the lowest frequency (42%), it was also considered useful in the Design phase. This implies that AI supports teachers in improving instructional planning, organizing learning materials, and aligning classroom activities with learning objectives, enhancing the efficiency and quality of instructional design, while reducing the time required for lesson preparation. These results aligned with the study of Alshammari et al. (2024), that AI-powered tools can generate lesson outlines by analyzing curriculum standards and reducing teachers’ workload while ensuring alignment with educational goals.

Table 2: Lesson Planning and Instructional Design

Indicators	Frequency	Percentage
for generating lesson plans	35	42
to suggest teaching strategies and activities	63	75
for creating outlines or modules	47	56
to recommend instructional resources (e.g., articles, videos)	48	57
to create assessments aligned with objectives	47	56

Table 3: Teaching Materials and Content Creations

Indicators	Frequency	Percentage
to create multimedia content	56	67
for designing interactive activities	46	55
to generate reading materials or summaries	43	51
to adapt content for different learning levels	26	31
in creating handouts, worksheets, or exam items	45	54

The Development phase focuses on utilizing artificial intelligence (AI) to create teaching materials. This phase is closely linked to the Design phase, as planned instructional strategies are converted into tangible learning materials and educational resources. Table 3 outlines the applications of AI during the Development phase. The most prevalent use of AI is the creation of multimedia content (67%), indicating that AI is effective in producing instructional materials and diverse content formats that enhance interactivity and engagement in teaching. The extensive use of AI for multimedia content development demonstrates its capacity to generate instructional resources that are student-friendly, visually appealing, and conducive to student learning. Additionally, the indicator 'adapting content for different learning levels' (ranked fifth) was identified as a significant application of AI (31%). The results indicate that AI supports faculty members in enhancing the efficiency of content development and facilitates differentiated instruction by adapting materials to students’ varying learning needs and levels.

Furthermore, AI aids educators in producing instructional resources that are more engaging, accessible, and organized, thereby potentially improving the overall teaching and learning process.

These findings are consistent with the study by Lumpo (2023), which noted that while AI is not a novel concept, its growing integration into education prompts critical questions about its effects on teachers' planning time and classroom instruction. Lumpo (2023) further highlighted that AI provides benefits in differentiation, automation, time management, and content creation, although it also introduces challenges that require attention. These observations reinforce the present study's conclusion that AI plays a significant role in the development of instructional materials and interactive learning resources for faculty members.

Table 4: Lesson Delivery and Classroom Management

Indicators	Frequency	Percentage
for presentation or teaching assistants	51	61
for interactive class discussions	40	48
to monitor student engagement during lessons	21	25
for classroom management systems	25	30
in virtual or hybrid learning delivery	43	51

The Implementation phase follows the initial three phases of the ADDIE Model: Analysis, Design, and Development. This phase emphasizes the application of artificial intelligence (AI) in lesson delivery and classroom management. Table 4 presents the reasons for AI utilization during this phase, with the indicator "for presentations or teaching assistants" (61%) identified as the most common. These results indicate that AI is extensively employed in lesson delivery, particularly for presentations and teaching assistance, thereby enhancing the engagement of teaching experiences. The use of AI in this context suggests that faculty members leverage it to provide timely support and deliver presentations that are aligned with students' needs and instructional materials.

Additionally, 21 respondents (25%) reported using AI to monitor student engagement during lessons, suggesting that AI can be effectively integrated into classroom discussions and management practices. AI also assists faculty members in tracking student participation, thereby supporting a more responsive and technology-enhanced learning environment. These findings are consistent with Roll and Wylie (2016), who found that AI systems serve as virtual teaching assistants by answering questions, guiding students through learning tasks, and promoting self-regulated learning. Similarly, Lin et al. (2023) noted that AI-enabled intelligent

tutoring systems adapt to students' real-time progress by providing targeted support. Overall, the use of AI by faculty members at DWCL in lesson delivery and classroom management demonstrates its utility across various instructional activities.

Table 5 presents the evaluation phase, which focuses on assessment, grading, and feedback conducted by teachers. This phase demonstrates the application of AI in evaluating student performance. The data indicate that the indicator "generating rubrics and scoring guides" was selected by 63% of respondents, suggesting that AI provides substantial support to faculty members in assessing students' performance in classroom activities and examinations. Additionally, AI assists faculty members in the automatic grading of quizzes and assignments, thereby increasing the efficiency and organization of the evaluation process. This approach may also align with the preceding four phases before the generation of rubrics for student grading.

Table 5: Assessment, Grading, and Feedback

Indicators	Frequency	Percentage
for automatic grading of quizzes and assignments	29	35
to provide instant feedback to students	22	26
to generate rubrics and scoring guides	53	63
to track student progress and performance	27	32
for outcome-based assessment reports	29	35

These findings indicate that faculty members at DWCL utilize AI to support assessment, grading, and feedback processes, as well as to monitor student progress and learning outcomes. This result is consistent with the findings of Fahimirad and Kotamjani (2018), who reported that AI can manage various tasks such as grading and providing constructive feedback on student performance. Overall, the evidence suggests that AI is useful for assessing, grading, and providing feedback on student outputs and projects.

II. Perceived effectiveness of AI integration in ADDIE Phases.

This section presents the perceived effectiveness of AI integration across the phases of the ADDIE Model, as reported by the respondents. Table 6 presents key indicators that demonstrate the effectiveness of AI integration during the Analysis phase.

The results indicate that all indicators were rated as Effective, with a general weighted mean (GWM) of 3.62. The indicator 'learning gaps are accurately identified' received the highest

rating (3.81). These findings suggest that integrating AI in the Analysis phase facilitates the identification of learning gaps and the diagnosis of student needs. Although the indicator 'potential dropouts are effectively identified' was rated as Moderately Effective (3.35), the data imply that while AI is generally effective in analyzing learner needs, its ability to identify at-risk students may require further enhancement. According to Essa et al. (2023), machine learning techniques enable AI to classify learners into distinct groups based on learning styles, thereby supporting more effective differentiated instruction. Overall, the perception among faculty members is that AI is an effective tool for identifying learning gaps and student needs.

Table 6: Identifying Learner Needs and Gaps (N=84)

Indicators	Weighted Mean	Interpretation
Learning gaps are accurately identified	3.81	Effective
Student needs are effectively diagnosed	3.65	Effective
Meaningful insights into class performance	3.74	Effective
Potential dropouts are effectively identified	3.35	Moderately Effective
Feedback generated accurately reflects students' learning experiences	3.56	Effective
General Weighted Mean (GWM)	**3.62**	**Effective**

Legend: 1.00–1.49 – Not Effective; 1.50–2.49 – Somewhat Effective; 2.50–3.49 – Moderately Effective; 3.50–4.49 – Effective; 4.50–5.00 – Highly Effective

Table 7 summarizes key aspects of AI integration during the Design phase.

Table 7: Lesson Planning and Instructional Design

Indicators	Weighted Mean	Interpretation
Lesson plans generated with AI align with intended learning outcomes	4.01	**Effective**
Teaching strategies are improved through recommendations	4.19	**Effective**
Well-structured and coherent modules are developed	3.99	**Effective**
Appropriate and relevant learning resources are selected	4.00	**Effective**
Valid and aligned assessments are created	3.95	**Effective**
GWM	**4.03**	**Effective**

The findings indicate that all indicators were rated as Effective, with a grand weighted mean (GWM) of 4.03. The indicator 'Teaching strategies are improved through recommendations'

received the highest score (4.19), suggesting that AI integration in lesson design is perceived as effective in enhancing teaching strategies, supporting faculty in improving lesson planning quality, and enriching student learning experiences. The study by Dhakal and Devkota (2024) supports these results, positing that AI technologies are transforming traditional teaching methods by providing personalized and data-driven learning experiences. These findings confirm that AI enhances instructional design by improving lesson planning, teaching strategy development, and facilitating the selection of appropriate and relevant learning resources.

Table 8 presents the results from the Development phase regarding the integration of artificial intelligence in teaching materials and content creation. The overall perceived effectiveness of AI integration yielded a General Weighted Mean (GWM) of 3.98, which is interpreted as Effective. The highest-rated indicator was "the quality of instructional and multimedia materials is enhanced" (4.10). These findings indicate that AI supports faculty members in improving the quality of instructional materials, developing interactive learning activities, and producing clear and accurate teaching resources. AI also enhances instructional delivery by facilitating the adaptation of content to diverse learner needs. These results are consistent with the study by Al Afnan (2024), which emphasized that AI supports the alignment of learning outcomes with educational frameworks such as Bloom's Taxonomy and that AI-driven curriculum tools assist educators in developing measurable objectives across cognitive levels.

Table 8: Teaching Materials and Content Creations

Indicators	Weighted Mean	Interpretation
The quality of instructional and multimedia materials is enhanced	4.10	Effective
Engaging and interactive learning activities are developed	4.01	Effective
Students' understanding of lessons is improved	3.93	Effective
Instructional content is effectively adapted to learners' needs	3.93	Effective
Clear and accurate instructional materials are produced	3.94	Effective
GWM	**3.98**	**Effective**

Table 9 presents the integration of AI in the implementation phase, particularly in Lesson Delivery and Classroom Management.

Table 9: Lesson Delivery and Classroom Management

Indicators	Weighted Mean	Interpretation
Lesson delivery is improved	4.12	Effective

Students' participation and classroom interaction are enhanced	3.98	Effective
Students' engagement is effectively monitored	3.80	Effective
Classroom management is supported	3.80	Effective
The virtual or hybrid learning experiences improve	4.05	Effective
GWM	**3.95**	**Effective**

The results show an overall effective interpretation throughout all indicators, with a general weighted mean (GWM) of 3.95. The indicator 'lesson delivery is improved' received the highest rating at 4.12 among the uses of AI in the implementation phase. These outcomes suggest that AI is perceived as effective in improving instructional delivery, increasing student participation, and supporting classroom management in both face-to-face and blended learning environments. This is consistent with the findings of Chen et al. (2020) and Zawacki-Richter et al. (2019), who emphasized that learning analytics dashboards powered by machine learning provide timely insights for monitoring student involvement, mastery, and interaction. These results show the role of AI in supporting faculty members, particularly in improving lesson delivery and classroom management.

Table 10 presents the integration of AI in the Evaluation phase, particularly in Assessment, Grading, and Feedback. Results show an overall perceived Effective interpretation throughout all indicators, with a GWM of 3.75, with "timely and meaningful feedback is provided (3.80) being the top indicator. The findings show that faculty members effectively utilize AI to provide feedback, guarantee equitable assessment practices, and evaluate student learning outcomes. In addition, student performance is accurately assessed (3.74), and student progress is effectively tracked (3.68), both of which are interpreted as effective. The results suggest that AI is perceived as effective in supporting faculty members by improving the effectiveness and correctness of assessment and feedback. This implies that including AI in evaluation helps faculty members enhance the quality of assessment and improve the observation of students' learning progress. This study is consistent with the findings of Mishra and Srivastava (2024), who emphasized the importance of adopting innovation responsibly while ensuring that education remains relevant and accessible in a swiftly evolving world.

Table 10: Assessment, Grading, and Feedback

Indicators	Weighted Mean	Interpretation
Student performance is accurately assessed	3.74	Effective
Timely and meaningful feedback is provided	3.80	Effective
Fair and consistent assessments are ensured	3.77	Effective

Student progress is effectively tracked	3.68	Effective
Learning outcomes are accurately evaluated	3.75	Effective
GWM	**3.75**	**Effective**

III. Challenges Encountered in Using AI in Teaching Strategies

From the participants' responses, several themes emerged from the content analysis made following the thematizing process. Examples of verbatim responses are presented.

THEME	**Respondents' comments**
Accuracy and Reliability of AI Outputs (6)	1. It sometimes 'hallucinates', ensuring absolute mathematical precision is difficult, as even small 'hallucinations' in engineering problems can lead to big errors (3). 2. AI Language Learning Models conjure incorrect information (3).
Need for Validation and Human Verification (4)	1. Some content needs to be checked to verify concrete or valid info (2) 2. The effectiveness of AI depends on the prompt given. (2)
Student Over-dependence and Critical Thinking Concerns (5)	1. Learners can become too dependent on AI products rather than learn to think critically. (3) 2. My biggest challenge is ensuring students don't treat AI like a magic wand. 3. There should be limitations, meaning students must think of what is/are the answers.
Academic Integrity and Ethical Issues (4)	1. Plagiarism and data privacy need constant monitoring. (2) 2. Making sure that I do not compromise any personal data before I use AI. 3. Cannot verify if the same is used by students to perform course requirements.
Limited Knowledge and AI Skills (7)	1. Computer literacy (2) 2. My lack of technical knowledge in navigating AI tools. (5)
Internet Connectivity (5)	1. Slow internet connection (3) 2. The institution's unstable internet connection (2)
Subscription Costs and Feature Limitations (5)	1. High cost of AI platform subscriptions. (2) 2. There are limitations on the use of AI. (3)
Prompting Challenges (3)	1. The effectiveness of AI depends on the command/prompting (2) 2. Limitations in prompting

Difficulty Aligning AI Content with Learning Outcomes (3)	1. There are times when the output of AI does not follow your intended learning outcome. (2) 2. AI-generated content is not always fully applicable to teaching the faith.
Positive Perception of AI as Teaching Support (3)	1. AI makes tasks easier. (3)

The challenges associated with using AI focus primarily on the precision and dependability of outputs, insufficient technical knowledge, and constraints related to connectivity and costs. Concerns about validation, excessive dependence on students, ethical issues surrounding prompting, and a lack of correspondence with learning outcomes were also identified. However, although there were challenges, faculty still viewed AI as an important aid in teaching strategy. The top two problems encountered by faculty members in using AI across the ADDIE phases were Limited Knowledge and AI Skills (7). Limited knowledge affects the development, implementation, and evaluation phases because machine-generated content must be verified before generating or promoting instructional materials. Precision and Trustworthiness of AI Outputs (6) may affect both development and evaluation, as faculty need to verify all outputs; all results provided by AI must be accurate and appropriate before being used in teaching.

IV. Recommendations to address Challenges

From the challenges encountered in using AI in their teaching strategies, the following recommendations were drawn from the emerging themes.

1. **Establish a stable internet connection. In**ternet connectivity issues are mentioned challenges where some respondents emphasized the need "*to have a stable internet" and* "U*nstable internet connection"*.

2. **Validate AI outputs.** Respondents shared that "*sometimes AI provides unreliable sources*," while others expressed, "AI *does not provide accurate answers*". *I*n addition, respondents noted challenges related to the **AI outputs.** *"One challenge I've experienced is that AI-generated content sometimes doesn't exactly match my lesson"* and *"There are times when the output of AI does not follow the intended learning outcome."*

3. Reduced AI dependency. Respondents highlighted concerns about using AI. "L*earners can become too dependent on AI rather than learn to think critically".*

4. Strict Monitoring on Ethics and Data Privacy. Concerns about **academic integrity, ethics, and data privacy** in utilizing AI were identified. They have also noted that *"issues around plagiarism and data privacy need constant monitoring".*

5. AI Prompting Training. Some responses expressed *"My lack of technological knowledge in navigating AI tools."* Additionally, respondents identified concerns in **prompting.** They mentioned *"The effectiveness of AI depends on the quality of the command or prompt."*

6. Purchase AI Tools. Respondents mentioned that **subscription costs and limited features** were key challenges in using AI tools. They highlighted the *"high cost of subscription for various AI platforms," "subscription needed," and "limited usage or capability usage because my access is only for free."* Respondents also pointed out *"the only challenge is the monthly bills that we personally cover."*

7. AI support teaching strategies. Respondents highlighted the p**ositive support of AI in teaching.** This was reflected in statements such as, *"it is easy and fast in answering all the questions and great help in teaching strategies."*

Conclusion

The integration of AI in each phase of instructional preparation and teaching strategies is helpful and effective, particularly in the Design phase, which emphasizes lesson planning and instructional design. However, there are challenges that DWCL consider in the application of AI in teaching, such as the accuracy and reliability of AI outputs, academic integrity and ethical issues, limited technical knowledge and AI skills, internet connectivity and technological limitations, subscription costs and limited features, and difficulties in prompting. These challenges may serve as bases for the review of the existing policy on the use of AI, the development of prompt guides, and the inclusion of AI integration in the institution's strategic vision.

Limitation of the study

This study is limited to examining the perceptions of DWCL faculty members regarding the use and effectiveness of artificial intelligence (AI) across the ADDIE instructional design phases. Future research could further investigate the application of AI by incorporating student learning outcomes, conducting classroom observations, comparing results across departments, assessing AI literacy, and performing longitudinal evaluations of AI policy implementation.

Additionally, the findings of this study may be utilized to validate effectiveness from the student perspective.

References

Adcock, P. K. (2008). Evolution of teaching and learning through technology. *The Delta Kappa Gamma Bulletin, 74*(4), 37–42. https://digitalcommons.unomaha.edu/cgi/viewcontent.cgi?article=1057&context=tedfacpub

Adelowo, K., Ahmad, A. B., & Pairan, M. R. B. (2024). Development of an effective instructional teaching module in TVET: A comparative review of ADDIE and Needham's five-phase instructional design model. *International Journal of Academic Research in Progressive Education and Development, 13*(4). https://doi.org/10.6007/IJARPED/v13-i4/22946

AlAfnan, M. A., & Al, M. (2024). Taxonomy of educational objectives: Teaching, learning, and assessing in the information and artificial intelligence era. *Journal of Curriculum and Teaching, 13*(4), 173–191.

Almelhi, A. M. (2021). Effectiveness of the ADDIE model within an e-learning environment in developing creative writing in EFL students. *English Language Teaching, 14*(2), 20–36.

Alshammari, A., & Al-Enezi, S. (2024). Role of artificial intelligence in enhancing learning outcomes of pre-service social studies teachers. *Journal of Social Studies Education Research, 15*(4), 163–196.

Chalifah, L., Leksono, I. P., & Karyono, H. (2020). The teacher's reflection on the development procedure of instructional material following the ADDIE model. *International Journal of Latest Research in Humanities and Social Science, 3*(5), 18–22.

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access, 8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Dhakal, A. P., & Devkota, B. (2024). Use of artificial intelligence in teaching and learning environment: A case of using ChatGPT. *NPRC Journal of Multidisciplinary Research, 1*(9), 12–23. https://doi.org/10.3126/nprcjmr.v1i9.74139

Edutopia. (2023). *7 AI tools that help teachers work more efficiently.* https://www.edutopia.org/article/7-ai-tools-that-help-teachers-work-more-efficiently/

Ebru, K. O. Ç. (2020). Design and evaluation of a higher education distance EAP course by using the ADDIE model. *Elektronik Sosyal Bilimler Dergisi, 19*(73), 522–531.

Essa, S. G., Celik, T., & Human-Hendricks, N. E. (2023). Personalized adaptive learning technologies based on machine learning techniques to identify learning styles: A systematic literature review. *IEEE Access, 11*, 48392–48409. https://doi.org/10.1109/ACCESS.2023.3284635

Fahimirad, M., & Kotamjani, S. S. (2018). A review on application of artificial intelligence in teaching and learning in educational contexts. *International Journal of Learning and Development, 8*(4), 106–118.

Handrianto, C., Jusoh, A. J., Goh, P. S. C., & Rashid, N. A. (2021). Using the ADDIE model for designing instructional strategies to improve teaching competency of secondary school teachers. *Proceeding Webinar Konvensyen Kaunseling Kebangsaan Kali Ke, 22*, 361–371.

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning.* Center for Curriculum Redesign.

Hongli, Z., & Leong, W. Y. (2024). AI solutions for accessible education in underserved communities. *Journal of Innovation and Technology.*

Jalil, A. H. A., & Shahri, M. I. (2021). Pembinaan rubrik kemahiran insaniah bagi matapelajaran kokurikulum pelajar program matrikulasi Kementerian Pendidikan Malaysia. *Jurnal Penyelidikan Dedikasi, 17*, 129–149.

Jamil, M., & Shah, J. H. (2011). Technology: Its potential effects on teaching in higher education. *New Horizons in Education, 59*(1), 38–51. https://files.eric.ed.gov/fulltext/EJ955474.pdf

Kakarala, M. K., & Rongali, S. K. (2025). *Data privacy and security in AI.* SSRN. https://doi.org/10.2139/ssrn.5795322

Lin, C. C., Huang, A. Y., & Lu, O. H. (2023). AI in intelligent tutoring systems toward sustainable education: A systematic review. *Smart Learning Environments, 10*(1), Article 41.

Morris, P., & Williamson, J. (1998). *Teacher education in the Asia-Pacific region: A comparative analysis.* eCite Digital Repository.

Murati, R., & Ceka, A. (2017). The use of technology in educational teaching. *Journal of Education and Practice, 8*(6), 197–199.

Rajagopalan, I. (2019). Concept of teaching. *Shanlax International Journal of Education, 7*(2), 5–8. https://doi.org/10.34293/education.v7i2.329

Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. *International Journal of Artificial Intelligence in Education, 26*(2), 582–599. https://doi.org/10.1007/s40593-016-0110-3

Rossett, A. (1987). *Training needs assessment.* Educational Technology Publications.

Sial, Z. A., Fatima, Z., & Fatima, S. Z. (2024). ADDIE model of instructional effectiveness: Analyzing the impact on students' learning. *Journal of Law & Social Studies, 6*(1), 64–72. https://doi.org/10.52279/JLSS.06.01.6472

Siau, K., & Wang, W. (2020). Artificial intelligence (AI) ethics. *Journal of Database Management, 31*(2), 74–87. https://doi.org/10.4018/JDM.2020040105

Slade, J. J., Byers, S. M., Becker-Blease, K. A., & Gurung, R. A. R. (2024). Navigating the new frontier: Recommendations to address the crisis and potential of AI in the classroom. *Teaching of Psychology.* Advance online publication. https://doi.org/10.1177/00986283241276098

Tang, K. H. D. (2024). Implications of artificial intelligence for teaching and learning. *Acta Pedagogia Asiana, 3*(2), 65–79.

Trinidad, E. M. C. (2018). The changing perspective of teaching as a profession. *The International Journal of Research in Teacher Education, 9*(4), 25–35. https://ijrte.penpublishing.net/makale/684

Trust, T., & Pektas, E. (2018). Using the ADDIE model and Universal Design for Learning principles to develop an open online course for teacher professional development. *Journal of Digital Learning in Teacher Education.* https://doi.org/10.1080/21532974.2018.1494521

United Nations. (n.d.). *Artificial intelligence.* https://www.un.org/en/global-issues/artificial-intelligence

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1). https://doi.org/10.1186/s41239-019-0171-0

P26017

Institutional Drivers of Academic Integrity Readiness in AI-Enabled Higher Education: The Roles of Governance, Culture, Pedagogy, and Operational Support

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Abstract. The increasing adoption of artificial intelligence (AI) in higher education has created new challenges related to academic integrity, institutional accountability, and responsible AI implementation. This study examined institutional factors associated with student-perceived Academic Integrity Readiness by investigating the roles of AI Governance, Pedagogical AI Practices, Operational AI Support, and Institutional Culture. Guided by Institutional Theory and Chan's AI Ecological Education Policy Framework, a descriptive-correlational predictive design was employed involving 543 undergraduate students selected through stratified random sampling. Data were collected using a validated questionnaire and analyzed using descriptive statistics, reliability analysis, confirmatory factor analysis, Pearson correlation, multiple regression, and Hayes' PROCESS Macro Model 4 for mediation analysis. All institutional dimensions were positively correlated with Academic Integrity Readiness. However, AI Governance did not show a significant unique association with Academic Integrity Readiness after Institutional Culture, Pedagogical AI Practices, and Operational AI Support were considered, and the hypothesized indirect effect through Institutional Culture was not supported. Institutional Culture showed the strongest unique positive association, followed by Pedagogical AI Practices. The findings refine the institutional perspective by distinguishing the presence of formal AI governance from the cultural and pedagogical enactment of responsible AI principles. They also suggest that Academic Integrity Readiness is best understood as a coordinated institutional condition rather than an outcome of policy presence alone. Because the study was cross-sectional and based on student self-reports from one institution, the results are interpreted as associations rather than causal effects. The study provides evidence for institutional monitoring, governance review, faculty development, and culture-based approaches to responsible AI adoption in higher education.

Keywords: *Artificial Intelligence; Academic Integrity; AI Governance; Institutional Readiness; Higher Education Policy; Institutional Culture*

Introduction

The rapid integration of artificial intelligence (AI) into higher education is reshaping teaching, learning, assessment, and institutional governance. While AI offers opportunities to enhance

educational quality and innovation, it also presents significant challenges related to academic integrity, institutional accountability, and responsible AI implementation (Lee et al., 2024). Although these tools can improve efficiency and widen access to knowledge, they also complicate long-standing expectations around authorship, originality, accountability, and fairness, creating new integrity pressures for institutions (Bin-Nashwan et al., 2023; Rasul et al., 2024). As AI becomes embedded in everyday academic routines, academic integrity concerns increasingly reflect not only individual choices but also how well institutions are prepared to guide and govern AI use (Bittle & El-Gayar, 2025).

Much of the discussion on AI and academic integrity focuses on risk detection or classroom-level controls. International organizations have increasingly emphasized that higher education institutions require comprehensive governance frameworks to ensure that AI enhances educational quality while safeguarding ethical standards, academic integrity, and public trust (UNESCO, 2023). Responsible AI integration requires institutional conditions where governance structures, pedagogical practices, operational support, and organizational values collectively promote ethical AI use. Complementing this perspective, Chan's (2023) AI Ecological Education Policy Framework explains how these institutional dimensions interact to support ethical and sustainable AI adoption in higher education (Chan, 2023; UNESCO, 2023). Institutional Theory provides the conceptual foundation for understanding how formal policies, organizational norms, and shared practices shape responsible AI implementation (DiMaggio & Powell, 1983). From this perspective, academic integrity in AI-enabled higher education depends on institutional structures that promote consistent ethical decision-making and responsible AI practices (Chan, 2023; Rasul et al., 2024).

Although previous studies have examined AI governance, academic integrity, pedagogical practices, and institutional support, limited empirical evidence explains how these institutional factors interact to collectively shape Academic Integrity Readiness as an institutional outcome in higher education (Bittle & El-Gayar, 2025). Addressing this gap is essential because universities require evidence on how governance structures, pedagogical approaches, operational support systems, and institutional culture contribute to ethical and responsible AI adoption. Without such evidence, institutional responses may remain fragmented rather than guided by comprehensive and evidence-informed AI governance strategies (Chan, 2023; Rasul et al., 2024).

Emerging empirical evidence further supports this institutional perspective. Bittle and El-Gayar (2025) observed that generative AI presents significant challenges to academic integrity, requiring comprehensive institutional strategies rather than isolated technological solutions. Analogously, Crompton and Burke (2023) reported that the educational value of AI depends largely on how institutions integrate AI into teaching, assessment, and faculty practice. Yusuf et al. (2024) likewise highlighted that responsible AI adoption requires coordinated efforts in AI literacy, authentic assessment, institutional support, and governance.

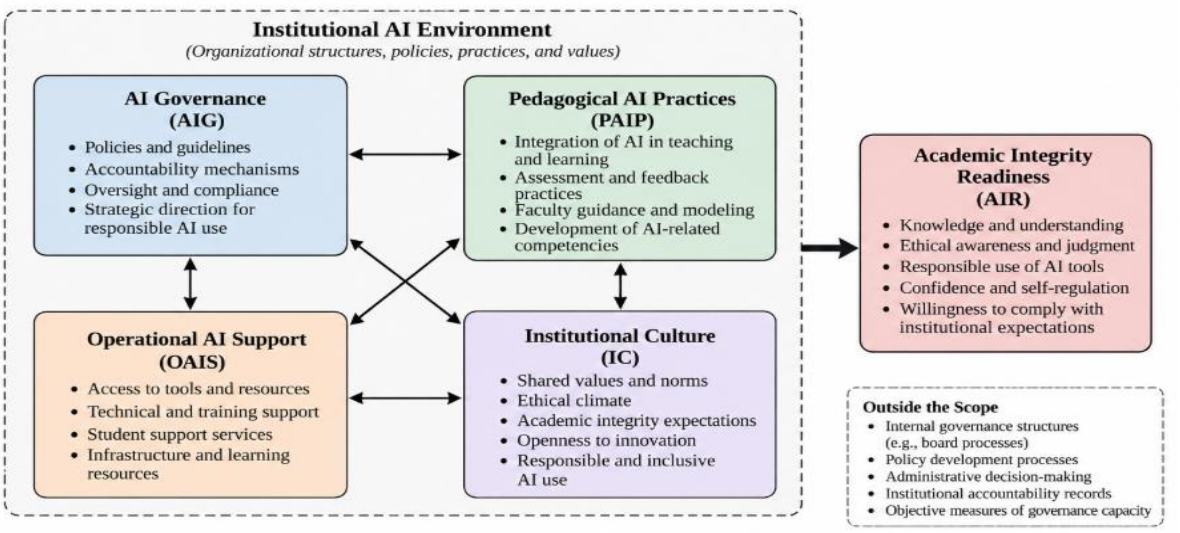
Academic Integrity Readiness in the Age of AI refers to the institutional and stakeholder preparedness to uphold honesty, transparency, accountability, and fairness while integrating AI into

academic activities. Unlike general AI readiness, which primarily focuses on technological capacity, digital competence, infrastructure, and willingness to adopt AI, Academic Integrity Readiness emphasizes the ethical and integrity-related dimensions of AI adoption. It extends beyond policy compliance, which reflects adherence to established rules and procedures, by capturing the institution's proactive capacity to cultivate responsible AI behaviors before integrity violations occur. Similarly, while ethical climate describes shared perceptions of ethical norms within an organization, Academic Integrity Readiness represents the outcome of coordinated governance structures, pedagogical practices, institutional support systems, and cultural values that enable responsible academic decision-making in AI-enabled higher education.

Institutional Culture was proposed as a potential mediating mechanism because formal governance becomes institutionally meaningful when its principles are reflected in shared values, norms, expectations, and routine academic practices. Institutional Theory suggests that formal structures acquire behavioral significance through processes of institutionalization, whereby externally or formally established expectations become embedded within organizational norms and everyday practices (DiMaggio & Powell, 1983; Scott, 2014). In AI-enabled higher education, governance may establish formal expectations regarding responsible AI use, whereas institutional culture reflects the extent to which ethical responsibility, transparency, accountability, and academic integrity are collectively reinforced within the academic environment. Institutional Culture was therefore examined as a theoretically plausible mechanism through which governance could be associated with Academic Integrity Readiness. The mediation analysis tests this proposed mechanism empirically rather than assuming that such institutionalization necessarily occurs.

Existing studies typically evaluate academic integrity through incidents of misconduct or policy compliance. However, these approaches provide limited insight into the extent to which institutions are prepared to foster ethical AI use before integrity issues arise. This study examined through students' perceptions of the governance, cultural, pedagogical, and operational environment they experience. Specifically, it assessed their relationships and predictive influence and examined whether Institutional Culture explains the relationship between AI Governance and Academic Integrity Readiness after accounting for other institutional factors. This framework enables the examination of whether institutional culture represents a potential organizational mechanism linking AI governance and Academic Integrity Readiness. Accordingly, this study addressed the overarching question: How are student-perceived AI Governance, Pedagogical AI Practices, Operational AI Support, and Institutional Culture associated with Academic Integrity Readiness, and does Institutional Culture statistically account for the association between AI Governance and Academic Integrity Readiness?

Figure 1. Conceptual Boundaries and Institutional Framework of Academic Integrity Readiness



Methodology

Research Design

This study employed a quantitative, descriptive-correlational design with mediation analysis using PROCESS Model 4 to examine the hypothesized relationships among AI Governance, Institutional Culture, Pedagogical AI Practices, Operational AI Support, and Academic Integrity Readiness. The design enabled the examination of associations among the study variables without manipulating the research environment (Creswell & Creswell, 2023).

Institutional Culture was specified as the mediator based on the theoretical proposition that formal AI governance may become associated with Academic Integrity Readiness when governance expectations are embedded in shared institutional values, norms, and routine academic practices. Pedagogical AI Practices and Operational AI Support were included as covariates because they represent related instructional and operational conditions that may independently account for variation in Academic Integrity Readiness. Their inclusion allowed the mediation model to estimate the governance–culture–readiness pathway while accounting for variance shared with pedagogical and operational conditions. This specification was theory-driven and should not be interpreted as excluding alternative models in which Pedagogical AI Practices or Operational AI Support may function as mediating or parallel institutional mechanisms.

Students were selected as respondents because the study focused on how institutional AI-related conditions are perceived and experienced within the academic environment. As direct recipients of institutional policies, instructional practices, support services, and academic integrity expectations, students are well positioned to assess the extent to which these institutional conditions are visible, communicated, accessible, and enacted in practice. Accordingly, AI Governance and Operational AI Support were operationalized as student-perceived institutional conditions rather than objective measures of internal governance structures or administrative capacity. The findings therefore reflect

students' perceptions of governance visibility, implementation, and support as experienced within the academic environment.

Participants and Sampling

A total of 543 university students participated in the study using proportionate stratified random sampling to ensure adequate representation across academic units. The sample allocation for each stratum was determined based on its proportion within the total student population. The target and actual number of respondents per stratum were documented to verify proportional representation. This sampling strategy was adopted to capture potential variations in students' perceptions of AI governance, institutional culture, pedagogical AI practices, operational AI support, and academic integrity readiness while minimizing sampling bias (Lohr, 2021). The final sample size was considered adequate for the planned regression and mediation analyses, as larger samples improve statistical power and enhance the stability of bootstrap confidence intervals used in estimating indirect effects (Hayes, 2022).

Data Collection Procedures

Data were collected using a researcher-developed, literature-informed questionnaire designed to assess five institutional dimensions relevant to responsible AI use in higher education: AI Governance, Pedagogical AI Practices, Operational AI Support, Institutional Culture, and Academic Integrity Readiness. The instrument comprised 35 items, with seven items representing each construct. Rather than adopting a single existing scale, the items were developed and adapted from constructs, indicators, and conceptual domains identified in the relevant literature and were subsequently contextualized to the study setting and student population.

Because the respondents were students, the institutional constructs were operationalized in terms of observable and experienced conditions within the academic environment. AI Governance therefore reflected students' perceptions of the visibility, clarity, communication, and implementation of institutional expectations for responsible AI use, rather than internal governance processes that may not be directly observable to them. Operational AI Support captured students' perceptions of the availability, accessibility, and adequacy of AI-related resources, guidance, and support services. Pedagogical AI Practices reflected students' experiences of AI integration in teaching, learning, and assessment, whereas Institutional Culture represented their perceptions of shared norms, expectations, and ethical practices related to responsible AI use. Accordingly, the constructs were interpreted as student-perceived institutional conditions rather than objective indicators of institution-level governance or organizational capacity.

The AI Governance items were informed by literature on institutional AI policy, accountability, transparency, ethical oversight, and responsible AI implementation, particularly Chan's (2023) AI policy framework and UNESCO's (2023) guidance on generative AI in education. Pedagogical AI Practices were derived from literature addressing responsible AI integration in teaching, assessment, AI literacy, and faculty-student instructional practices (Chan, 2023; Crompton & Burke, 2023; Yusuf et al., 2024).

Operational AI Support was informed by literature on institutional infrastructure, access to AI-related resources, technical and academic support, and organizational capacity for responsible AI implementation (Chan, 2023; UNESCO, 2023; Yusuf et al., 2024). Institutional Culture was grounded in Institutional Theory, particularly the role of shared norms, values, expectations, and institutionalized practices in shaping organizational behavior (DiMaggio & Powell, 1983; Scott, 2014), and was contextualized to responsible AI use in higher education. Academic Integrity Readiness was informed by contemporary literature on academic integrity in AI-enabled education, including institutional preparedness, ethical AI use, transparency, accountability, and preventive responses to integrity-related challenges (Rasul et al., 2024; Bittle & El-Gayar, 2025; UNESCO, 2023).

Academic Integrity Readiness was operationalized as students' perceived preparedness to uphold honesty, transparency, accountability, and ethical AI practices within an AI-enabled academic environment. Although conceptualized as an institutional condition, it was measured through students' perceptions of the institutional environment and should therefore be interpreted as student-perceived Academic Integrity Readiness rather than as an objective institution-level measure. All items were rated using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), with higher scores indicating stronger perceptions of the corresponding construct.

Prior to the main data collection, the initial item pool underwent content validation by eight subject-matter experts with expertise in higher education, artificial intelligence, educational management, and research methodology. The experts evaluated the items for relevance, clarity, representativeness, and comprehensiveness, and their recommendations were incorporated into the final instrument. The overall Scale Content Validity Index (S-CVI = .951) indicated excellent content validity. The revised questionnaire was subsequently pilot tested with 30 university students who were not included in the main sample to assess clarity, feasibility, and internal consistency. Cronbach's alpha coefficients were .938 for AI Governance, .840 for Pedagogical AI Practices, .905 for Operational AI Support, .888 for Institutional Culture, and .876 for Academic Integrity Readiness, indicating satisfactory to excellent internal consistency and supporting the instrument's use in the main study.

Confirmatory factor analysis (CFA) using maximum likelihood estimation was conducted to evaluate the five-factor measurement model with 35 observed indicators. Results indicated excellent model fit (CMIN/DF = 1.66, GFI = .936, AGFI = .923, NFI = .913, IFI = .925, TLI = .910, CFI = .951, RMR = .031, RMSEA = .035, 90% CI [.035, .052], PCLOSE = .875). All indicators loaded strongly on their intended constructs, with standardized factor loadings ranging from .773 to .908 across the five-factor measurement model. Specifically, loadings ranged from .805 to .867 for AI Governance, .787 to .842 for Pedagogical AI Practices, .773 to .867 for Operational AI Support, .809 to .860 for Institutional Culture, and .845 to .908 for Academic Integrity Readiness. The CFA therefore supported the adequacy of the proposed five-factor measurement structure. Because factor-model fit and significant loadings do not by themselves establish discriminant validity, convergent and discriminant validity were examined separately using composite reliability, average variance extracted (AVE), interconstruct correlations, and the Fornell-Larcker comparison reported in the Results section.

Following approval from the University's Research Ethics Board, the finalized questionnaire was administered to the selected respondents. Participants received an invitation explaining the study's purpose, the voluntary nature of participation, confidentiality safeguards, and informed consent procedures before completing the survey. No personally identifiable information was collected. These anonymity and confidentiality procedures reduced evaluation apprehension and provided a basic procedural safeguard against common method concerns; however, because all constructs were measured through the same self-report survey at one point in time, common method bias could not be fully excluded and is addressed as a study limitation.

Data were analyzed using IBM SPSS Statistics and Hayes' PROCESS Macro Version 5.0. Descriptive statistics, including means and standard deviations, were used to summarize respondents' perceptions of the study variables. Internal consistency was evaluated using Cronbach's alpha and composite reliability, while convergent validity was assessed using average variance extracted (AVE). Discriminant validity was examined using the Fornell-Larcker criterion by comparing the square root of each construct's AVE with its correlations with the remaining constructs. Pearson's correlation coefficient was used to assess bivariate associations among the study variables.

Prior to interpreting the regression models, diagnostic procedures were conducted to evaluate the assumptions of multiple linear regression. Linearity and homoscedasticity were assessed through residual-versus-predicted plots, while the distribution of residuals was examined using graphical diagnostics. Independence of errors and potentially influential observations were also evaluated using appropriate residual and influence statistics. Tolerance and variance inflation factor (VIF) values were examined to assess multicollinearity. No substantial assumption violations were identified that would preclude interpretation of the regression estimates.

Multiple linear regression was then used to estimate the unique statistical contributions of AI Governance, Pedagogical AI Practices, Operational AI Support, and Institutional Culture to Academic Integrity Readiness. In addition to statistical significance, Cohen's f^2 was reported for the overall outcome model and for local predictor effects to provide estimates of substantive contribution.

Mediation analysis was subsequently conducted using PROCESS Macro Model 4 with 5,000 bootstrap resamples to estimate the indirect association between AI Governance and Academic Integrity Readiness through Institutional Culture, with Pedagogical AI Practices and Operational AI Support included as covariates. The indirect effect was considered statistically significant when the 95% bias-corrected bootstrap confidence interval did not include zero (Hayes, 2022). Given the cross-sectional design, all regression and mediation coefficients were interpreted as statistical associations rather than evidence of temporal sequence or causal effects.

Ethical Considerations

The study adhered to the ethical principles governing research involving human participants. Ethical approval was obtained from the University's Institutional Research Ethics Board prior to data collection. Participation was voluntary, and informed consent was obtained electronically from all

respondents before survey administration. Participants were informed of their right to decline participation or withdraw from the study at any stage without penalty. To ensure confidentiality and privacy, no personally identifiable information was collected, and all data were anonymized, securely stored, and used exclusively for research purposes in accordance with established ethical guidelines for social and educational research (Resnik, 2020).

Results

Descriptive Statistics, Reliability, Convergent Validity, and Discriminant Validity

As shown in Table 1, all five constructs demonstrated satisfactory internal consistency and convergent validity. Cronbach's alpha coefficients ranged from .855 for Pedagogical AI Practices to .961 for Academic Integrity Readiness. Composite reliability coefficients ranged from .936 to .961, exceeding the recommended .70 criterion for all constructs. Average variance extracted (AVE) values ranged from .675 to .779, with all constructs exceeding the recommended .50 threshold. Specifically, AVE values were .710 for AI Governance, .675 for Pedagogical AI Practices, .693 for Operational AI Support, .715 for Institutional Culture, and .779 for Academic Integrity Readiness. These results support the internal consistency and convergent validity of the five measurement constructs.

Table 1. *Descriptive Statistics, Reliability, Convergent Validity, and Discriminant Validity Heterotrait-Monotrait Ratios of the Study Construct (n = 543)*

Construct	α	CR	AVE	√AVE	AIG	PAIP	OAIS	IC	AIR
AI Governance (AIG)	.945	.945	.710	.843	—				
Pedagogical AI Practices (PAIP)	.855	.936	.675	.822	.932	—			
Operational AI Support (OAIS)	.941	.940	.693	.833	.900	.886	—		
Institutional Culture (IC)	.947	.946	.715	.846	.871	.931	.906	—	
Academic Integrity Readiness (AIR)	.961	.961	.779	.883	.735	.863	.699	.875	—

The square roots of AVE were .843 for AI Governance, .822 for Pedagogical AI Practices, .833 for Operational AI Support, .846 for Institutional Culture, and .883 for Academic Integrity Readiness. These values were compared with the corresponding interconstruct correlations to assess discriminant validity using the Fornell-Larcker criterion. Academic Integrity Readiness satisfied the criterion because its square root of AVE (.883) exceeded its correlations with AI Governance (r = .702), Pedagogical AI Practices (r = .820), Operational AI Support (r = .663), and Institutional Culture (r = .835). However, the criterion was not fully satisfied among several institutional predictor constructs. The correlation between AI Governance and Pedagogical AI Practices (r = .876) exceeded the square roots of AVE for both constructs, while the correlation between AI Governance and Operational AI Support (r = .846) slightly exceeded their corresponding square-root AVE values. Similarly, the Pedagogical AI Practices–Institutional Culture correlation (r = .879) and the Operational AI Support–

Institutional Culture correlation ($r = .852$) exceeded the relevant square-root AVE values. These findings indicate that discriminant validity was only partially supported among the institutional predictors.

Discriminant validity was assessed using both the Fornell-Larcker criterion and the heterotrait-monotrait ratio of correlations (HTMT), with HTMT values below .90 considered acceptable for theoretically related constructs. Academic Integrity Readiness demonstrated acceptable HTMT values with AI Governance (.735), Pedagogical AI Practices (.863), Operational AI Support (.699), and Institutional Culture (.875), further supporting its empirical distinctiveness from the institutional predictors. However, several predictor pairs exceeded or approached the .90 criterion. The HTMT ratio was .932 between AI Governance and Pedagogical AI Practices, .931 between Pedagogical AI Practices and Institutional Culture, and .906 between Operational AI Support and Institutional Culture. The ratio between AI Governance and Operational AI Support was .900, indicating a borderline level of discriminant validity. In contrast, AI Governance and Institutional Culture (.871) and Pedagogical AI Practices and Operational AI Support (.886) remained below the .90 threshold.

Taken together, the Fornell-Larcker and HTMT assessments indicate that discriminant validity was partially rather than fully supported. Importantly, Academic Integrity Readiness demonstrated acceptable empirical separation from all four institutional predictors under both approaches. The primary measurement concern involved overlap among AI Governance, Pedagogical AI Practices, Operational AI Support, and Institutional Culture. These constructs were nevertheless retained because they represent theoretically distinct dimensions of the institutional AI environment. Their substantial empirical overlap, however, requires caution when interpreting their unique statistical contributions in subsequent regression and mediation analyses.

Pearson correlation analysis further showed that all study variables were positively and significantly associated ($p < .01$). Academic Integrity Readiness was most strongly correlated with Institutional Culture ($r = .835$), followed by Pedagogical AI Practices ($r = .820$), AI Governance ($r = .702$), and Operational AI Support ($r = .663$). Among the institutional predictors, the strongest relationships were observed between Pedagogical AI Practices and Institutional Culture ($r = .879$), AI Governance and Pedagogical AI Practices ($r = .876$), and Operational AI Support and Institutional Culture ($r = .852$). These strong relationships are consistent with the measurement-validity findings and suggest that governance, pedagogy, operational support, and institutional culture represent closely interconnected dimensions of the broader institutional AI environment.

Given these high intercorrelations, multicollinearity diagnostics were examined before interpreting the regression coefficients. Tolerance values ranged from .158 to .208, while variance inflation factor (VIF) values ranged from 4.817 to 6.342. These values indicate moderate to substantial multicollinearity and confirm that the institutional predictors share considerable variance. Although the observed values do not necessarily preclude estimation of the regression model, they reduce the stability and independence of the individual regression coefficients. The predictors were retained because they were specified a priori as theoretically distinct institutional dimensions; consequently, each regression

coefficient was interpreted as the predictor's unique association with Academic Integrity Readiness after variance shared with the other institutional predictors had been statistically controlled.

This consideration is particularly important for Operational AI Support. Although Operational AI Support showed a positive bivariate correlation with Academic Integrity Readiness (r = .663), its coefficient became negative in the multivariable model after AI Governance, Pedagogical AI Practices, and Institutional Culture were simultaneously controlled. Given the substantial correlations, elevated VIF values, and partial discriminant validity among the institutional predictors, this coefficient reversal is more appropriately interpreted as a possible suppression or shared-variance effect than as evidence that stronger Operational AI Support is associated with lower Academic Integrity Readiness. Accordingly, the direction and magnitude of the unique regression coefficients were interpreted cautiously throughout the subsequent analyses.

Regression Models Predicting Institutional Culture and Academic Integrity Readiness

Table 2 presents the regression models estimated using PROCESS Model 4. The mediator model predicting Institutional Culture was statistically significant, $F(3, 539) = 812.97$, $p < .001$, explaining 81.9% of the variance in Institutional Culture ($R^2 = .819$). While Pedagogical AI Practices ($B = 0.527$, $p < .001$) and Operational AI Support ($B = 0.394$, $p < .001$) significantly and positively predicted Institutional Culture, AI Governance did not demonstrate a significant effect ($B = 0.038$, $p = .379$).

Table 2. *Regression Models Predicting Institutional Culture and Academic Integrity Readiness (PROCESS Model 4)*

Predictor	**Institutional Culture (Mediator)**			**Academic Integrity Readiness (Outcome)**		
	B (SE)	***t***	***p***	**B (SE)**	***t***	***p***
Constant	*0.028 (0.055)*	*0.503*	*.615*	*0.095 (0.071)*	*1.338*	*.181*
AI Governance	0.038 (0.043)	0.880	.379	-0.088 (0.056)	-1.591	.112
Pedagogical AI Practices	0.527 (0.041)	12.778	< .001	0.608 (0.061)	9.955	< .001
Operational AI Support	0.394 (0.037)	10.571	< .001	-0.335 (0.053)	-6.310	< .001
Institutional Culture	—	—	—	0.764 (0.056)	13.561	< .001
Model Statistics	**Mediator Model**			**Outcome Model**		
R	.905			.871		
R^2	.819			.758		
F	812.97			421.29		
df	(3, 539)			(4, 533)		
p	< .001			< .001		

The Academic Integrity Readiness outcome model was statistically significant, $F(4, 533) = 421.29$, $p < .001$, accounting for 75.8% of the variance in Academic Integrity Readiness ($R^2 = .758$). The overall model effect was large (Cohen's $f^2 = 3.13$). Institutional Culture showed the strongest positive coefficient ($B = 0.764$, $p < .001$), followed by Pedagogical AI Practices ($B = 0.608$, $p < .001$). Operational AI Support showed a significant negative coefficient ($B = -0.335$, $p < .001$), whereas AI Governance was not statistically significant ($B = -0.088$, $p = .112$). Local effect-size estimates, calculated from each t statistic relative to the residual degrees of freedom, were approximately $f^2 = .288$ for Institutional Culture, .155 for Pedagogical AI Practices, .062 for Operational AI Support, and .004 for AI Governance. Thus, Institutional Culture and Pedagogical AI Practices contributed the largest unique explanatory information in the model, while the unique contribution of AI Governance was negligible after the shared variance among institutional predictors was controlled.

These results do not imply that AI Governance is unimportant. AI Governance was positively correlated with Academic Integrity Readiness at the bivariate level, but its unique coefficient became non-significant once the overlapping contributions of Institutional Culture, Pedagogical AI Practices, and Operational AI Support were considered. This pattern suggests that governance may operate as a broader enabling or organizing institutional capability whose relevance is expressed through, or shared with, cultural and pedagogical practices rather than as an isolated direct determinant of readiness.

The mediation model tested whether Institutional Culture statistically accounted for the association between AI Governance and Academic Integrity Readiness after Pedagogical AI Practices and Operational AI Support were included as covariates. This test directly examined the proposed institutionalization mechanism without assuming that formal governance necessarily produces cultural change.

Table 3. Direct, Indirect, and Total Effects of AI Governance on Academic Integrity Readiness Through Institutional Culture

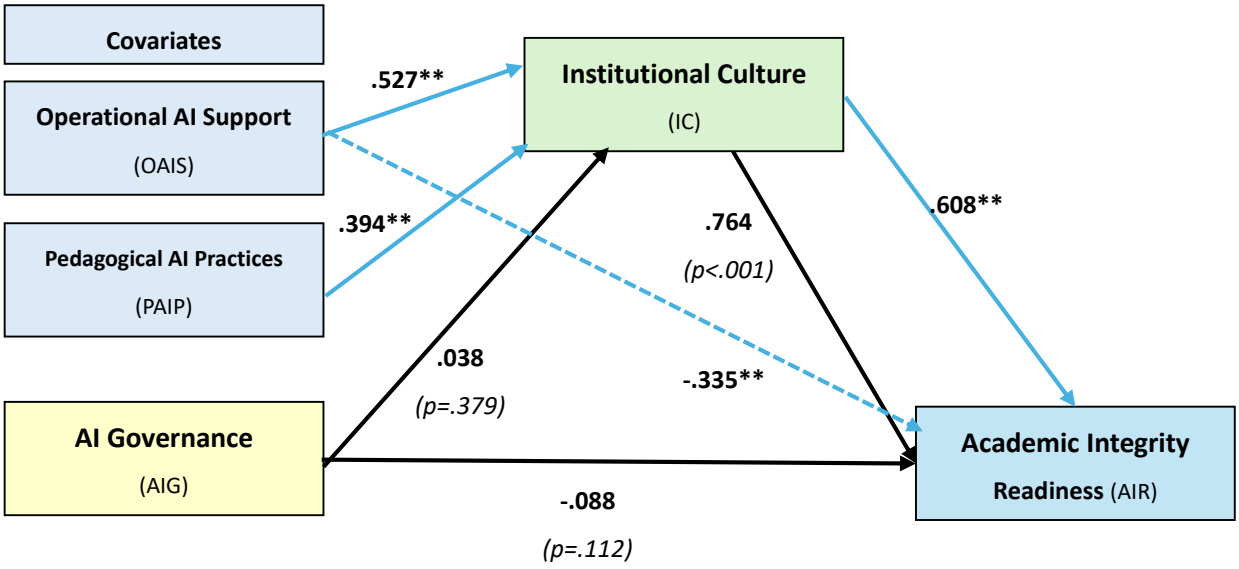
Effect	Estimate (B)	BootSE	*t*	*p*	95% Bootstrap CI
Total Effect (c path)	-0.060	0.064	-0.925	.355	[-0.185, 0.066]
Direct Effect (c′ path)	-0.088	0.056	-1.591	.112	[-0.198, 0.021]
Indirect Effect (a × b)	0.029	0.046	—	—	[-0.059, 0.122]

The direct association between AI Governance and Academic Integrity Readiness was not statistically significant after accounting for Institutional Culture, Pedagogical AI Practices, and Operational AI Support ($B = -0.088$, $SE = 0.056$, $t = -1.591$, $p = .112$, 95% CI [−0.198, 0.021]). The covariate-adjusted total effect was likewise non-significant ($B = -0.060$, $SE = 0.064$, $t = -0.925$, $p = .355$). This adjusted estimate should be distinguished from the positive zero-order correlation between AI Governance and Academic Integrity Readiness ($r = .702$), as Pedagogical AI Practices and

Operational AI Support were retained as covariates in the PROCESS model. Accordingly, the total effect reflects the governance-readiness association after accounting for variance shared with these related institutional conditions rather than the unadjusted bivariate relationship. Taken together, the results indicate that AI Governance did not explain significant unique variation in Academic Integrity Readiness within the specified multivariable model.

The indirect effect of AI Governance on Academic Integrity Readiness through Institutional Culture was also not statistically significant (B = 0.029, BootSE = 0.046, 95% CI [−0.059, 0.122]), as the bootstrap confidence interval included zero. Thus, the hypothesized mediation effect was not supported. This finding should not be interpreted as evidence that Institutional Culture was unrelated to Academic Integrity Readiness. Rather, Institutional Culture showed a strong positive association with Academic Integrity Readiness, whereas AI Governance was not significantly associated with Institutional Culture after the covariates were considered. Consequently, the proposed governance–culture–readiness pathway was not supported by the present cross-sectional data.

Figure 2. PROCESS Macro Model 4: Mediation of Institutional Culture in the Relationship between AI Governance and Academic Integrity Readiness (Covariates: Pedagogical AI Practices and Operational AI Support) N =543, Bootstrap samples = 5,000



Mediation Analysis

Figure 2 summarizes the mediation model examining whether Institutional Culture accounts for the association between AI Governance and Academic Integrity Readiness while Pedagogical AI Practices and Operational AI Support are controlled. The hypothesized indirect pathway was not supported. The model nevertheless shows that Institutional Culture and Pedagogical AI Practices retained strong positive associations with Academic Integrity Readiness, whereas AI Governance did

not contribute significant unique explanatory information once the other institutional factors were considered.

PROCESS Macro Model 4 with 5,000 bootstrap resamples was used to estimate the indirect effect through Institutional Culture. Bootstrapping was used to evaluate the precision of the indirect effect estimate without relying on normality assumptions for its sampling distribution. Because the design was cross-sectional, the statistical mediation model is interpreted as a test of a proposed pattern of associations rather than as evidence that AI Governance temporally causes changes in Institutional Culture or Academic Integrity Readiness.

AI Governance did not significantly predict Institutional Culture after Pedagogical AI Practices and Operational AI Support were controlled (B = 0.038, SE = 0.043, t = 0.880, p = .379). Thus, within the tested model, students who perceived stronger formal AI governance did not necessarily report a stronger institutional culture once the shared influence of pedagogical and operational conditions was considered.

Institutional Culture significantly predicted Academic Integrity Readiness (B = 0.764, SE = 0.056, t = 13.561, $p < .001$), indicating a strong positive unique association between shared ethical norms and readiness after the other institutional predictors were considered. However, because the governance-to-culture path and the bootstrap indirect effect were non-significant, the evidence did not support Institutional Culture as the mechanism linking AI Governance to Academic Integrity Readiness in this model.

Both regression models demonstrated substantial explanatory power: 81.9% of the variance in Institutional Culture was explained by AI Governance, Pedagogical AI Practices, and Operational AI Support collectively ($R^2 = .819$), and 75.8% of the variance in Academic Integrity Readiness was explained by the full outcome model ($R^2 = .758$). These high values should be interpreted together with the strong intercorrelations and incomplete discriminant validity among predictors. The model therefore captures a tightly connected institutional configuration, but the coefficients should not be treated as independent causal effects.

Discussion

This study examined the institutional conditions associated with student-perceived Academic Integrity Readiness and tested whether Institutional Culture statistically accounted for the association between AI Governance and readiness. Although all institutional dimensions were positively related to Academic Integrity Readiness at the bivariate level, AI Governance did not retain a significant unique association with either Institutional Culture or Academic Integrity Readiness after Pedagogical AI Practices and Operational AI Support were considered. In contrast, Institutional Culture and Pedagogical AI Practices demonstrated the strongest unique positive associations with readiness. These findings suggest that students' perceptions of institutional preparedness for responsible AI use are more closely associated

with how ethical expectations are embedded in shared norms and enacted through teaching, assessment, and everyday academic practice than with the visibility of formal governance alone.

The findings should be interpreted alongside the substantial empirical overlap among the institutional predictors. Both the Fornell-Larcker and HTMT assessments indicated considerable shared variance among AI Governance, Pedagogical AI Practices, Operational AI Support, and Institutional Culture, whereas Academic Integrity Readiness demonstrated clearer empirical separation from these dimensions. This pattern suggests that students may experience governance, pedagogy, operational support, and culture as interconnected elements of a broader institutional AI environment rather than as fully independent domains. Accordingly, the unique regression coefficients should be interpreted cautiously, while the observed interrelationships also support an ecological perspective in which responsible AI implementation depends on coordinated institutional conditions.

From the perspective of Institutional Theory, the findings distinguish formal governance structures from their enactment in organizational practice. AI policies, governance arrangements, and institutional responsibilities may establish legitimacy, accountability, expectations, and strategic direction, but their relevance to Academic Integrity Readiness appears to depend on whether these expectations become embedded in institutional norms, teaching practices, assessment processes, and routine academic behavior. The nonsignificant unique association of AI Governance therefore suggests a possible governance-enactment gap, in which policy presence alone may be insufficient to differentiate levels of perceived readiness once culture and pedagogy are considered. This interpretation is consistent with evidence that AI governance becomes more meaningful when it is integrated into teaching, assessment, and institutional practice rather than remaining primarily at the policy level (Luo, 2024; Yusuf et al., 2024).

The unsupported mediation hypothesis further refines this interpretation. Institutional Theory provided a reasonable basis for proposing that governance expectations could become institutionalized through shared culture and subsequently relate to Academic Integrity Readiness. However, this pathway was not supported in the present model. Institutional Culture remained strongly associated with readiness, whereas AI Governance did not demonstrate a significant unique association with Institutional Culture after the other institutional conditions were considered. This suggests that institutional culture may not simply develop as a downstream consequence of formal governance but may also emerge from leadership practices, faculty behavior, assessment norms, peer expectations, disciplinary traditions, and accumulated institutional experiences. The nonsignificant mediation result is therefore theoretically meaningful because it indicates that the governance-culture-readiness relationship may involve additional mechanisms or boundary conditions.

The findings also refine the application of Chan's (2023) AI Ecological Education Policy Framework. The strong relationships among governance, pedagogy, operational support,

and institutional culture are consistent with an ecological perspective in which responsible AI implementation depends on mutually reinforcing institutional conditions. However, these dimensions did not contribute equally when considered simultaneously. Institutional Culture and Pedagogical AI Practices emerged as the most substantively important unique contributors, emphasizing the importance of environments in which honesty, transparency, accountability, AI literacy, responsible assessment, and ethical AI use are embedded in shared academic norms and instructional practice. In this sense, the study extends Institutional Theory and the ecological framework by showing that formal structures may be less consequential than the extent to which responsible AI principles become institutionalized in everyday academic experiences (DiMaggio & Powell, 1983; Scott, 2014; Chan, 2023; Crompton & Burke, 2023; Bittle & El-Gayar, 2025).

The negative coefficient for Operational AI Support also requires cautious interpretation. Although Operational AI Support was positively correlated with Academic Integrity Readiness at the bivariate level, its coefficient became negative after the other highly correlated institutional predictors were controlled. Given the strong intercorrelations and partial discriminant validity among the predictors, this reversal is more consistent with statistical suppression or overlapping explanatory variance than with evidence that greater operational support is associated with lower readiness. The coefficient represents the residual component of Operational AI Support after variance shared with governance, pedagogy, and culture has been removed. Its direction should therefore not be interpreted substantively in isolation, and future studies should examine alternative model specifications and measures with stronger discriminant validity before drawing firm conclusions about its unique role (Cohen et al., 2003; Hayes, 2022).

The findings are particularly relevant to the Philippine higher education context, where institutions are expanding AI adoption while strengthening expectations for ethical governance and responsible implementation. The Philippine National AI Strategy Roadmap 2.0 emphasizes governance, institutional capacity, and responsible AI development (Department of Trade and Industry [DTI], 2024). Within this setting, the findings suggest that formal governance may have limited distinct relevance to students unless institutional expectations are translated into visible norms, responsible teaching and assessment practices, accessible support mechanisms, and consistent academic expectations.

The interpretation should also be situated within the diversity of Asian higher education systems. Universities across Asia operate under varying levels of regulatory centralization, institutional autonomy, technological capacity, policy maturity, and cultural expectations regarding authority, assessment, and academic integrity. Consequently, the relative importance of governance, institutional culture, and pedagogical practice may differ across national and institutional settings. The present findings should therefore be viewed as context-specific

evidence from a Philippine institution rather than as uniformly generalizable across Asian higher education, while still providing a useful basis for future comparative research.

Several methodological limitations should also be considered. Students are appropriate respondents for examining how institutional policies, pedagogical practices, operational support, and academic integrity expectations are experienced within the academic environment, but they may have limited knowledge of internal governance structures, policy-development processes, accountability mechanisms, and administrative oversight. The findings therefore reflect student-perceived governance visibility and institutional implementation rather than objective measures of institutional governance capacity. In addition, the cross-sectional, single-source design raises the possibility of common method variance and does not establish temporal or causal relationships. The mediation findings should consequently be interpreted as a proposed pattern of statistical associations rather than evidence that AI Governance causes changes in Institutional Culture that subsequently influence Academic Integrity Readiness. Measurement limitations should likewise be acknowledged because discriminant validity among several institutional predictors was only partially supported, indicating a need for further refinement of the measures (Barus et al., 2025; Johnston et al., 2024; Cheung et al., 2024; Fang et al., 2024).

Future research should employ longitudinal, multi-institutional, and multi-source designs that combine student perceptions with faculty and administrator perspectives, institutional policies, governance records, assessment practices, and implementation indicators. Scale-development studies should refine the indicators of AI Governance, Pedagogical AI Practices, Operational AI Support, and Institutional Culture and compare alternative measurement structures, including higher-order models of the institutional AI environment. Future studies should also examine whether leadership, faculty AI readiness, AI literacy, policy clarity, assessment design, institutional type, disciplinary context, or governance maturity condition the relationship between formal governance and responsible academic practice. Comparative research across Philippine and other Asian higher education systems would further clarify the boundary conditions of the relationships identified in the present study.

Taken together, the findings position Academic Integrity Readiness as a useful student-perceived indicator of institutional preparedness for responsible AI use while demonstrating that its institutional correlates are highly interconnected. AI Governance may be better understood as an enabling institutional capability whose relevance is intertwined with organizational culture, pedagogical practice, and operational support rather than as an isolated direct determinant of readiness. The study's principal contribution therefore lies in distinguishing formal governance from enacted readiness**,** identifying the limits of the proposed governance-culture mediation pathway, and demonstrating the particularly important roles of Institutional Culture and Pedagogical AI Practices. Responsible AI readiness in higher education is thus better understood as an institutional process that depends on how governance

principles are translated into shared norms and everyday academic practice rather than as an outcome of policy presence alone.

Conclusions

This study examined the institutional conditions associated with student-perceived Academic Integrity Readiness in AI-enabled higher education. Although AI Governance, Pedagogical AI Practices, Operational AI Support, and Institutional Culture were positively associated with readiness at the bivariate level, Institutional Culture and Pedagogical AI Practices showed the strongest unique positive associations when considered simultaneously. AI Governance did not retain a significant unique association, while the proposed indirect association through Institutional Culture was not supported. The negative coefficient for Operational AI Support should be interpreted cautiously because of substantial shared variance among the institutional predictors. The measurement model demonstrated strong reliability and convergent validity, while partial discriminant validity indicated that students may perceive governance, pedagogy, operational support, and culture as interconnected components of a broader institutional AI environment.

The study contributes theoretically by distinguishing formal AI governance from its institutional enactment**.** The findings suggest a possible governance-enactment gap in which the presence of policies and accountability structures may be insufficient to differentiate Academic Integrity Readiness unless responsible AI principles are embedded in institutional norms, teaching, assessment, and everyday academic practice. This interpretation extends Institutional Theory and refines Chan's AI Ecological Education Policy Framework by showing that institutional conditions are closely interconnected but may differ in their unique relevance to readiness. In particular, Institutional Culture and Pedagogical AI Practices appear important in translating responsible AI principles into students' academic experiences.

Practically, higher education institutions should move beyond policy formulation toward measurable and coordinated implementation. AI governance maturity indicators may be used to assess policy clarity, awareness, accountability, ethical oversight, and consistency of implementation. At the same time, faculty development should strengthen AI literacy, ethical assessment design, transparent expectations for acceptable AI use, and responsible integration of AI into teaching and learning. Institutional culture should reinforce honesty, transparency, accountability, and responsible AI use across academic policies and practices.

Institutional Research offices can support this process through recurring assessment and evidence-informed monitoring. An Academic Integrity Readiness dashboard may integrate indicators of student-perceived readiness, AI policy awareness, governance maturity, faculty AI-literacy benchmarks, pedagogical practices, institutional culture, and operational support. Such evidence can inform quality assurance, policy review, faculty development, and strategic planning. However, the findings should be interpreted within the limitations of the cross-sectional, single-institution, and student self-report design. Future research should use

longitudinal, multi-institutional, and multi-source approaches, refine the measurement of overlapping institutional constructs, and examine potential moderators and alternative models across Philippine and other Asian higher education contexts.

Taken together, Academic Integrity Readiness is best understood not as a consequence of formal AI policy alone but as a coordinated institutional condition emerging from the interaction of governance, culture, pedagogy, and support systems. Strengthening readiness therefore requires universities to translate governance principles into visible academic practices, shared ethical norms, faculty capability, and sustained institutional monitoring. This shift from policy presence to policy enactment provides a practical and theoretical basis for building more responsible, transparent, and integrity-oriented AI environments in higher education.

Acknowledgements

The authors wish to thank the students who participated in the survey.

Author contributions

All authors contributed substantially to the conceptualization, methodology, data collection, statistical analysis, interpretation of findings, manuscript preparation, and approval of the final version of the manuscript.

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations Competing interests

The authors declare that they have no competing interests.

References

An, Y., Yu, J. H., & James, S. (2025). Investigating the higher education institutions' guidelines and policies regarding the use of generative AI in teaching, learning, research, and administration. *International Journal of Educational Technology in Higher Education, 22*, Article 10. https://doi.org/10.1186/s41239-025-00507-3

Barus, O. P., Hidayanto, A. N., Handri, E. Y., Sensuse, D. I., & Yaiprasert, C. (2025). Shaping generative AI governance in higher education: Insights from student perception. *International Journal of Educational Research Open, 8*, Article 100452. https://doi.org/10.1016/j.ijedro.2025.100452

Bin-Nashwan, S. A., Sadallah, M., & Bouteraa, M. (2023). Use of ChatGPT in academia: Academic integrity hangs in the balance. *Technology in Society, 75*, 102370. https://doi.org/10.1016/j.techsoc.2023.102370

Bittle, K., & El-Gayar, O. (2025). Generative AI and academic integrity in higher education: A systematic review and research agenda. *Information, 16*(4), 296. https://doi.org/10.3390/info16040296

Chan, C. K. Y. (2023). *A comprehensive AI policy education framework for university teaching and learning*. *International Journal of Educational Technology in Higher Education, 20*, Article 38. https://doi.org/10.1186/s41239-023-00408-3

Chan, C. K. Y. (2025). Students' perceptions of "AI-giarism": Investigating changes in understandings of academic misconduct. *Education and Information Technologies, 30*, 8087–8108. https://doi.org/10.1007/s10639-024-13151-7

Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management, 41*, 745–783. https://doi.org/10.1007/s10490-023-09871-y

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). *Applied multiple regression/correlation analysis for the behavioral sciences* (3rd ed.). Lawrence Erlbaum Associates.

Creswell, J. W., & Creswell, J. D. (2023). *Research design: Qualitative, quantitative, and mixed methods approaches* (6th ed.). SAGE Publications.

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education, 20*, Article 22. https://doi.org/10.1186/s41239-023-00392-8

Department of Trade and Industry. (2024, July 5). *DTI drives AI innovation with National Roadmap 2.0 and CAIR launch*.

DeVellis, R. F., & Thorpe, C. T. (2021). *Scale development: Theory and applications* (5th ed.). SAGE Publications.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review, 48*(2), 147–160. https://doi.org/10.2307/2095101

Fang, J., Wen, Z., & Hau, K.-T. (2024). Mediation analyses of intensive longitudinal data with dynamic structural equation modeling. *Structural Equation Modeling: A Multidisciplinary Journal, 31*(4), 728–741. https://doi.org/10.1080/10705511.2023.2268293

Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). Sage.

Gruenhagen, J. H., Sinclair, P. M., Carroll, J.-A., Baker, P. R. A., Wilson, A., & Demant, D. (2024). The rapid rise of generative AI and its implications for academic integrity: Students' perceptions and use of chatbots for assistance with assessments. *Computers and Education: Artificial Intelligence, 7*, Article 100273. https://doi.org/10.1016/j.caeai.2024.100273

Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (3rd ed.). Guilford Press.

Johnston, H., Wells, R. F., Shanks, E. M., Boey, T., & Parsons, B. N. (2024). Student perspectives on the use of generative artificial intelligence technologies in higher education. *International Journal for Educational Integrity, 20*, Article 2. https://doi.org/10.1007/s40979-024-00149-4

Karkoulian, S., Sayegh, N., & Sayegh, N. (2025). ChatGPT unveiled: Understanding perceptions of academic integrity in higher education: A qualitative approach. *Journal of Academic Ethics, 23*, 1171–1188. https://doi.org/10.1007/s10805-024-09543-6

Khoza, M. S., Wamba, S. F., & Nyawa, S. (2026). Mapping the landscape of AI governance in higher education. *Assessment & Evaluation in Higher Education*. Advance online publication. https://doi.org/10.1080/02602938.2026.2712521

Kim, M., Kim, Y., & Park, J. (2025). Common statistical methods used in medical research. *Kosin Medical Journal, 40*(1). https://doi.org/10.7180/kmj.24.160

Kofinas, A. K., Dervin, F., Tsinakos, A., & Karakostas, A. (2025). The impact of generative AI on academic integrity of authentic assessment in higher education. *British Journal of Educational Technology*. https://doi.org/10.1111/bjet.13585

Lee, D., Arnold, M., Srivastava, A., Plastow, K., Strelan, P., Ploeckl, F., Lekkas, D., & Palmer, E. (2024). The impact of generative AI on higher education learning and teaching: A study of educators' perspectives. *Computers and Education: Artificial Intelligence, 5*, 100221. https://doi.org/10.1016/j.caeai.2024.100221

Lohr, S. L. (2021). *Sampling: Design and analysis* (3rd ed.). Chapman and Hall/CRC.

Luo, J. (2024). A critical review of GenAI policies in higher education assessment: A call to reconsider the originality of students' work. *Assessment & Evaluation in Higher Education*. https://doi.org/10.1080/02602938.2024.2309963

Lynn, M. R. (1986). Determination and quantification of content validity. *Nursing Research, 35*(6), 382–385. https://doi.org/10.1097/00006199-198611000-00017

Maleki, A. (2026). Rethinking ethical academic integrity ecosystems in higher education in the age of artificial intelligence. *Discover Artificial Intelligence, 6*, Article 145. https://doi.org/10.1007/s44163-026-00887-z

Miao, F., & Holmes, W. (2023). *Guidance for generative AI in education and research*. UNESCO. https://doi.org/10.54675/EWZM9535

Mishra, P., Pandey, C. M., Singh, U., Gupta, A., Sahu, C., & Keshri, A. (2019). Application of student's t-test, analysis of variance, and covariance. *Annals of Cardiac Anaesthesia, 22*(4), 407–411. https://doi.org/10.4103/aca.ACA_94_19

Polit, D. F., & Beck, C. T. (2006). The content validity index: Are you sure you know what's being reported? Critique and recommendations. *Research in Nursing & Health, 29*(5), 489–497. https://doi.org/10.1002/nur.20147

Rasul, T., Nair, S., Kalendra, D., Balaji, M. S., Santini, F. O., Ladeira, W. J., Rather, R. A., Yasin, N., Rodriguez, R. V., Kokkalis, P., Murad, M. W., & Hossain, M. U. (2024). Enhancing academic integrity among students in GenAI era: A holistic framework. *The International Journal of Management Education, 22*(3), Article 101041. https://doi.org/10.1016/j.ijme.2024.101041

Resnik, D. B. (2020). What is ethics in research and why is it important? *National Institute of Environmental Health Sciences*. https://doi.org/10.1093/acrefore/9780190228637.013.36

Scott, W. R. (2014). *Institutions and organizations: Ideas, interests, and identities* (4th ed.). SAGE Publications.

UNESCO. (2023). *Guidance for generative AI in education and research*. UNESCO. https://doi.org/10.54675/UZZZ9166

Ying, J. (2026). Academic integrity in the age of generative AI: A scoping review of research on higher education student voices. *Journal of Academic Ethics, 24*, Article 78. https://doi.org/10.1007/s10805-026-09752-1

Yusuf, A., Pervin, N., & Román-González, M. (2024). Generative AI and the future of higher education: A threat to academic integrity or reformation? *International Journal of Educational Technology in Higher Education, 21*, Article 21. https://doi.org/10.1186/s41239-024-00453-6

P26018

RESEARCH FATIGUE AND SCIENTIFIC WRITING DIFFICULTIES AMONG THESIS AND DISSERTATION WRITERS IN A CATHOLIC UNIVERSITY: AN EXPLORATORY SEQUENTIAL MIXED METHODS INQUIRY

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ABSTRACT

Graduate education places rigorous pressure on students to produce high-quality research, which can trigger research fatigue. This academic exhaustion often leads to substantial difficulties with scientific writing, leaving students feeling unequipped in terms of knowledge, skills, and attitude that hinders the completion of their theses/dissertations. This study explored the presence of research fatigue and scientific writing difficulties among thesis and dissertation writers, while investigating whether research fatigue acts as a predictor for writing difficulties. Using an exploratory sequential mixed-methods design, the study began with qualitative data collection, followed by a quantitative phase. Data collection involved semi-structured interviews and a researcher-made questionnaire. Qualitative insights were analyzed using Lichtman's 3Cs (coding, categorizing, and conceptualizing), while quantitative data were evaluated using descriptive and inferential statistics. Qualitative analysis revealed three core themes for research fatigue, which include physiological and psychosomatic manifestations, cognitive and psychological exhaustion, and functional disruption and role strain. In addition, three themes of writing difficulties include structural and logical organization hurdles, technical and methodological barriers, and information literacy and pedagogical gaps. Quantitative findings indicated that students experience moderate levels of both research fatigue and writing difficulties, with physiological manifestations showing the highest scores. Finally, cognitive and psychological exhaustion alongside functional disruption and role strain significantly predict scientific writing difficulties.

Keywords: Research Fatigue, Scientific Writing Difficulties, Thesis and Dissertation Writers, Exploratory-Sequential, Graduate Education, Philippines

1.0 Introduction

Graduate education is a demanding journey that requires students to engage in rigorous research activities (Tang et al., 2021; Valencia-Arias et al., 2026). The increasing pressure to produce high-quality research outputs, coupled with the complexities of the research process, can lead to research fatigue (Broskevičová et al., 2024; Cresencio & Yabut, 2023). Research fatigue has emerged as a growing concern among graduate students. Studies have shown that a significant proportion of graduate students experience symptoms of research fatigue, such as emotional exhaustion, reduced efficacy, cynicism (Abreu et al., 2024; Daniel, 2022), including physiological and psychosomatic manifestations, cognitive and psychological exhaustion, and functional disruption and role strain, during the duration of the thesis/dissertation writing process. This fatigue can be attributed to various factors, including heavy workloads, lack of control over research decisions, perfectionism, inadequate preparation in terms of skills, and support systems (Pyhältö et al., 2021; Merga & Mason, 2021).

The consequences of research fatigue can be far-reaching, affecting not only students' mental health (Gumasing, 2022; Kalmakis et al., 2022) and physical health (Branscheidt et al., 2019), but also their academic progress and career (Yaacob et al., 2023; Fan & Smith, 2020). In addition, this state of exhaustion and diminished motivation can significantly impact a student's overall well-being (Fan & Smith, 2020; Wong Aitken et al., 2024). It can also lead students to experience difficulties with scientific writing, as they feel they lack the knowledge, skills, and attitudes (Skala & Zemková, 2022) necessary to conduct scientific research effectively. Difficulty with scientific writing is common among graduate students, hindering the conduct of research skillfully and sensibly and the reporting of its findings (Ouchikh et al., 2024; Zhang et al., 2024; Daniel, 2022). In addition, structural and logical organization hurdles, technical and methodological barriers, and information literacy and pedagogical gaps are becoming challenges for graduate students in completing their scientific writing.

In the Philippines, graduate students are expected to demonstrate research know-how to complete their educational goals (CMO 53, s. 2007). Across all graduate work orientations and levels, the goal is to advance 21st-century skills and competencies that strengthen the nation's innovation, research, and development. Further, graduate education sustains knowledge acquisition, generation, sharing, and exchange through professional experience via research (CMO 15, s. 2019). These national mandates resonate with Sustainable Development Goal 4 (Quality Education), which calls for equitable access to high-quality tertiary instruction and the development of specialized research capabilities, as well as Sustainable Development Goal 3 (Good Health and Well-Being) to foster supportive, psychologically sound academic environments. However, graduate students faced challenges further compounded by the unique context of the higher education system. Limited research funding (Wong Aitken et al., 2024; Valencia-Arias et al., 2026), inadequate research infrastructure (Zou et al., 2025), and a culture that often prioritizes teaching over research can contribute to increased stress and fatigue

among graduate students (Agyapong et al., 2022; Vera et al., 2025). Additionally, the pressure to publish in international journals and compete in a globalized academic landscape can intensify the challenges faced by Filipino graduate students.

At the institutional level, thesis and dissertation writers in graduate school are expected to complete their studies within one to two semesters to meet graduation requirements. However, many of these writers have been observed to struggle to adhere to this timeline. This delay can be attributed to various challenges, including a lack of motivation, exhaustion stemming from the demanding research process, and inadequate scientific writing readiness in terms of research knowledge, skills, and attitude. These challenges, coupled with the inherent rigor of research, can lead to research fatigue, potentially hindering their ability to conduct research effectively and accomplish the project on time.

Several studies examined research fatigue among research participants (Patel et al., 2020; Casal–Ribeiro, 2024) and the individual factors contributing to it (Way, 2013; Brunton et al., 2019; Ashley, 2020). Also, studies examined the difficulty of scientific writing (Alostath, 2021; Sulaiman & Muhajir, 2019; Gupta et al., 2022; Adrianty & Hafizh, 2023). However, despite growing recognition of research fatigue and scientific writing difficulty as significant issues in graduate education, there remains a gap in the understanding of research fatigue among researchers and in the specific relationship between research fatigue and scientific writing difficulty. This is the gap the researcher wishes to fill.

To address this gap, the researcher explored research fatigue and difficulties with scientific writing among thesis and dissertation writers at a Catholic university for the Academic Year 2025-2026. This study also investigated whether research fatigue predicts scientific writing difficulties. These findings informed the creation of the *Proposed RBGS CORE: Center for Recoletos Research Excellence & Wellness,* a comprehensive research development and wellness program specifically designed for graduate students. This program prioritized targeted training in language and scientific writing to enhance technical capabilities, while simultaneously incorporating well-being interventions to eliminate fatigue and promote long-term academic resilience.

2.0 Methodology

2.1. Research Design. This study utilized an exploratory sequential mixed-methods research design, which is characterized by an initial qualitative data collection and analysis phase followed by a subsequent quantitative phase (Creswell & Creswell, 2018). The initial descriptive qualitative approach assessed the lived experiences of participants regarding research fatigue and scientific writing difficulties through interviews and thematic analysis. The quantitative phase utilized a survey to collect data on the specific levels of these challenges among thesis and dissertation writers to address questions of generalizability. This structural

framework allows for the systematic integration of both data types to provide a deeper, more nuanced understanding of the phenomenon under investigation.

2.2. Respondents. During the qualitative phase, purposive sampling was employed to select 11 thesis and dissertation writers who are representatives of the different programs to identify information-rich cases and maximize resource utility (Campbell et al., 2020; Creswell & Plano Clark, 2018). These participants were chosen based on specific inclusion criteria: official enrollment, current professional employment, and the successful initiation and presentation of a concept paper. In the subsequent quantitative phase, 146 respondents were randomly selected from the total population of enrolled thesis and dissertation writers at the Catholic University during the 2025–2026 academic year.

2.3. Research Instrument. The primary instrument for qualitative data collection is the semi-structured interview, which serves to gather detailed accounts of participants' experiences, attitudes, perceptions, and beliefs regarding the topic (DeJonckheere et al., 2019; Ruslin et al., 2022). By allowing the researcher to pose questions and open-ended follow-ups for elaboration, the qualitative insights/themes directly inform the development of a subsequent researcher-made survey questionnaire for quantitative data collection. The items comprising the research instrument for the quantitative phase were based on the codes and categories identified in the qualitative phase. The survey questionnaire is divided into three sections: Part 1 collects respondents' sociodemographic information and professional profiles, while Part 2 measures research fatigue across 37 items spanning physiological, cognitive, and functional dimensions. Part 3 complements this by evaluating scientific writing difficulties through 38 items distributed across three subparts that target structural organization hurdles, technical-methodological barriers, and information literacy gaps.

To ensure the instrument's psychometric rigor, the tool underwent validity testing using Lawshe's (1975) Content Validity Ratio (CVR) with 10 subject matter experts, including registered psychologists, yielding a Content Validity Index (CVI) of 0.97, exceeding the 0.78 threshold. Furthermore, a pilot test with 30 thesis and dissertation writers demonstrated high internal consistency, achieving a Cronbach’s alpha of 0.978.

2.4. Data Collection Procedure. Prior to data collection, institutional approval was secured from the Vice President for Academics and Research, alongside signed informed consent, ethical clarifications, and rapport-building with participants. During the qualitative semi-structured interviews, data saturation was achieved and objectivity was maintained through bracketing judgment and probing questions in the participants' preferred language, followed by participant debriefing, tokens of appreciation, and secure audio storage for transcription. For the quantitative phase, invitation letters and Google Form survey links were digitally distributed to all graduate writers to foster completely voluntary participation. Throughout the active collection process, respondent progress was systematically monitored to

ensure comprehensive completion, after which data were statistically analyzed and all research materials securely stored for a five-year retention period before final disposal.

2.5. Data Analysis procedure. To analyze the qualitative data, a recursive textual analysis using Lichtman's (2013) 3Cs was conducted to identify the experiences of thesis and dissertation writers through the progressive stages of coding, categorizing, and conceptualizing. During coding, participants' responses were summarized into initial codes, which the researcher subsequently reviewed, refined, and renamed to remove redundancies upon re-examining the data. After modifying the codes, the researcher organized them into categories by eliminating less relevant ones and merging others to establish coherent concepts and themes.

For the quantitative phase, descriptive analyses profiled the respondents and evaluated their levels of fatigue and writing difficulty, while inferential analyses, including the independent-samples t-test, one-way ANOVA, multiple linear regression, and a Shapiro–Wilk normality test, investigated institutional differences and predictive relationships between the core variables.

2.6. Data Trustworthiness. To establish data analysis trustworthiness, the researcher adopted Lincoln and Guba's (1986) evaluation criteria framework, achieving *credibility* through member checking and *dependability* by strictly maintaining research protocols, interview recordings, and detailed field notes. Furthermore, *transferability* was established by culling rich, thick descriptions to contextualize participants' experiences, while *confirmability* was secured through an audit trail and an external audit process to certify that themes emerged solely from genuine participant responses.

2.7. Ethical Considerations. The researcher adhered to the Philippine Health Research Ethics Board (PHREB) ethical guidelines and addressed the general principles of respect for persons, beneficence, and justice to ensure the ethical soundness of the study.

3.0. Results and Discussion

3.1. Qualitative Results

The qualitative phase of this study utilized a thematic analysis to explore the experiences of thesis and dissertation writers, specifically focusing on the phenomena of Research Fatigue and Scientific Writing Difficulties. Specific to Research Fatigue, similar insights were organized into three (3) themes and nine (9) sub-themes. Regarding Scientific Writing Difficulties, similar insights were organized into three (3) themes and eight (8) sub-themes.

3.1.1. On Research Fatigue

3.1.1.1. Physiological and Psychosomatic Manifestations

Physiological Disruptions. Research fatigue manifests as a serious physical toll driven by work and academic writing pressures, resulting in deep exhaustion, eye strain, frequent

headaches, and elevated blood pressure. This continuous stress is compounded by poor nutrition and sleep deprivation due to deadline pressure, creating a heavy bodily burden that ultimately increases vulnerability to frequent illness. The participants shared:

> Due to work overload, I often felt physically and mentally drained. (Jonel, February 11, 2026, Lines 9-11)
>
> *Wala ko gana magkaon kay ang akon attention sa akon Ing gina obra nga research*. I do not have an appetite because my attention is on my research work. (Cherry, February 10, 2026, Lines 39-40)
>
> I experienced high blood pressure, had to consult the doctor, take maintenance, and experienced loss of energy and motivation. (Jomar, February 11, 2026, Lines 11-12)

The narratives of the participants indicate that the physical toll of overwork in academic settings frequently manifests as severe somatic complaints, such as persistent tiredness, headaches, and cardiovascular strain (Urbina-Garcia, 2020; Suiyhi et al., 2025). These conditions are further intensified by presenteeism, where scholars continue working during the early morning hours despite illness (Gerlach et al., 2024; Ruhle et al., 2020). Physical symptoms, including dizziness and low energy stemming from autonomic imbalance (Queirós et al., 2020), serve as primary bodily indicators of underlying mental burnout.

Somatic Indicators of Mental Drain. Mental drain induces a profound cognitive fog that severely impairs focus and leads to processing errors, such as forgetting words or losing a train of thought mid-sentence. This exhaustion ultimately depletes writing stamina through distinct somatic indicators, ranging from total physical heaviness and restlessness to headaches and panic attacks, creating a tangible barrier to productive scientific writing. The participants shared:

> One specific sign that the mental drain has won is when I start making simple mistakes, like typing the wrong words, forgetting what I was about to write, or losing my train of thought in the middle of a sentence. (Jonel, February 11, 2026, Lines 40-42)
>
> There is also a mental fog, where it becomes harder to focus or form clear thoughts. (Donna, February 22, 2026, Lines 53-55)
>
> I experienced feeling drained, overwhelmed, and mentally tired even before starting work. (Donna, February 22, 2026, Lines 12-13)

Physical signs serve as objective indicators of cognitive exhaustion, with a fatigued brain directly manifesting as bodily restlessness and heavy limbs (Rantanen et al., 2021; Shi & Qu, 2021). This state of mental drain is characterized by cognitive fog, which impairs basic information retrieval and increases simple procedural errors (Sonakawade et al., 2026; Yao et al., 2025). When neural capacity is exceeded, symptoms such as headaches and dizziness act as protective defense mechanisms (Insantuan et al., 2026), functioning as a physical "stop signal" that limits writing endurance (Hancock et al., 2021).

Age-Related Stamina. Age-related stamina significantly influences how researchers experience exhaustion, as a notable decline in physical energy over time makes demanding scientific writing increasingly taxing on fragile health. This physiological shift accelerates the onset of tiredness, directly undermining the sustained motivation required for complex academic pursuits and highlighting physical capacity as a critical, depleting institutional resource. Some participants shared:

> Sometimes I would tell myself, I should have done this in my early years, when I still had the energy and my health was not yet fragile. (Marina, February 12, 2026, Lines 35-37)
>
> It is more of physical exhaustion, perhaps due to age… hahaha. I get easily tired. (Jomar, February 11, 2026, Line 65)
>
> I think both, as I said, perhaps due to age, I easily get tired, and so I have no motivation to write my paper at all... (Jomar, February 11, 2026, Lines 79-80)

The age-related decline in physical endurance significantly impacts scholarly activity, as the natural aging process depletes energy reserves needed for sustained intellectual labor (Wong et al., 2019; Debelak et al., 2025; Mahin et al., 2025). Furthermore, older researchers experience greater physical discomfort and faster fatigue from the prolonged immobility of writing (Steltenpohl et al., 2020; Vanhove & Heras, 2022), compounded by longer recovery times following intensive work periods (Amano et al., 2020).

3.1.1.2. Cognitive and Psychological Exhaustion

Persistent Mental Preoccupation. Persistent mental preoccupation transforms the research process into an inescapable presence that haunts writers during periods of rest, making it nearly impossible to mentally disconnect or achieve restorative sleep. This constant fixation on timelines and writing tasks forces an exhausted body to keep processing the dissertation, inducing an overwhelming cycle of worry that ultimately degrades concentration. The participants shared:

> *Magtulog ko na gakapaminsaran ko pa gyapon kung ano akon isulat nga indi ko katulog.* Even when I am about to sleep, I am still thinking about what to write, to the point that I can no longer sleep. (Cherry, February 10, 2026, Lines 47-48)
>
> In the process of doing my work, I can feel only my energy increasing as I work; my mind keeps on traveling, exploring, and it cannot rest, even in my sleep. (Marina, February 12, 2026, Lines 13-14)
>
> However, it seems that wherever I go or what I do, I always think of my research paper; it haunts me. (Jomar, February 11, 2026, Lines 37-38)

Persistent cognitive preoccupation and affective rumination over unfinished tasks, often driven by the Zeigarnik effect, prevent mental detachment, relaxation, and recovery well beyond the working day (Bennett et al., 2020; Sonnentag et al., 2022; Steed et al., 2021; Syrek

et al., 2017; Vahle-Hinz et al., 2019). This ongoing cognitive strain and failure to detach serve as critical predictors of academic writing burnout (Kinnunen & Mäkikangas, 2023).

Information Processing Failure. Information processing failure occurs when cognitive overload creates a state of mental static, rendering researchers unable to absorb, organize, or register written information despite repeated reading. This breakdown fills the brain with distractions and anxious "what-ifs" instead of task-focused thoughts, causing a complete loss of the right words and leaving the writer feeling increasingly lost within their own work. The participants shared:

> In some cases, I also feel like no matter how hard I try to think of something to write, it seems that nothing is coming into my brain, but I am only full of what-ifs. (Liza, February 25, 2026, Lines 45-47)
>
> Other times, it feels more like mental static. I am looking directly at the information, trying to understand it, but it will not fully register. (Donna, February 22, 2026, Lines 66-68)
>
> I would sometimes have blank stares with mixed ideas, which I get confused as to what I will do first. (Dolly, March 27, 2026, Lines 15-16)

In accordance with cognitive load theory, brain overload occurs when working memory capacity is exceeded, demonstrating the physiological limit on simultaneous information processing (Kalyuga & Singh, 2021). This depletion of cognitive resources causes processing redundancies, such as repeatedly rereading text without comprehension (Alsuwaylin et al., 2026; Chen et al., 2018; Sweller et al., 2019), while hindering literature synthesis and conceptual integration (Paas & van Merriënboer, 2020; Zhu et al., 2021). Additionally, continuous mental exertion without adequate rest triggers cognitive tunneling, leaving researchers unable to maintain the structural coherence of their manuscripts (Wong et al., 2019).

Anxiety-Driven Paralysis. Anxiety-driven paralysis manifests as a debilitating mental freeze triggered by deadline pressures, rendering researchers physically unable to type due to a deep-seated fear of criticism and intense self-doubt. This state of panic and emotional exhaustion ultimately replaces writing motivation with persistent dread, trapping the author in a non-productive cycle of second-guessing and fear of making mistakes. The participants shared:

> When I see a deadline approaching, feel physically unable to move the cursor, my first thought is often, " You need to finish this. The deadline is approaching. You cannot afford to stop. There is a sense of urgency that creates anxiety. (Jonel, February 11, 2026, Lines 51-53)
>
> When I am pressured by deadlines, which most of the time I myself have imposed, I could feel emotional exhaustion, and I panic. (Marina, February 12, 2026, Lines 11-12)
>
> It is on the anxiety side; I kept on thinking and thinking, but this has nothing to do with the task at hand. (Jomar, February 11, 2026, Lines 35-36)

Anxiety-driven paralysis in academic writing operates primarily as a fight-or-flight response, where perceived urgency induces procrastination and the physical inability to type or move the cursor (Rozental et al., 2022; Steel & Klingsieck, 2016). This immobilization stems from executive dysfunction driven by an acute fear of failure that impedes task completion (Gustavson et al., 2019; Sirois, 2023). Acting as an emotional defense against self-imposed pressure (Gaba, 2026), this paralysis provides empirical evidence of anxiety's debilitating effect on academic motivation (Vitasari et al., 2021).

3.1.1.3. Functional Disruption and Role Strain

Reduced Occupational Efficacy. Reduced occupational efficacy occurs when the exhaustive demands of scientific writing spill into professional life, depleting the energy and motivation researchers need to perform their primary job roles effectively. This intense dual pressure frequently triggers burnout, forcing individuals to compromise output quality simply to meet deadlines or, in extreme cases, abandon their academic and organizational careers entirely. The participants shared:

> *Kun kis a I do not have the energy to deliver my lesson all out kay I am tired of doing my research paper.* Sometimes I do not have the energy to deliver my lesson at my best because I am tired of doing my research paper. (Cherry, February 10, 2026, Lines 73-74)
>
> Apart from my dissertation, I have a full-time job that requires my focus due to its demands. (Liza, February 25, 2026, Lines 15-16)
>
> By day, I am an instructor... Also, I serve as a student council adviser... Then at night... I return to my own academic battle... (Cynthia, March 10, 2026, Lines 162-163)

Reduced occupational efficiency among researchers often stems from cognitive spillover, where dissertation-related exhaustion and blurred boundaries between professional and academic identities escalate inter-role conflict and impair workplace performance (Chawla et al., 2020; Jin et al., 2022). This dynamic induces academic presenteeism, manifesting as reduced productivity on the job while racing to meet thesis/dissertation deadlines (Gerich, 2020; Lohmueller et al., 2022), while persistent high-pressure research demands diminish perceptions of professional growth (Vullinghs et al., 2021). Literature confirms that such task saturation serves as a primary driver of diminished self-efficacy across complex organizational responsibilities (Khurana et al., 2021).

Social and Family Sacrifice. Social and family sacrifice emerges as a profound emotional burden when the relentless demands of research collide with the non-negotiable needs of loved ones, trapping researchers in a precarious balance between academic deadlines and caregiving roles. This persistent trade-off forces a deep sense of isolation as social connections are severed, while the added pressure of managing family emergencies introduces acute layers of discouragement and emotional strain. The participants shared:

> *Very seldom do I have time to go out with my friends because ang time ko pirmi ara na lng sa sulat.* Very seldom do I have time to go out with my friends because I spend most of my time on thesis writing. (Cherry, February 10, 2026, Lines 81-82)
>
> However, I mostly sacrifice my deadlines to my personal and family responsibilities. (Nate, February 27, 2026, Line 66-67)
>
> I targeted to do and finished my documents... but my mother was confined in the hospital until January. (Nate, February 27, 2026, Lines 68-69)

Through the spillover-crossover model of work-life interference, the intensive cognitive demands of dissertation completion can destabilize domestic life, placing primary caregivers at risk of role overload when scholarly tasks collide with emotional family responsibilities (Shockley et al., 2021; Vaziri et al., 2020). This conflict is intensified by blurred boundaries that lead scholars to miss social engagements (Allen et al., 2021; Lapierre et al., 2022), alongside the compounding costs and dual pressures of simultaneous family maintenance and advanced study (Griggs et al., 2022). Thus, prioritizing protracted research over personal relationships frequently results in profound emotional strain and social isolation.

Avoidance and Procrastination. Avoidance and procrastination emerge as divergent coping mechanisms when the overwhelming toxicity of research fatigue causes a complete loss of task interest and writing motivation. To escape the negativity and irritation associated with the dissertation process, researchers choose a strategic, yet guilt-ridden, withdrawal into unrelated distractions to protect their remaining emotional energy, persisting in this cycle of delay even as deadlines loom. The participants shared:

> *Hambal ko gani sa self ko, not to cram, not to procrastinate. Pero ga procrastinate man ko bi dyapon (laugh).* I even tell myself not to cram or procrastinate. However, I still end up procrastinating anyway (laughs). (Cherry, February 10, 2026, Lines 69-70)
>
> I keep on delaying tasks despite knowing deadlines are near. (Donna, February 22, 2026, Lines 14-15)
>
> I tend to set my dissertation aside because I know I can always go back to it when I have time. (Jude, March 17, 2026, Lines 39-41)

Avoidance and procrastination operate primarily as short-term emotional regulation rather than poor time management, as the brain delays tasks to stabilize mood when academic writing triggers negative affect (Pychyl & Sirois, 2020; Sirois, 2023). This withdrawal is further driven by perfectionistic paralysis and the fear of generating substandard scholarship (Gaba, 2026; Sirois et al., 2019), with resulting irritability and distractibility serving as clinical indicators of academic writing boredom and frustration (Wypych et al., 2019). Accordingly, researchers become trapped in a recurring cycle marked by chronic delay interspersed with high-pressure bursts of activity (Rozental et al., 2022).

3.1.2. On Scientific Writing Difficulties

3.1.2.1. Structural and Logical Organization Hurdles

Synthesis and Cohesion. Synthesis and cohesion present a major bottleneck in scientific writing as researchers struggle to transform competing ideas into a logically flowing narrative, particularly when systematically organizing thoughts to connect findings with established literature. This challenge is most pronounced in the Review of Related Literature (RRL), where the difficulty of blending diverse perspectives disrupts sequential clarity, leaving readers disoriented and compromising the professional structure of the work. The participants shared:

> The blending stage is the bottleneck in the process of revision. (Marina, February 12, 2026, Lines 146-147)
>
> ...it is more about the logical structure of the sentences. I keep writing down the ideas in my mind, but I do not know if they are cohesive enough. (Jomar, February 11, 2026, Lines 58-60)
>
> There are instances when a series of ideas comes to mind, but I cannot organize them in a way that everyone can understand. (Liza, February 25, 2026, Lines 44-45)

Achieving coherence and integration in scientific writing is hindered by disrupted relational processing and heightened cognitive load when transitioning from analysis to theoretical contextualization (O'Brien et al., 2020; Pratiwi & Kurniawan, 2021). This bottleneck is compounded by underdeveloped metadiscourse skills needed to guide readers through arguments (Hyland, 2021; Wingate, 2015), as well as the substantial integrative complexity required to synthesize diverse perspectives (Stavans et al., 2019). Organizing and outlining content represents the most cognitively demanding stage of manuscript development (Hadi et al., 2024).

Language and Grammar Obstacles. Language and grammar obstacles constitute a major hurdle in scientific writing, often consuming nearly half of the process as researchers grapple with sentence clarity and deep-seated anxieties over structural errors. This pressure frequently induces repetitive phrasing and circular thinking that impedes conceptual expression, shifting the author's focus toward constant mechanical refinement at the expense of substantive content generation and academic progress. The participants shared:

> One of my difficulties is that I cannot perfect my grammar; I am not sure of my grammar usage. (Marina, February 12, 2026, Lines 166-167)
>
> I also struggle with using formal academic language. I constantly worry if my sentences are clear enough, scholarly enough, or grammatically correct. (Cynthia, March 10, 2026, Lines 354-355)
>
> I sometimes found myself writing lengthy paragraphs that lacked clarity. (Dolly, March 27, 2026, Lines 168-169)

Linguistic anxiety acts as cognitive interference in academic writing, shifting attention from conceptual synthesis to grammatical mechanics due to the fear of audience rejection and

manuscript dismissal (Hyland, 2019; Luo & Hyland, 2021). This perfectionism, coupled with the rigorous demands of academic English, elevates mental load and induces circular thinking (Dewaele & Dewaele, 2020; MacIntyre et al., 2020). Furthermore, time constraints impair self-monitoring, resulting in minor errors that demand laborious proofreading (Li & Casanave, 2022), confirming grammatical uncertainty as a primary driver of writing fatigue (Tardy, 2019).

3.1.2.2. Technical and Methodological Barriers

Methodological Unfamiliarity. Methodological unfamiliarity poses a significant barrier to scientific writing, as researchers often struggle to justify and defend the technical rationale behind complex frameworks like mixed-methods designs under tight time constraints. Lacking a high level of expertise, authors frequently battle deep insecurities regarding instrument validity and participant selection, turning the writing process into a series of hesitant justifications that stall overall manuscript progress. The participants shared:

> At present, I do not have enough knowledge on how to do it [mixed methods], but thanks to the samples uploaded by Dean as a basis. (Marina, February 12, 2026, Lines 109-110)
>
> *Indi man ako doc expert in programming so may gusto ko nga output pero indi ko mabal an kung paano himuon.* I am not an expert in programming, Doc, so there is a specific output I want, but I do not know how to make it happen. (Nate, February 27, 2026, Lines 100-101)
>
> While describing the research design was manageable, justifying why I chose certain methods, instruments, or procedures was more difficult. (Dolly, March 27, 2026, Lines 174-175)

Unfamiliarity with research methodology generates epistemological anxiety, as validating research design to an academic audience demands extensive methodological fluency that many students find daunting (Creamer, 2022; Schoonenboom & Johnson, 2021). This challenge intensifies in mixed-methods studies, where the "integration crisis" disrupts conventional manuscript structures (Fetters & Molina-Azorin, 2020; Guetterman et al., 2015). Moreover, the pressure to justify foundational procedural choices, such as sampling and instrument validity, induces acute self-doubt (Poth, 2020), confirming methodological complexity as a primary predictor of writing delay (Molina-Azorin, 2021).

Statistical Phobia. Statistical interpretation struggle, often bordering on a phobia, represents a significant hurdle for researchers who feel ill-equipped to translate numerical data into meaningful narrative explanations. This deficiency in statistical literacy directly impairs the author's confidence to write with authority, creating a severe bottleneck as they move from the comfort of data collection to the exhausting, high-stakes task of quantitative interpretation. The participants shared:

> Sometimes, I struggle with translating numbers, themes, or patterns into meaningful explanations. (Jonel, February 11, 2026, Lines 81-82)

> Personally, I am not good at statistics. So, I definitely am not good at writing about these statistical tools in the paper. (Cherry, February 10, 2026, Lines 117-118)
>
> *…daw nabudlayan ko sa interpretation of result. Pero kung dira na ko nga part, basi makaya ko man doc.* It feels like I am struggling to interpret the results. But when I actually reach that part, maybe I can handle it, Doc. (Nate, February 27, 2026, Lines 106-107)

Statistical anxiety acts as a potent cognitive inhibitor that impedes the translation of quantitative data into conceptual narratives (Coutinho et al., 2020; Walsh, 2021). This difficulty is compounded by low statistical self-efficacy and a heightened fear of misinterpreting analytical outputs (Earp, 2022; Saidi & Siew, 2019), which frequently prompts statistical avoidance and delays in drafting results sections due to self-doubt (Stanton, 2020). Consequently, deficient numerical literacy emerges as a key driver of paralysis in academic writing (Chew & Dillon, 2021).

Conceptual-to-Technical Translation Hurdles. Conceptual-to-technical translation hurdles represent a critical gap where researchers struggle to convert abstract mental concepts into the specialized, high-vocabulary language required for formal scientific prose. This difficulty is compounded by the challenge of anchoring empirical findings to complex theoretical frameworks and operational definitions, a breakdown that can stall the writing process for months as authors fight to build a defensible academic structure. The participants shared:

> I find it challenging to clearly explain the significance of the findings, especially when I need to connect them to my research questions and related literature. (Jonel, February 11, 2026, Lines 79-81)
>
> ...without enough technical knowledge, this will be another struggle on my part as a writer. (Marina, February 12, 2026, Lines 184-185)
>
> I have the ideas, but it is hard to translate them into writing. (Jomar, February 11, 2026, Line 52-53)

Translating conceptual frameworks into technical prose presents a pronounced semantic barrier when researchers struggle to express abstract mental models through formal academic terminology. Grounding evidence within disciplined rhetoric requires advanced disciplinary literacy (Hyland, 2019; Luo & Hyland, 2021), as moving from concept to finalized methodology frequently leaves scholars disoriented regarding manuscript coherence (Badenhorst, 2022; Kamler & Thomson, 2021). This difficulty is intensified because system logics and process flows are inherently challenging to convert from diagrammatic representations into structured text (Wong et al., 2019), confirming that articulating abstract concepts within technical sections serves as a major source of writing fatigue (Paltridge & Starfield, 2020).

3.1.2.3. Information Literacy and Pedagogical Gaps

The Context Gap. The context gap poses a significant hurdle in scientific writing, as researchers struggle to weave existing literature into a cohesive, original narrative rather than simply repeating prior authors. This process is further complicated by the technical strain of simultaneous reading and writing under limited source access, making it difficult to paraphrase without plagiarism or to build meaningful, tone-aligned interpretations. The participants shared:

> What makes it difficult for me is organizing everything clearly. Sometimes I struggle to connect my findings smoothly to related studies without simply repeating what the authors said. (Jonel, February 11, 2026, Lines 96-98)
>
> *Difficult gid to find a way to connect it with my study para indi sya magtam an ka layo.* It is really difficult to find a way to connect it to my study without making it too far-fetched or irrelevant. (Cherry, February 10, 2026, Lines 166-167)
>
> The most challenging part is crafting the study's background and reviewing related literature, since I have to weave a story from the authors' ideas and present it in a way that aligns with the tone of my research paper. (Jomar, February 11, 2026, Lines 105-107)

The contextual gap in academic writing creates a substantial cognitive barrier as researchers transition from passive reading to critical synthesis, frequently struggling with rhetorical positioning and merely summarizing authors rather than integrating empirical insights (Hyland, 2019; Paltridge & Starfield, 2020). This difficulty is compounded by restricted access to open-access literature, which fragments developing research narratives (Piwowar et al., 2019; Tennant et al., 2020). Moreover, balancing concurrent reading and writing imposes an immense cognitive load that inhibits the deep reflection needed for high-level paraphrasing (Wong et al., 2019), rendering the framing of the research problem in the Introduction and Literature Review the most mentally taxing phase for novice scholars (Badenhorst, 2022).

The AI Learning Curve. The AI learning curve presents a dual challenge for researchers who recognize its potential to ease physical writing strain but remain hindered by a personal lack of technical proficiency. This skill deficit creates a gap between the desire for digital efficiency and actual mastery, forcing a continued reliance on exhausting manual workflows because learning the new tools feels as taxing as the writing itself. The participants shared:

> *It is easier for me because of the help of technology. In formatting, for example, mahelp gid ko sg mg available applications. Pero indi gid ko sagad sagad man bi.* It is easier for me because of the help of technology. In formatting, for example. However, I am not really good at using technology. (Cherry, February 10, 2026, Lines 255-256)
>
> However, I still lack practice in using these tools [AI], which is why I am still more into manual writing. (Marina, February 12, 2026, Lines 130-131)
>
> It is time consuming to write manually and it strains me physically. (Marina, February 12, 2026, Line 131)

The transition from manual composition to AI-integrated research is often hampered by digital literacy gaps, where the steep learning curve of emerging academic technologies induces technostress and temporarily inflates workloads (Bencsik & Juhász, 2023; Grassini, 2023). Although AI tools can assist with manuscript formatting and structural organization, a lack of operational fluency prevents scholars from realizing genuine efficiencies (Dwivedi et al., 2023; Kasneci et al., 2023). Furthermore, because adopting AI demands substantial cognitive and temporal investment (Sullivan et al., 2023), the labor required to verify generated content frequently drives researchers back to manual drafting as a safer, albeit more fatiguing, alternative (Bond et al., 2024).

Mechanical Composition. Mechanical composition occurs when researchers shift from deep, critical analysis to a rigid, compliance-oriented writing style to satisfy institutional and panel requirements. This defensive posture slows the writing process as authors meticulously double-check every sentence, transforming scientific writing from a genuine topic exploration into a mechanical exercise of merely following instructions. The participants shared:

> There were times when I noticed that my writing became more mechanical. I was simply writing to complete the requirements rather than engaging in deeper analysis and organizing everything. (Jonel, February 11, 2026, Lines 26-28)
>
> Since these parts are unfamiliar to me, I followed the panel members' recommendations on what should be placed in their section, but they were not taught to us. (Jomar, February 11, 2026, Lines 125-127)
>
> The sentences become shorter and more direct... the paragraphs feel rough, almost mechanical, but at least I am moving forward. (Cynthia, March 10, 2026, Lines 225-226)

Mechanical composition in advanced research functions as a survivalist rhetorical strategy, where meeting bureaucratic demands supersedes intellectual engagement and fear of repeated revisions suppresses critical analysis (Badenhorst, 2022; Kamler & Thomson, 2021). This compliance-oriented drafting produces a defensive tone rooted in pronounced power asymmetries between candidates and examining committees (Hyland, 2019; Paltridge & Starfield, 2020). Compounding this issue, adhering strictly to unfamiliar templates without conceptual mastery induces alienation and disorientation (Bazeley, 2021), reinforcing institutional hierarchies as a major impediment to authentic authorial voice (Wingate, 2015).

3.2. Quantitative Results

3.2.1. Level of Research Fatigue

Overall level of research fatigue. Table 1 displays the level of research fatigue across physiological and psychosomatic manifestations, cognitive and psychological exhaustion, functional disruption and role strain, and overall research fatigue. As a whole, the overall level of research fatigue was moderate ($M = 3.04, SD = 0.84$). However, rather than presenting a

uniform state of burnout, the dimensional breakdown reveals an unexpected pattern: *Physiological and Psychosomatic Manifestations* emerged as the most severe dimension ($M = 3.48, SD = 0.75$, High level), outpacing *Cognitive and Psychological Exhaustion* ($M = 3.37, SD = 0.80$, Moderate) and *Functional Disruption and Role Strain* ($M = 3.04, SD = 0.84$, Moderate). In academic settings where burnout is traditionally conceptualized as intellectual depletion or work–life imbalance, it is counterintuitive that the body registers the highest degree of acute strain, turning somatic distress into the foremost indicator of the research ordeal.

This physical predominance is consistent with empirical evidence showing that sustained cognitive and academic writing pressure often registers biologically before translating into full psychological disengagement (March-Amengual et al., 2022; Popescu et al., 2023). Bodily manifestations, such as persistent physical weariness and psychosomatic complaints, routinely manifest as the earliest and most acute indicators of graduate distress, even while cognitive and functional capabilities remain comparatively preserved (March-Amengual et al., 2022; Popescu et al., 2023).

A closer examination of the demographic patterns reveals two additional unexpected results. First, across age groups, participants aged 35 years and below and those over 35 years reported identical physiological fatigue scores ($M = 3.48$) and comparable overall fatigue ($M = 3.08$ vs. $M = 2.98$). This quantitative parity contradicts the qualitative narratives in Sub-theme 1.3 (*Age-Related Stamina*), where older participants attributed their exhaustion to declining biological endurance. Second, single writers consistently scored higher across every fatigue dimension than their married counterparts, reaching "High" levels in both physiological ($M = 3.55$) and cognitive ($M = 3.50$) fatigue. This unexpected disparity challenges the assumption that family and marital duties inherently amplify research fatigue, indicating instead that the absence of household co-regulation and emotional buffering leaves single writers uniquely exposed to cumulative fatigue.

The physiological similarity observed across age cohorts validates findings that the bodily toll of prolonged research labor acts as a uniform environmental strain that transcends chronological endurance (March-Amengual et al., 2022; Wu et al., 2025). Furthermore, while domestic obligations are typically presumed to compound academic writing distress, empirical evidence affirms that spousal co-regulation and shared household support provide vital emotional buffering, effectively shielding married scholars from the intensified fatigue documented among solitary researchers (March-Amengual et al., 2022; Popescu et al., 2023).

Physiological and psychosomatic manifestations. In terms of physiological and psychosomatic manifestations, the respondents exhibited a high level overall ($M = 3.48, SD = 0.75$), ranking as the highest dimension of research fatigue. This indicates that thesis and dissertation writers frequently experience acute physical symptoms, such as headaches, sleep deprivation, and cardiovascular strain, during the research process. However, this prominent

descriptive score yields an unexpected paradox when viewed alongside the predictive outcomes of the study: although bodily exhaustion is the most acutely felt manifestation of research fatigue, multiple regression analysis reveals that physiological manifestations do not significantly predict scientific writing difficulties ($\beta = 0.035, p = 0.696$). This counterintuitive outcome indicates that while the somatic toll of academic labor is pervasive, it operates primarily as a secondary biological byproduct of chronic pressure rather than as a direct functional inhibitor of scholarly composition.

This distinction is substantiated by prior literature showing that although relentless academic writing demands induce weakening bodily wear and disrupted sleep architecture, somatic symptoms rarely account for direct variances in technical output (Christopoulou et al., 2026; Wong Aitken et al., 2024). Instead, writers appear capable of sustaining complex cognitive and rhetorical tasks despite substantial somatic distress, confirming that physical weariness runs concurrent with, rather than directly driving, compositional failure (Karki et al., 2026; Kocsis & Pusztai, 2024).

A further unexpected finding emerges across age groups. Despite qualitative accounts emphasizing *Age-Related Stamina*, wherein older respondents attributed physical decline and fatigue to biological aging, participants aged 35 years and below and those over 35 years reported identical physiological fatigue ratings ($M = 3.48, SD = 0.79$ and $M = 3.48, SD = 0.70$, respectively). This empirical parity challenges subjective perceptions of age-induced physical decline, demonstrating that the somatic burden of graduate writing is not driven by chronological age, but rather is uniformly induced by the shared, sedentary demands and deadline pressures of scholarly production.

This quantitative equivalence aligns with research demonstrating that the physiological depletion experienced during graduate writing stems from institutional conditions, such as task saturation and prolonged sedentariness, which affect scholars symmetrically across developmental stages (Christopoulou et al., 2026; Kocsis & Pusztai, 2024). Thus, the exhaustion of adaptive biological reserves reflects the severe baseline environment of thesis production rather than individual age-related vulnerability (Karki et al., 2026; Wong Aitken et al., 2024).

Cognitive and psychological exhaustion. With respect to cognitive and psychological exhaustion, which ranked second highest, the respondents demonstrated a moderate level overall ($M = 3.37, SD = 0.80$). This indicates that thesis and dissertation writers experience substantial mental weariness and information overload, though without perceiving total cognitive collapse. However, this ranking presents an unexpected conceptual divergence: in an intensely intellectual enterprise such as graduate research, mental exhaustion was unexpectedly surpassed in severity by bodily and somatic complaints ($M = 3.48$). Despite being subjectively evaluated at a lower intensity than physical symptoms, multiple linear regression reveals that cognitive and psychological exhaustion is a significant positive predictor of scientific writing

difficulties ($\beta = 0.286, p = 0.003$). This disconnect illustrates that while somatic aches dominate subjective discomfort, it is the direct depletion of working memory and executive faculties that decisively undermines compositional output.

This dynamic is confirmed by cognitive performance literature showing that mental exhaustion specifically degrades selective attention, abstract reasoning, and memory retrieval, faculties fundamental to complex scholarly synthesis (Ravi & Vedaiappan, 2025; van As et al., 2021). Even when psychological weariness remains moderate, the resulting cognitive load systematically elevates performance anxiety and induces writing blocks, directly impeding task completion where physical strain does not (Hamzah et al., 2025; Steward & Chib, 2024).

Furthermore, an examination of Table 1 demonstrates that cognitive exhaustion varies in unexpected ways across demographic profiles. Although rated moderate overall, cognitive exhaustion reached a "High" level among single respondents ($M = 3.50, SD = 0.75$), lowest-income earners ($M = 3.50, SD = 0.75$), and doctoral candidates ($M = 3.46, SD = 0.86$). The elevation among single writers runs counter to the expectation that unencumbered scholars experience less mental strain, suggesting instead that the lack of domestic co-regulation and emotional venting channels leaves unmarried researchers vulnerable to unmitigated cognitive rumination and task-related anxiety. Similarly, the high mental exhaustion among lower-income scholars suggests that financial precarity directly depletes the cognitive bandwidth needed to resolve complex academic problems.

These heightened scores across single, low-income, and doctoral researchers reflect empirical evidence that emotional isolation and socio-economic insecurity substantially restrict mental bandwidth and accelerate academic writing burnout (van As et al., 2021; Zhang et al., 2025). The lack of shared domestic buffering amplifies solitary cognitive strain, while financial instability and advanced doctoral milestone demands tax the self-regulatory reserves needed to sustain independent problem-solving (Steward & Chib, 2024; Zhang et al., 2025).

Functional disruption and role strain. Given that functional disruption and role strain ranked lowest among the fatigue dimensions, the respondents demonstrated a moderate level overall ($M = 3.04, SD = 0.84$). This suggests that while research obligations intrude upon occupational and family duties, writers perceive their daily functional routines as relatively intact compared to their physical and cognitive exhaustion. However, this lowest-ranked descriptive score yields a striking paradox when juxtaposed with the study's predictive model: despite scoring lowest in perceived intensity, *Functional Disruption and Role Strain* emerged as the strongest, most decisive predictor of scientific writing difficulties in the multiple regression analysis ($\beta = 0.449, t = 5.187, p = 0.000$). This counterintuitive outcome reveals that students tend to underestimate the corrosive impact of role conflict; while they identify somatic aches or mental weariness as their primary hurdles, it is the behavioral breakdown of competing schedules, manifesting as task avoidance, fragmentation, and eleventh-hour drafting, that most severely impairs scholarly composition.

This finding aligns with evidence that although researchers maintain functional resilience to prevent outright role failure, the underlying tension of competing responsibilities directly fractures compositional focus (Lu et al., 2024; Sverdlik et al., 2018). When multiple professional demands reach a saturation threshold, scholars experience acute behavioral friction and task disengagement, rendering role strain far more predictive of manuscript disruption than subjective feelings of fatigue alone (Pyhältö et al., 2023; Soetan & Johnson, 2025).

Furthermore, the data uncover an unexpected demographic divergence. Contrary to the prevailing assumption that married scholars carry heavier role strain due to domestic and caregiving duties, single writers reported substantially higher functional disruption ($M = 3.25, SD = 0.81$) than their married peers ($M = 2.77, SD = 0.82$). This contradicts the qualitative narratives where married participants lamented severe family-related disruptions, indicating instead that single graduate students face greater unmitigated role strain because they lack shared domestic support systems and must shoulder work, personal, and academic demands in isolation.

This demographic disparity is supported by research demonstrating that while married individuals manage visible domestic obligations, they also benefit from established household co-regulation and emotional scaffolding that insulate their work routines (Costa et al., 2023; Lu et al., 2024). In contrast, solitary scholars bear all operational, financial, and scholarly pressures without shared logistical relief, leaving them uniquely susceptible to unbuffered role overload and severe academic strain (Commey-Mintah et al., 2025; Mahabir, 2022).

Table 1. Level of Research Fatigue Among Thesis and Dissertation Writers

Variable	Physiological and Psychosomatic Manifestations			Cognitive and Psychological Exhaustion			Functional Disruption and Role Strain			Research Fatigue		
	M	SD	Int	M	SD	Int	M	SD	Int	M	SD	Int
Degree Program												
Masters	3.43	0.72	High	3.34	0.79	Moderate	3.02	0.79	Moderate	3.02	0.79	Moderate
Doctorate	3.63	0.83	High	3.46	0.86	High	3.12	1.00	Moderate	3.12	1.00	Moderate
Research Funding												
With Scholarship	3.32	0.71	Moderate	3.36	0.83	Moderate	3.06	0.84	Moderate	3.06	0.84	Moderate
Personal Fund	3.52	0.76	High	3.38	0.80	Moderate	3.04	0.85	Moderate	3.04	0.85	Moderate
Age												
35 years old and below	3.48	0.79	High	3.41	0.83	Moderate	3.08	0.87	Moderate	3.08	0.87	Moderate
Over 35 years old	3.48	0.70	High	3.32	0.78	Moderate	2.98	0.81	Moderate	2.98	0.81	Moderate
Civil Status												
Single	3.55	0.75	High	3.50	0.75	High	3.25	0.81	Moderate	3.25	0.81	Moderate
Married	3.39	0.75	Moderate	3.21	0.84	Moderate	2.77	0.82	Moderate	2.77	0.82	Moderate
Monthly Income												
Below Php 25,000	3.53	0.72	High	3.50	0.75	High	3.11	0.80	Moderate	3.11	0.80	Moderate
Php 25,000 - Php 44,999	3.49	0.77	High	3.32	0.80	Moderate	3.06	0.90	Moderate	3.06	0.90	Moderate
Php 45,000 and above	3.36	0.78	Moderate	3.27	0.92	Moderate	2.87	0.78	Moderate	2.87	0.78	Moderate
Whole	***3.48***	***0.75***	***High***	***3.37***	***0.80***	***Moderate***	***3.04***	***0.84***	***Moderate***	***3.04***	***0.84***	***Moderate***

3.2.2. Level of Scientific Writing Difficulty

Overall level of scientific writing difficulty. Table 2 presents the levels of scientific writing difficulties in terms of structural and logical organization hurdles, technical and methodological barriers, information literacy and pedagogical gaps, and overall scientific

writing difficulties, both as a whole and by profile. As a whole, difficulties with scientific writing were evaluated as moderate ($M = 3.10, SD = 0.80$), with structural and logical organization hurdles ranking as the most pronounced challenge ($M = 3.37, SD = 0.84$), followed by technical and methodological barriers ($M = 3.09, SD = 0.92$) and information literacy and pedagogical gaps ($M = 2.92, SD = 0.80$).

This pattern is consistent with empirical observations that advanced academic writing difficulties stem primarily from higher-order discursive demands rather than technical mechanics alone (Azizah et al., 2025). Specifically, structural and organizational hurdles emerge as the primary stumbling block because formulating genre-specific rhetoric and cohesive macro-structures imposes heavy cognitive load on developing scholars (Oliveira & de Barba, 2022). Even when writers report moderate technical competence, underlying gaps in synthesizing complex evidence undermine overall clarity and scholarly execution (Deng et al., 2022).

However, an inspection of the demographic breakdown in Table 2 reveals several counterintuitive and unexpected findings. First, master's and doctoral writers recorded identical overall scientific writing difficulties ($M = 3.10, SD = 0.75$ and $M = 3.10, SD = 0.92$, respectively), with near-identical scores across technical and structural subdimensions. This quantitative parity contradicts traditional developmental expectations that doctoral candidates, possessing prior thesis completion experience and advanced graduate training, demonstrate greater authorial autonomy and fewer rhetorical hurdles than master's students. This reveals that scientific composition hurdles, especially thematic synthesis and discursive logic, are systemic pedagogical barriers that persist irrespective of graduate level.

Second, writers receiving research scholarships reported higher overall writing difficulties ($M = 3.26, SD = 0.78$) and a "High" level of structural organization hurdles ($M = 3.63, SD = 0.95$) compared to self-funded students ($M = 3.06$ and $M = 3.31$, respectively). Rather than funding serving as an academic buffer, scholarship recipients appear to face heightened scrutiny, rigid milestone deliverables, and intense publication pressures that magnify their perceived writing hurdles. Finally, single writers consistently reported higher difficulties across all subscales than married writers ($M = 3.26$ vs. $M = 2.90$), confirming that writing difficulties are not merely intellectual hurdles, but are socially mediated processes that intensify in the absence of domestic co-regulation and personal support systems.

These demographic disparities corroborate findings that rhetorical mastery cannot be assumed through advanced matriculation alone, as doctoral programs often emphasize specialized research content over direct instructional scaffolding in advanced scientific discourse (Al Marwani, 2020; Wang & Troia, 2023). Furthermore, external pressures from performance-contingent funding amplify compositional anxiety, while the absence of social and domestic co-regulation leaves solitary writers uniquely exposed to chronic writing blocks and affective strain (Costa et al., 2023; Mahabir, 2022).

Structural and logical organization hurdles. Regarding structural and logical organization hurdles, the respondents demonstrated a moderate level overall ($M = 3.37, SD = 0.84$), ranking as the highest challenge among all scientific writing dimensions. This indicates that mastering macro-level cohesion, integrating diverse literature, and establishing logical transitions across IMRaD sections pose a more persistent difficulty than discrete grammatical or technical tasks. This prioritization is consistently mirrored in academic discourse, which emphasizes that achieving logical flow and discursive cohesion is a sophisticated cognitive endeavor requiring writers to advance beyond sentence-level syntax into complex thematic mapping and rhetorical sequencing (Amnuai, 2019; Karim, 2022). Without explicit modeling of genre-specific rhetorical conventions common in high-impact publishing, developing authors struggle to balance rigorous technical evidence with the overarching narrative logic demanded of scientific arguments (Hiver et al., 2020; Truong, 2023).

However, an examination of Table 2 reveals several counterintuitive patterns across respondent profiles. Most prominently, scholarship recipients reported an exceptionally High level of structural and logical organization hurdles ($M = 3.63, SD = 0.95$), significantly exceeding their self-funded counterparts ($M = 3.31, SD = 0.80$, Moderate). This challenges the common assumption that funded scholars possess greater compositional fluency and encounter fewer academic roadblocks; instead, external funding conditions, such as mandatory publication quotas, rigid grant timelines, and heightened panel scrutiny, appear to amplify the cognitive stakes of structuring an argument.

Equally unexpected is the negligible difference between master's ($M = 3.39, SD = 0.81$) and doctoral ($M = 3.32, SD = 0.93$) writers. Despite doctoral candidates having completed previous theses and advanced seminar coursework, they struggle almost equally with thematic synthesis and structural cohesion, demonstrating that organizational hurdles do not naturally diminish with academic progression. Furthermore, structural difficulty spiked into the "High" tier among younger (≤ 35 years: $M = 3.42$) and single ($M = 3.54$) scholars, revealing that rhetorical composition is deeply sensitive to early-career isolation and the absence of relational buffering systems.

These empirical patterns corroborate findings that advanced structural competencies are neither automatically acquired through degree advancement nor alleviated by financial stipends alone (Al Marwani, 2020; Wang & Troia, 2023). Rather, heightened milestone expectations attached to competitive funding intensify cognitive load during the drafting phase (Oliveira & de Barba, 2022), while solitary and early-career researchers face these compositional hurdles without the collaborative co-regulation and emotional support systems essential for navigating complex manuscript production (Costa et al., 2023; Mahabir, 2022).

Technical and methodological barriers. With respect to technical and methodological barriers, the respondents demonstrated a moderate level overall ($M = 3.09, SD = 0.92$), ranking second among the scientific writing dimensions. This indicates that while graduate

writers possess foundational knowledge of research procedures, translating methodological frameworks, statistical outputs, and analytical procedures into formal scholarly prose remains a substantial source of friction. This tension is widely documented in academic writing literature, which emphasizes that articulating methodological rigor requires a specialized rhetorical competence that novice and developing researchers often find cognitively overwhelming (Barroga & Matanguihan, 2021; Truong, 2023). Translating complex experimental designs and quantitative analyses into precise, transparent prose frequently induces cognitive overload, particularly as open-science standards and high-impact publishing criteria grow increasingly demanding (Amnuai, 2019; Karim, 2022).

An inspection of the demographic distributions in Table 2 reveals unexpected trends that challenge conventional developmental assumptions in graduate education. Most notably, doctoral candidates reported nearly the identical level of technical and methodological difficulty ($M = 3.08, SD = 1.04$) as master's students ($M = 3.09, SD = 0.89$), alongside a wider standard deviation indicating divergent individual competence. Because doctoral scholars have already defended a master's thesis and completed advanced methodology coursework, they are conventionally expected to possess higher methodological self-efficacy. This parity suggests that technical and statistical hurdles do not naturally resolve with academic advancement, particularly as doctoral inquiry introduces complex, non-conventional designs such as mixed methods.

Furthermore, an unexpected disparity emerged regarding research funding and civil status. Scholarship recipients reported greater technical and methodological barriers ($M = 3.25, SD = 0.93$) than self-funded scholars ($M = 3.05, SD = 0.92$). Rather than funding serving as an academic buffer, scholarship requirements appear to push candidates toward complex, high-stakes methodologies to satisfy grant deliverables, thereby magnifying analytical friction. Finally, single researchers experienced higher technical barriers ($M = 3.30$) than married researchers ($M = 2.82$), reinforcing that technical anxiety is amplified when scholars lack domestic buffering systems to alleviate the cognitive strain of quantitative interpretation and methodological justification.

These demographic disparities corroborate findings that methodological self-efficacy does not increase linearly with academic degree progression, as advanced doctoral research demands novel epistemological and analytical frameworks that exceed baseline graduate coursework (Al Marwani, 2020; Wang & Troia, 2023). Furthermore, external grant expectations impose performance-contingent burdens that heighten technical scrutiny, while solitary writers must process complex analytical challenges without the co-regulation and emotional scaffolding that mitigate academic and statistical anxiety (Costa et al., 2023; Mahabir, 2022).

Information literacy and pedagogical gaps. In terms of information literacy and pedagogical gaps, the respondents demonstrated a moderate level overall ($M = 2.92, SD =$

0.80), ranking as the lowest difficulty dimension among scientific writing hurdles. While this suggests that graduate writers find baseline literature searching and bibliographic formatting relatively manageable compared to structural or methodological synthesis, the empirical data reveal important unexpected trends.

Most notably, Table 2 shows that doctoral candidates reported higher information literacy and pedagogical gaps ($M = 2.97, SD = 0.92$) than master's students ($M = 2.90, SD = 0.77$). This runs counter to standard academic progression models, which presume that advanced doctoral researchers possess greater bibliometric autonomy, digital acumen, and information retrieval skills developed from completing prior graduate degrees. Instead, this elevation indicates that doctoral dissertation expectations, such as navigating high-impact indexed databases, curating cutting-edge international literature, and adopting unfamiliar AI-assisted synthesis tools, create an expanded instructional void that standard graduate curricula fail to address.

Furthermore, the lowest descriptive ranking of this dimension presents an unexpected divergence when juxtaposed with the qualitative narratives. During the qualitative phase, participants highlighted severe instructional and literacy frictions, including the frustrating *AI Learning Curve* that drives writers back to exhausting manual workflows, as well as *Mechanical Composition*, where the absence of instructional modeling forces writers into superficial compliance simply to satisfy panel instructions. This demonstrates that while researchers may not perceive database searching and citation retrieval as major hurdles on a survey scale, the deeper pedagogical disconnect in translating source literature into critical, cohesive discourse remains a subtle yet potent barrier.

These outcomes align with evidence that advanced scholarship requires sophisticated evaluative, critical, and digital navigation skills that frequently outstrip institutional writing pedagogies (Wang & Troia, 2023; Zou et al., 2025). Rather than reflecting simple operational deficits, higher gaps among doctoral writers highlight the mounting complexities of digital scholarly ecosystems and emerging AI curation tools, which demand updated blended instructional scaffolding (Alsalhi, 2026). Without explicit modeling and curricular support, researchers remain trapped in fragmented, manual drafting habits, diminishing their authorial agency and perceived academic efficacy (Mtika & Abbott, 2023).

Table 2. Level of Scientific Writing Difficulties Among Thesis and Dissertation Writers

Variable	Structural and Logical Organization Hurdles			Technical and Methodological Barriers			Information Literacy and Pedagogical Gaps			Scientific Writing Difficulties		
	M	SD	Int	M	SD	Int	M	SD	Int	M	SD	Int
Degree Program												
Masters	3.39	0.81	Moderate	3.09	0.89	Moderate	2.90	0.77	Moderate	3.10	0.75	Moderate
Doctorate	3.32	0.93	Moderate	3.08	1.04	Moderate	2.97	0.92	Moderate	3.10	0.92	Moderate
Research Funding												
With Scholarship	3.63	0.95	High	3.25	0.93	Moderate	3.01	0.77	Moderate	3.26	0.78	Moderate
Personal Fund	3.31	0.80	Moderate	3.05	0.92	Moderate	2.89	0.81	Moderate	3.06	0.80	Moderate
Age												
35 years old and below	3.42	0.88	High	3.12	0.96	Moderate	2.92	0.86	Moderate	3.13	0.84	Moderate
Over 35 years old	3.30	0.79	Moderate	3.05	0.87	Moderate	2.91	0.72	Moderate	3.07	0.74	Moderate
Civil Status												
Single	3.54	0.80	High	3.30	0.86	Moderate	3.01	0.79	Moderate	3.26	0.74	Moderate
Married	3.16	0.85	Moderate	2.82	0.94	Moderate	2.80	0.81	Moderate	2.90	0.83	Moderate
Monthly Income												
Below Php 25,000	3.43	0.75	High	3.17	0.84	Moderate	2.91	0.78	Moderate	3.14	0.73	Moderate
Php 25,000 - Php 44,999	3.35	0.93	Moderate	3.06	0.99	Moderate	2.94	0.84	Moderate	3.09	0.85	Moderate
Php 45,000 and above	3.31	0.77	Moderate	3.02	0.90	Moderate	2.88	0.77	Moderate	3.04	0.78	Moderate
Whole	***3.37***	***0.84***	***Moderate***	***3.09***	***0.92***	***Moderate***	***2.92***	***0.80***	***Moderate***	***3.10***	***0.80***	***Moderate***

3.2.3. Difference in Research Fatigue When Grouped According to Profile Variables

The Shapiro–Wilk test was conducted to evaluate the normality of the data distribution. For research fatigue, the result ($W = 0.991, p = 0.475$) confirmed a normal distribution, as the p-value exceeded the 0.05 threshold. Similarly, scientific writing difficulties demonstrated normality ($W = 0.992, p = 0.639$). Because the normality assumption was satisfied, parametric inferential tests were deemed appropriate for evaluating group differences across demographic profiles.

An independent-samples t-test and a one-way ANOVA were subsequently performed to determine whether research fatigue varied significantly across demographic variables. As shown in Table 3, only civil status yielded a statistically significant difference [$t(144) = 3.530, p = 0.001$], whereas age [$t(144) = 0.766, p = 0.445$] and monthly income [$F(2,143) = 0.747, p = 0.476$] demonstrated no significant variation.

These outcomes highlight two unexpected findings when juxtaposed with prevailing assumptions and the study's qualitative insights. First, the significant divergence by civil status reveals that unmarried scholars experience substantially greater cumulative strain than married peers, indicating that the absence of household co-regulation and shared domestic support leaves single researchers uniquely vulnerable to research fatigue. Second, the absence of significant differences across age cohorts contradicts the strong qualitative narratives surrounding *Age-Related Stamina*, where mature scholars attributed their exhaustion to declining biological endurance. This statistical equivalence demonstrates that research fatigue is not governed by chronological aging, but instead represents a systemic strain imposed uniformly by the sedentary and cognitive rigors of scholarly labor.

The significant variance across civil status validates empirical evidence that spousal and domestic networks provide indispensable emotional buffering and restorative resources, effectively mitigating acute burnout in academic degree completion (Arafat et al., 2025; Costa

et al., 2023; Mahabir, 2022). Conversely, the parity observed across age cohorts aligns with literature demonstrating that research-induced fatigue is an institutional condition driven by workload saturation and prolonged sedentary demands, impacting scholars symmetrically irrespective of biological endurance (March-Amengual et al., 2022; Wu et al., 2025).

Table 3. Difference in Research Fatigue When Grouped According to Profile Variables

Variable	t	df	p
Age	0.766	144	0.445
Civil Status	3.530*	144	0.001
	F	**df**	**p**
Monthly Income	0.747	2, 143	0.476

Note: difference is significant when p≤0.05

3.2.4. Difference in Scientific Writing Difficulties When Grouped According to Profile Variables

An independent-samples t-test and a one-way ANOVA were utilized to evaluate differences in scientific writing difficulties across demographic profiles. As presented in Table 4, only civil status demonstrated a statistically significant difference [$t(144) = 2.727, p = 0.007$], while age [$t(144) = 0.446, p = 0.656$] and monthly income [$F(2,143) = 0.140, p = 0.870$] did not differ significantly.

This pattern yields crucial insights into how personal and structural factors intersect with the writing process. Most notably, the significant disparity across civil status reveals that writing difficulties are deeply socially mediated, with single writers experiencing greater compositional friction due to the absence of domestic co-regulation and relational support systems. Conversely, the statistical parity observed across age cohorts and income tiers indicates that academic writing hurdles are universal rather than resource- or age-dependent. While greater financial resources might be presumed to ease technical barriers through access to editorial software, methodological consultants, or paid repositories, income failed to buffer scholars from compositional strain. Similarly, writing barriers persisted symmetrically across age groups, demonstrating that rhetorical fluency and discursive competence do not automatically accrue through chronological maturity or career tenure.

These empirical outcomes align with literature establishing that marital and domestic partnerships provide vital emotional and psychological buffering against academic writing burnout, fostering the cognitive resilience necessary to manage the complex linguistic demands of thesis production (Arafat et al., 2025; Costa et al., 2023; Mahabir, 2022). In contrast, the absence of variation by age and socioeconomic standing corroborates evidence that scientific writing challenges are fundamentally rooted in disciplinary conventions, structural move-structures, and pedagogical gaps that external capital and biological maturation cannot inherently alleviate (Al Marwani, 2020; Bulqiyah et al., 2021).

Table 4. Difference in Scientific Writing Difficulties When Grouped According to Profile Variables

Variable	t	df	p
Age	0.446	144	0.656
Civil Status	2.727*	144	0.007
	F	**df**	**p**
Monthly Income	0.140	2, 143	0.870

Note: difference is significant when p≤0.05

3.2.5. Multiple Regression Analysis of Dimensions of Research Fatigue as Predictors of Scientific Writing Difficulties

The regression model exposes a striking divergence between descriptive intensity and predictive validity. Although *Physiological and Psychosomatic Manifestations* scored the highest overall mean ($M = 3.48, SD = 0.75$, High level) among the fatigue dimensions, it failed to significantly predict scientific writing difficulties ($\beta = 0.035, t = 0.391, p = 0.696$). This counterintuitive outcome indicates that while physical symptoms, such as headaches, cardiovascular strain, and sleep loss, represent the most acutely felt somatic experiences of academic writing stress, they function primarily as secondary biological byproducts rather than direct operational inhibitors of manuscript production. Instead, scientific writing difficulties are governed decisively by *Functional Disruption and Role Strain* as the primary predictor ($\beta = 0.449, t = 5.187, p = 0.000$), followed by *Cognitive and Psychological Exhaustion* ($\beta = 0.286, t = 3.006, p = 0.003$). Two distinct structural and psychological mechanisms elucidate why these two dimensions uniquely drive compositional impairment:

First, the predominant predictive influence of *Functional Disruption and Role Strain* operates through cognitive fragmentation and maladaptive emotional regulation. Because many graduate scholars maintain concurrent professional careers, pervasive inter-role conflicts relegate scholarly writing to late-night, disjointed blocks of time. When role saturation occurs, writers engage in *Avoidance and Procrastination* not due to poor time management, but as an emotional coping mechanism to evade acute performance anxiety. This chronic postponement leads directly to *Mechanical Composition*, wherein authors abandon deep conceptual synthesis in favor of superficial, compliance-oriented drafting simply to satisfy panel mandates and urgent deadlines.

This dynamic aligns with literature establishing that role conflict and task saturation are the principal behavioral drivers of academic impairment, far exceeding the impact of general physical fatigue (Allen et al., 2020; Zeinollakizi, 2026). When professional and scholarly demands collide, resulting behavioral disruptions systematically undermine self-regulated writing routines, triggering avoidance cycles and eleventh-hour drafting that compromise manuscript rigor (Bülbül & Odacı, 2023).

Second, the operational mechanism underlying *Cognitive and Psychological Exhaustion* is rooted in working memory depletion and executive dysfunction. As

conceptualized by Cognitive Load Theory, scientific discourse requires intense relational processing to structure the IMRaD framework, synthesize contradictory literature, and establish metadiscourse. However, the qualitative phenomenon of *Persistent Mental Preoccupation*, reflecting the Zeigarnik effect of unresolved dissertation chapters, generates continuous affective rumination and sleep disruption that exhausts executive faculties. This induces *Information Processing Failure*, manifesting as mental fog and cognitive tunneling. Depleted writers lack the working memory capacity required to resolve synthesis bottlenecks, interpret complex quantitative outputs, and bridge conceptual ideas with technical prose.

This cognitive breakdown is corroborated by empirical research demonstrating that mental weariness and academic writing burnout directly degrade the executive control functions vital for sophisticated scientific reasoning (van As et al., 2021; Wang, 2026). When mental faculties are systematically overburdened, scholars experience elevated cognitive strain and affective distress, which directly constrains their capacity to execute rigorous rhetorical synthesis and maintain methodological precision (Chongjin, 2025; Steward & Chib, 2024).

Table 5. Multiple Regression Analysis of Dimensions of Research Fatigue as Predictors of Scientific Writing Difficulties

R	R^2	Adjusted R Square	F	df	p
0.747	0.558	0.549	59.850	3, 142	0.000
Variable		**Beta**		**t**	**p**
(Constant)		0.651		3.005	0.003
Physiological and Psychosomatic Manifestations		0.035		0.391	0.696
Cognitive and Psychological Exhaustion		0.286		3.006	0.003
Functional Disruption and Role Strain		0.449		5.187	0.000

3.2.6. Joint Display

Table 6 presents the joint display integrating the qualitative findings and quantitative results to establish comprehensive meta-inferences on research fatigue and scientific writing difficulties. Side-by-side alignment of both data strands illustrates how the lived experiences of thesis and dissertation writers correspond with, contextualize, and explain their survey ratings. Through this integration, unexpected divergences between the high descriptive intensity of somatic symptoms and their non-significant predictive role are clearly delineated. Furthermore, the matrix highlights the underlying behavioral and cognitive mechanisms that explain why functional role strain and psychological exhaustion serve as significant drivers of writing hurdles. This synthesized joint display provides an empirical foundation for developing holistic academic interventions that address both writing competence and graduate student well-being.

Table 6. Joint Display of the Qualitative and Quantitative Results

Qualitative Results	Quantitative Results	Meta-Inferences
On Research Fatigue Theme 1: Physiological and Psychosomatic Manifestations *1.1: Physiological Disruptions* *1.2: Somatic Indicators of Mental Drain* *1.3: Age-Related Stamina*	Overall, research fatigue was interpreted as moderate (M = 3.04, SD = 0.84). In terms of physiological and psychosomatic manifestations, the respondents exhibited a high level overall (M=3.48, SD=0.75).	**Unexpected Divergence:** While bodily exhaustion and somatic symptoms are experienced most acutely by researchers, they operate primarily as downstream physical reactions to stress rather than direct functional causes of writing difficulty. Physical exhaustion does not directly predict writing deficits.
Theme 2: Cognitive and Psychological Exhaustion *2.1: Persistent Mental Preoccupation* *2.2: Information Processing Failure* *2.3: Anxiety-Driven Paralysis*	In terms of cognitive and psychological exhaustion, the respondents demonstrated a moderate level (M=3.37, SD=0.80).	The qualitative themes of mental preoccupation and processing failure are supported by a moderate quantitative score, indicating that cognitive and psychological exhaustion significantly impairs the researchers' ability to function effectively. This synthesis suggests that anxiety and information overload create a mental barrier that manifests as both a perceived and measurable state of paralysis.
Theme 3: Functional Disruption and Role Strain *3.1: Reduced Occupational Efficacy* *3.2: Social and Family Sacrifice* *3.3: Avoidance and Procrastination*	In terms of functional disruption and role strain, the respondents demonstrated a moderate level overall (M=3.04, SD=0.84).	**Primary Explanatory Mechanism:** Qualitative findings of avoidance, procrastination, and inter-role conflict explain why this dimension is the most powerful predictor. Role strain fragments academic engagement, inducing emotional avoidance and resulting in disjointed, mechanical composition under high-stakes deadlines.
On Scientific Writing Difficulty Theme 1: Structural and Logical Organization Hurdles *1.1: Synthesis and Cohesion* *1.2: Language and Grammar Obstacles*	As a whole, the difficulty of scientific writing was interpreted as moderate (M=3.10, SD=0.80). In terms of structural and logical organization hurdles, the respondents demonstrated a moderate level (M=3.37, SD=0.84).	The qualitative focus on synthesis and linguistic barriers aligns with the moderate-to-high quantitative score, identifying structural and linguistic organization as a primary challenge in scientific writing. Together, these data indicate that the difficulty in achieving logical flow and cohesion is a significant contributor to the overall moderate difficulty of the research process.
Theme 2: Technical and Methodological Barriers *2.1: Methodological Unfamiliarity* *2.2: Statistical Phobia* *2.3: Conceptual-to-Technical Translation Hurdles*	With respect to technical and methodological barriers, the respondents demonstrated a moderate level overall (M=3.09, SD=0.92).	The qualitative themes of methodological unfamiliarity and statistical phobia are corroborated by a moderate quantitative score, identifying technical and methodological barriers as a significant source of researcher anxiety. This synthesis suggests that the primary hurdle lies in the challenge of translating conceptual ideas into rigorous technical and statistical frameworks.
Theme 3: Information Literacy and Pedagogical Gaps *3.1: The Context Gap* *3.2: The AI Learning Curve* *3.3: Mechanical Composition*	In terms of information literacy and pedagogical gaps, the respondents also demonstrated a moderate level as a whole (M=2.92, SD=0.80).	The qualitative focus on the AI learning curve and contextual gaps is supported by a moderate quantitative score, indicating that information literacy and pedagogical gaps present a persistent challenge to researchers. This synthesis suggests that while researchers are navigating new tools like AI, a lack of foundational training in mechanical composition and context still hinders their overall writing efficacy.

4.0. Conclusion

The study underscores that research fatigue and scientific writing difficulties are not merely individual academic hurdles, but systemic issues requiring a holistic shift in graduate education. It is essential to balance the traditional focus on technical proficiency with robust institutional support that prioritizes the physiological and psychological well-being of graduate students. Given that functional role strain and cognitive-psychological exhaustion are primary predictors of writing difficulty, there is an urgent need for structured institutional interventions, such as writing cohorts and flexible completion timelines, to mitigate the professional isolation and overwhelming workloads inherent in high-stakes scholarly inquiry. Furthermore, the transition from consumer to producer of research requires intentional pedagogical support to bridge the gap between abstract conceptualization and the formal composition of a logical narrative. For students navigating these demanding research environments, resilience is deeply influenced by social support systems, highlighting the need for inclusive research communities. Ultimately, progress requires a research culture that prioritizes the human element, ensuring that the pursuit of academic excellence does not come at the cost of the researcher's professional efficacy or personal health and well-being.

5.0. Directions for Future Research

Future studies should adopt longitudinal designs to track how research fatigue and writing difficulties evolve across the entire duration of a graduate program. Researchers should also expand the participant pool to include a more balanced representation of doctoral candidates and students from diverse secular or state-run institutions. To enhance generalizability, future inquiries should utilize standardized international instruments alongside researcher-made tools to cross-validate findings across different cultural contexts. Investigations could further explore the impact of institutional funding and financial support systems on reducing research-related stress and increasing writing self-efficacy. Finally, qualitative explorations should involve larger, more diverse samples to capture a broader spectrum of researcher experiences and coping mechanisms.

6.0. Limitations of the Findings

The findings of the study acknowledge various limitations. The findings are limited to graduate students at a single Catholic university in Bacolod City, Philippines, which limits generalizability to other contexts. Likewise, this is limited to those enrolled during the 2025-2026 academic year, providing a cross-sectional snapshot that does not capture the longitudinal progression of research fatigue over time. The findings are limited to the self-reported data of the participants regarding their subjective perceptions of research fatigue and writing difficulty, which may introduce inherent biases compared to standardized international tools. The findings are also limited to the demographics employed, which were heavily skewed toward master's students and self-funded respondents, potentially overshadowing the chronic exhaustion patterns of doctoral candidates. Furthermore, the qualitative phase is limited to a small purposive sample of eleven participants, potentially narrowing the diversity of reported research experiences. Finally, the findings are also limited to the exploratory sequential mixed methods approach used.

7.0. References

Andrade, D., Ribeiro, I. J. S., Prémusz, V., & Maté, O. (2023). Academic Burnout, Family Functionality, Perceived Social Support and Coping among Graduate Students during the COVID-19 Pandemic. *International Journal of Environmental Research and Public Health, 20*(6), 4832. https://doi.org/10.3390/ijerph20064832

Adrianty, U., & Hafizh, M. (2023). The difficulties of EFL graduate students in writing a scientific article. In *Proceedings of the International Conference on English Language and Teaching (ICOELT 2022)* (pp. 147–153). Atlantis Press. https://doi.org/10.2991/978-2-38476-166-1_21

Agyapong, B., Obuobi-Donkor, G., Burback, L., & Wei, Y. (2022). Stress, burnout, anxiety and depression among teachers: A scoping review. *International Journal of Environmental Research and Public Health, 19*(17), Article 10706. https://doi.org/10.3390/ijerph191710706

Allen, T. D., Merlo, K., Lawrence, R. C., Slutsky, J., & Gray, C. E. (2021). Boundary Management and Work-Nonwork Balance While Working from Home. *Applied Psychology*, *70*(1), 60-84. https://doi.org/10.1111/apps.12300

Alostath, K. (2021). Graduate students' challenges in academic writing. *ResearchGate*. https://doi.org/10.13140/RG.2.2.20113.92008

Alsalhi, N. R., Eltahir, M. E., Al Gharaibeh, F., & Qusef, A. (2026). Blended learning after the COVID-19 pandemic: Undergraduate students' perspectives on the application of blended learning in higher education. *Contemporary Educational Technology, 18*(2), Article ep641. https://doi.org/10.30935/cedtech/18057

Amnuai, W. (2019). Analyses of Rhetorical Moves and Linguistic Realizations in Accounting Research Article Abstracts Published in International and Thai-Based Journals. *SAGE Open*. 9. 215824401882238. https://doi.org/10.1177/2158244018822384

Arafat, Md. Y., Alam, Md,Tabassum, N., Fahmida, F., Riche, I., & Chakma, S. (2025). Economic Hardship and Academic Pursuit: A Study of Students in Higher Education. 3. 9-20. https://doi.org/10.54099/ijesd.v3i2.1579

Azizah, R.N., Nurhayati, L., & Purnawan, A. (2025). Exploring EFL Graduate Students' Difficulties in Completing Academic Writing: A Narrative Inquiry. *Ideas: Journal on English Language Teaching and Learning, Linguistics and Literature*, 13(2). https://doi.org/10.24256/ideas.v13i2.8415

Badenhorst, C. (2022). *Productive writing: Becoming a prolific academic writer*. Routledge.

Barroga, E., & Matanguihan, G. J. (2021). Creating Logical Flow When Writing Scientific Articles. *Journal of Korean Medical Science*, *36*(40), e275. https://doi.org/10.3346/jkms.2021.36.e275

Bazeley, P. (2021). *Qualitative data analysis*. (Vols. 1-0). SAGE Publications Ltd, https://doi.org/10.4135/9781036233808

Bencsik, A., & Juhász, T. (2023). The impact of technostress on organizational functioning. *Problems and Perspectives in Management*. 21. 230-241. https://doi.org/10.21511/ppm.21(1).2023.20

Bennett, A. A., Gabriel, A. S., & Calderwood, C. (2020). Examining the interplay of micro-break durations and activities for employee recovery: A mixed-methods investigation. *Journal of Occupational Health Psychology*, *25*(2), 126–142. https://doi.org/10.1037/ocp0000168

Bond, M., Khosravi, H., Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S.W., & Siemens, G. (2024). A meta systematic review of Artificial Intelligence in Higher Education: A call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education*. 21. 1-41. https://doi.org/10.1186/s41239-023-00436-z.

Branscheidt, M., Kassavetis, P., Anaya, M., Rogers, D., Huang, H. D., Lindquist, M. A., & Celnik, P. (2019). Fatigue induces long-lasting detrimental changes in motor-skill learning. *eLife*, *8*, Article e40578. https://doi.org/10.7554/eLife.40578

Broskevičová, Z., Gřundělová, B., & Kowolová, I. (2024). It puts them in the role of zoo animals: Gatekeeping, research fatigue, and over-researched populations in Czech social work research. *Journal of Social Service Research*, *50*(4), 548–561. https://doi.org/10.1080/01488376.2024.2348530

Brunton, L. K., McPhee, P. G., & Gorter, J. W. (2019). Self-reported factors contributing to fatigue and its management in adolescents and adults with cerebral palsy. *Disability and Rehabilitation*, *43*(7), 929–935. https://doi.org/10.1080/09638288.2019.1647294

Bülbül, K. & Odacı, H. (2023). Analysis of Studies about Academic Anxiety: A Thematic Review. *Psikiyatride Güncel Yaklaşımlar.* 15. 370-384. https://doi.org/10.18863/pgy.1124868

Campbell, S., Greenwood, M., Prior, S., Shearer, T., Walkem, K., Young, S., Bywaters, D., & Walker, K. (2020). Purposive sampling: Complex or simple? Research case examples. *Journal of Research in Nursing*, *25*(8), 652–661. https://doi.org/10.1177/1744987120927206

Casal–Ribeiro, M., Peixoto, U. I., Medeiros–Leal, W., & Santos, R. (2024). Research fatigue's impact on small-scale fishers' engagement: A case study from Azores fisheries. *Marine Policy*, *170*. https://doi.org/10.1016/j.marpol.2024.106404

Chen, O., Castro-Alonso, J.C., Paas, F., & Sweller, J. (2018). Extending Cognitive Load Theory to Incorporate Working Memory Resource Depletion: Evidence from the Spacing Effect. *Educ Psychol Rev* 30, 483–501. https://doi.org/10.1007/s10648-017-9426-2

Chongjin, W., Charan, I. A., & Soomro, S. (2025). Examining the Effects of Academic Stress, Self-Efficacy, Cognitive-Behavioral Outcomes, Psychological Distress, and Prosocial Behavior: A Moderated-Mediation Model. *Brain and Behavior*, *15*(10), e70907. https://doi.org/10.1002/brb3.70907

Christopoulou, S., Antonopoulou, H., Zapantis, R., Gkintoni, E., & Halkiopoulos, C. (2026). Teacher Well-Being and Burnout Resilience: Dimensional Independence, Pandemic Burden, and Profile Analysis in Primary Education. *International Journal of Environmental Research and Public Health*, *23*(2), 190. https://doi.org/10.3390/ijerph23020190

Commey-Mintah, P., Adjei-Boateng, E., Maison, R. S., Adasi, G. S., & Okrah, A. K. (2025). Balancing Books and Bonds: Exploring the Relationship between Academic Stress and Marital Satisfaction in Married Graduate Students. *Papers in Education and Development*, *43*(1), 180-201. https://doi.org/10.1163/26650746-20250004

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

Creamer, E. G. (2022). *Advancing the power of mixed methods research*. SAGE Publications.

Daniel, B. (2022). Common challenges postgraduate students and early-career academics face when engaging with the scholarly literature. *Electronic Journal of Business Research Methods*, *20*(3), 142–152. https://doi.org/10.34190/ejbrm.20.3.2503

Debelak, K., Grah, B., & Penger, S. (2025). Successful Aging at Work: A Comprehensive Literature Review, ENTRENOVA - ENTerprise REsearch InNOVAtion, ISSN 2706-4735, *IRENET* -

Society for Advancing Innovation and Research in Economy, Zagreb, Vol. 10, Iss. 1, pp. 191-203, https://doi.org/10.54820/entrenova-2024-0017

DeJonckheere, M., & Vaughn, L. M. (2019). Semistructured interviewing in primary care research: a balance of relationship and rigour. *Family Medicine and Community Health*, *7*(2), e000057. https://doi.org/10.1136/fmch-2018-000057

Deng, Y., Cherian, J., Khan, N. U. N., Kumari, K., Sial, M. S., Comite, U., Gavurova, B., & Popp, J. (2022). Family and academic stress and their impact on students' depression level and academic performance. *Frontiers in Psychiatry*, *13*. https://doi.org/10.3389/fpsyt.2022.869337

Dewaele, J. M., & Dewaele, L. (2020). Are foreign language learners' enjoyment and anxiety specific to the teacher? An investigation into the dynamics of learners' classroom emotions. *Studies in Second Language Learning and Teaching*. 10 (1), 45-65. http://dx.doi.org/10.14746/ssllt.2020.10.1.3

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... & Wright, R. (2023). "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI. *International Journal of Information Management*, *71*, Article 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

Fan, J., & Smith, A. P. (2020). Effects of occupational fatigue on cognitive performance of staff from a train operating company: A field study. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.558520

Fetters, M. D., & Molina-Azorin, J. F. (2020). The Mixed Methods Research Reporting Standards (MMRRS). *Journal of Mixed Methods Research*, *14*(3), 283–294. https://doi.org/10.1177/15586898211049629

Gaba, K. (2026). A Study on Perfectionism, Procrastination and Burnout among University Students. *International Journal of Interdisciplinary Approaches in Psychology*. 4. https://doi.org/10.61113/ijiap.v4i3.1312.

Gerlach, M., Blozik, E., Meichtry, A., Hägerbäumer, M., Kilcher, G., Golz, C. (2024). Factors of presenteeism and its association with detrimental effects among employees in Switzerland working in different sectors - a cross-sectional study using a multi-item instrument. *Int Arch Occup Environ Health*. 97(7):767-778. https://doi.org/10.1007/s00420-024-02083-x

Grassini, S. (2023). Shaping the Future of Education: Exploring the Potential and Consequences of AI and ChatGPT in Educational Settings. *Education Sciences*, *13*(7), 692. https://doi.org/10.3390/educsci13070692

Guetterman, T., Fetters, M., & Creswell, J. (2015). Integrating Quantitative and Qualitative Results in Health Science Mixed Methods Research Through Joint Displays. *The Annals of Family Medicine*. 13. 554-561. https://doi.org/10.1370/afm.1865

Gumasing, J. (2022). Evaluation of mental fatigue of students: A comparison between traditional and online learning in college students. In *Proceedings of the 2nd Indian International Conference*

on Industrial Engineering and Operations Management. https://doi.org/10.46254/IN02.20220642

Gupta, S., Jaiswal, A., Paramasivam, A., & Kotecha, J. (2022). Academic writing challenges and supports: Perspectives of international doctoral students and their supervisors. *Frontiers in Education*, *7*, Article 891534. https://doi.org/10.3389/feduc.2022.891534

Hamzah, F. B., Abdul Manan, D. I., Mohtaram, S., Abdullah, N. M., & Abdul Aziz, M. A. (2025). Exhausted Minds, Passionate Hearts: The Silent Struggle of Academic Burnout. *Journal of Applied Science, Engineering, Technology, and Education*, *7*(2), 365–376. https://doi.org/10.35877/454RI.asci4106

Hancock, P. A., Desmond, P. A., & Matthews, G. (2021). *The experience of fatigue*. Cambridge University Press.

Hiver, P., Al-Hoorie, A. H., & Mercer, S. (2020). *Student engagement in the language classroom*. Multilingual Matters. https://www.researchgate.net/publication/342479956_Student_Engagement_in_the_Language_Classroom

Holt-Lunstad, J. (2024). Social connection as a critical factor for mental and physical health: Evidence, trends, challenges, and future implications. *World Psychiatry*, *23*(3), 312–332. https://doi.org/10.1002/wps.21224

Hyland, K. (2019). *Metadiscourse: Exploring interaction in writing*. Bloomsbury Publishing.

Insantuan, B., Sihotang, H., Murniarti, E., & Buaton, J. (2026). The Impact of Academic Stress on Students' Mental Health: A Qualitative Study of Student Experiences. *Journal La Sociale*, *7*(2), 624-636. https://doi.org/10.37899/journal-la-sociale.v7i2.2897

Javaid, R., Momina, A., Sarwar, Z., & Naqi, S. (2020). Quality of Sleep and Academic Performance among Medical University Students. *Journal of the College of Physicians and Surgeons Pakistan*. 30. 844-848. https://doi.org/10.29271/jcpsp.2020.08.844

Jin, S., Zhu, X., Fu, X., & Wang, J. (2022). Family Supportive Leadership and Counterproductive Work Behavior: The Roles of Work-Family Conflict, Moral Disengagement and Personal Life Attribution. *Frontiers in Psychology*, *13*, 906877. https://doi.org/10.3389/fpsyg.2022.906877

Kalmakis, K. A., Kent, N. M., Alhowaymel, F., & Chiodo, L. M. (2022). Perceived stress, fatigue symptoms, and posttraumatic stress disorder symptoms among young adult college students. *Journal of Child and Adolescent Psychiatric Nursing*, *35*(1), 60–67. https://doi.org/10.1111/jcap.12352

Karim, M. (2022). The Standard Structure of a Research Article. https://www.researchgate.net/publication/362537450_The_Standard_Structure_of_a_Research_Article

Karki, R., Tamang, A., & Kaphle, M. (2026). Perceived Academic Stress and Its Correlates Among Secondary School Adolescents in Kathmandu, Nepal. *Public Health Challenges*, *5*(1), e70186. https://doi.org/10.1002/puh2.70186

Kim, J., Hwang, E. H., Shin, S., & Kim, K. H. (2022). University Students' Sleep and Mental Health Correlates in South Korea. *Healthcare (Basel, Switzerland)*, *10*(9), 1635. https://doi.org/10.3390/healthcare10091635

Kinnunen, U., & Mäkikangas, A. (2023). Longitudinal Profiles of Recovery-Enhancing Processes: Job-Related Antecedents and Well-Being Outcomes. *Int. J. Environ. Res. Public Health*, 20, 5382. https://doi.org/10.3390/ijerph20075382

Kocsis, Z., & Pusztai, G. (2024). Learning/earning: Characteristics of student work and its impact on academic careers at a regional Hungarian university. *Education Sciences*, *14*(9), Article 981. https://doi.org/10.3390/educsci14090981

Krishnan, P. (2025). Publish or Perish: How Relevant is the Statement Today? *Journal of the Association of Neuroscientists of Eastern India* 1(2):p 35-36. https://doi.org/10.4103/JANEI.JANEI_12_25

Li, W., Chen, J., Li, M., Smith, A. P., & Fan, J. (2022). The effect of exercise on academic fatigue and sleep quality among university students. *Frontiers in Psychology*, *13,* Article 1025280. https://doi.org/10.3389/fpsyg.2022.1025280

Li, Y., & Casanave, C. P. (2022). *Write like a scientist: A guide to scientific writing*. Oxford University Press.

Lincoln, Y.S., & Guba, E.G. (1986). But is it rigorous? Trustworthiness and authenticity in naturalistic evaluation. *New Directions for Program Evaluation*, 1986: 73-84. https://doi.org/10.1002/ev.1427

Lu, Z., Yu, D., Wang, L., & Fu, P. (2024). Association between depression status and hearing loss among older adults: The role of outdoor activity engagement. *Journal of Affective Disorders*, 345. https://doi.org/10.1016/j.jad.2023.10.050.

Mahabir, B. (2022). The influence of loneliness : mental health's impact on workaholism among graduate students. *Legacy Theses & Dissertations* (2009 - 2024). 2963. https://doi.org/10.54014/TA94-S47Q

Mahin, M., Rahman, M. S., Rahman, S. M., Ilias, F. B., Hasan, M. M., Akter, M., & Mredul, A. R. (2025). Factors impacting university students' quality of life. *PloS One*, *20*(8), e0329851. https://doi.org/10.1371/journal.pone.0329851

March-Amengual, J.-M., Cambra Badii, I., Casas-Baroy, J.-C., et al. (2022). Psychological Distress, Burnout, and Academic Performance in First Year College Students. *International Journal of Environmental Research and Public Health*, *19*(6), 3356. https://doi.org/10.3390/ijerph19063356

Merga, M.K., & Mason, S. (2021). Mentor and peer support for early career researchers sharing research with academia and beyond. *Heliyon*, 7(2). https://doi.org/10.1016/j.heliyon.2021.e06172

Mtika, P., & Abbott, P. (2023). Literacy and quality of life: A study of adults with poor literacy capabilities in western Rwanda. *Compare: A Journal of Comparative and International Education*, 1–17. https://doi.org/10.1080/03057925.2023.2254222

Oliveira, E., & de Barba, P. (2022). The Impact of Cognitive Load on Students' Academic Writing: An Authorship Verification Investigation. *ASCILITE Publications*. e22177. https://doi.org/10.14742/apubs.2022.177

Paas, F., & van Merriënboer, J. J. (2020). Cognitive-load theory: Methods to manage working memory load in the learning of complex tasks. *Current Directions in Psychological Science*, *29*(4), 394–398. https://doi.org/10.1177/0963721420922183

Paltridge, B., & Starfield, S. (2020). *Thesis and dissertation writing in a second language: A handbook for students and their supervisors*. Routledge.

Patel, S. S., Webster, R. K., Greenberg, N., Weston, D., & Brooks, S. K. (2020). Research fatigue in COVID-19 pandemic and post-disaster research: Causes, consequences and recommendations. *Disaster Prevention and Management*, *29*(4), 445–455. https://doi.org/10.1108/DPM-05-2020-0164

Popescu, B., Maricuțoiu, L. P., & De Witte, H. (2023). The student version of the Burnout assessement tool (BAT): psychometric properties and evidence regarding measurement validity on a romanian sample. *Current Psychology*, *43*, 2037-2051. https://doi.org/10.1007/s12144-023-04232-w

Pratiwi, S., & Kurniawan, E. (2021). Rhetorical move and genre knowledge development of English and Indonesian abstracts: A comparative analysis. *Studies in English Language and Education*. 8. 885-900. https://doi.org/10.24815/siele.v8i3.21038

Queirós, C., Passos, F., Bártolo, A., Marques, A. J., da Silva, C. F., & Pereira, A. (2020). Burnout and Stress Measurement in Police Officers: Literature Review and a Study With the Operational Police Stress Questionnaire. *Frontiers in Psychology*, *11*, 587. https://doi.org/10.3389/fpsyg.2020.00587

Rantanen, J., Lyyra, P., Feldt, T., Villi, M., & Parviainen, T. (2021). Intensified Job Demands and Cognitive Stress Symptoms: The Moderator Role of Individual Characteristics. *Frontiers in Psychology*, *12*, 607172. https://doi.org/10.3389/fpsyg.2021.607172

Ravi, N., & Vedaiappan, V. (2025). Relationship between mental fatigue and academic performance among college students. *International Journal of Scientific Research*. 6-7. https://doi.org/10.36106/ijsr/8302815.

Rozental, A., Forsström, D., Hussoon, A., & Klingsieck, K. B. (2022). Procrastination among university students: Differentiating severe cases in need of support from less severe cases. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.783570

Ruslin, R., Mashuri, S., Sarib, M., Alhabsyi, F., & Syam, H. (2022). Semi-structured interview: A methodological reflection on the development of a qualitative research instrument in educational studies. *Journal of Research & Method in Education*, *12*(1), 22–29. https://doi.org/10.9790/7388-1201052229

Schoonenboom, J., & Johnson, R. B. (2021). How to construct a mixed methods research design. *Kölner Zeitschrift für Soziologie und Sozialpsychologie*. 69. https://doi.org/10.1007/s11577-017-0454-1

Shi, Y. & Qu, S. (2021). Cognition and Academic Performance: Mediating Role of Personality Characteristics and Psychology Health. *Front. Psychol.* 12:774548. https://doi.org/10.3389/fpsyg.2021.774548

Sirois F. M. (2023). Procrastination and Stress: A Conceptual Review of Why Context Matters. *International Journal of Environmental Research and Public Health*, *20*(6), 5031. https://doi.org/10.3390/ijerph20065031

Skala, F., & Zemková, E. (2022). Effects of acute fatigue on cognitive performance in team sport players: Does it change the way they perform? A scoping review. *Applied Sciences*, *12*(3), Article 1736. https://doi.org/10.3390/app12031736

Soetan, T., & Johnson, W. (2025). Understanding the Psychological and Behavioral Drivers of Survey Fatigue Among Users of Digital Health Technologies: A Multi-Disciplinary Approach. 4. 22. https://www.researchgate.net/publication/392862457_Understanding_the_Psychological_and_Behavioral_Drivers_of_Survey_Fatigue_Among_Users_of_Digital_Health_Technologies_A_Multi-Disciplinary_Approach

Sonakawade, S., Angadi, G., & Kattimani, P. (2026). Unravelling the Relationship between Brain Fog, Cognitive Fatigue, AI Tool Use, and Research Productivity among Research Scholars: A Correlational Study. 8. 131-146. https://sl1nk.com/1b0nfmb

Sonnentag, S., Cheng, B.H., & Parker, S.L. (2022). Recovery from Work: Advancing the Field Toward the Future. *Annual Review of Organizational Psychology and Organizational Behavior*, 9(1), pp. 33-60. http://dx.doi.org/10.1146/annurev-orgpsych-012420-091355

Steel, P. & Klingsieck, K.B. (2016). Academic procrastination. *Australian Psychologist*, 51: 36-46. https://doi.org/10.1111/ap.12173

Steward, G,, & Chib, V.S. (2024). The Neurobiology of Cognitive Fatigue and Its Influence on Effort-Based Choice. bioRxiv [Preprint]. 18:2024.07.15.603598. https://doi.org/10.1101/2024.07.15.603598. Update in: *J Neurosci*. 2025 Jun 11;45(24):e1612242025. https://doi.org/10.1523/JNEUROSCI.1612-24.2025

Suiyhi, M., Alami, A., Boumaaize, Z., Darif, H., Babou, A., & el Madhi, Y. (2025). The Impact of Academic Workload and Perceived Stress on Anxiety and Depression among Nursing Students: A Cross-Sectional Study. *Universal Journal of Public Health*. 13. 852-862. https://doi.org/10.13189/ujph.2025.130408.

Sulaiman, R., & Muhajir, M. (2019). The difficulties of writing scientific work at the English education students. *Journal of English Education*, *4*(1), 54–60. https://doi.org/10.31327/jee.v4i1.923

Sverdlik, A., Hall, N. C., McAlpine, L., & Hubbard, K. (2018). The PhD experience: A review of the factors influencing doctoral students' completion, achievement, and well-being. *International Journal of Doctoral Studies*, *13*, 361–388. https://doi.org/10.28945/4113

Sweller, J., van Merriënboer, J.J.G. & Paas, F. Cognitive Architecture and Instructional Design: 20 Years Later. *Educ Psychol Rev* 31, 261–292 (2019). https://doi.org/10.1007/s10648-019-09465-5

Syrek, C. J., Weigelt, O., Peifer, C., & Antoni, C. H. (2017). Zeigarnik's sleepless nights: How unfinished tasks at the end of the week impair employee sleep on the weekend through rumination. *Journal of Occupational Health Psychology*, *22*(2), 225-238. https://doi.org/10.1037/ocp0000031

Truong, N. (2023). Difficulties of Vietnamese Students in Learning Academic Writing. *International Journal of Asian Education.* 4. 106-114. https://doi.org/10.46966/ijae.v4i2.340

Urbina-Garcia A. (2020). What do we know about university academics' mental health? A systematic literature review. *Stress and Health : Journal of the International Society for the Investigation of Stress*, *36*(5), 563–585. https://doi.org/10.1002/smi.2956

Valencia-Arias, A., Valera Aredo, JC., Valencia, J., Cardona-Acevedo, S., Patiño-Vanegas, JC., & Uribe Bedoya, H. (2026). Key determinants of university dropout: Academic, economic, and psychosocial factors in student retention. *Frontiers in Education*, *10*, Article 1701644. https://doi.org/10.3389/feduc.2025.1701644

van As, S., Beckers, DGJ, Geurts, SAE, Kompier, MAJ, Husain, M., & Veling, H. (2021). The Impact of Cognitive and Physical Effort Exertion on Physical Effort Decisions: A Pilot Experiment. *Front Psychol*, 12(645037). https://doi.org/10.3389/fpsyg.2021.645037

Vaziri, H., Casper, W. J., Wayne, J. H., & Matthews, R. A. (2020). Changes to the work-family interface during the COVID-19 pandemic: Examining predictors and implications using latent transition analysis. *The Journal of Applied Psychology*, *105*(10), 1073–1087. https://doi.org/10.1037/apl0000819

Wang, X., Madon, Z.B., Ghani, M.S.A., & Long, X. (2026). The relationship between academic burnout and problematic smartphone use: a three-level meta-analysis. *Front. Psychol.* 17:1768092. https://doi.org/10.3389/fpsyg.2026.1768092

Way, E. (2013). Understanding Research Fatigue in the Context of Community-University Relations. *Local Knowledge: Worcester Area Community-Based Research*. 3. https://commons.clarku.edu/localknowledge/3

Wingate, U. (2015). Academic literacy and student diversity: The case for inclusive practice. *Multilingual Matters*. https://doi.org/10.1093/elt/ccx015

Wong, K., Chan, A.H.S., & Ngan, S.C. (2019) The Effect of Long Working Hours and Overtime on Occupational Health: A Meta-Analysis of Evidence from 1998 to 2018. *International Journal of Environmental Research and Public Health*, 16, 2102. https://doi.org/10.3390/ijerph16122102

Wong Aitken, H. G., Rabanal-León, H. C., Saldaña-Bocanegra, J. C., Carranza-Yuncor, N. R., & Rondon-Eusebio, R. F. (2024). Variables linked to academic stress related to the psychological well-being of college students inside and outside the context of the COVID-19 pandemic. *Education Sciences*, *14*(7), Article 739. https://doi.org/10.3390/educsci14070739

Wu, J., Zhang, M., Yao, Y., Sun, M., Cao, X., Qian, Z., Wang, Y., Duan, H., & Xue, F. (2025). Research on fatigue symptom trajectories and influencing factors among nursing undergraduates. *BMC Nursing*, *24*(1), 1444. https://doi.org/10.1186/s12912-025-04092-8

Yaacob, Z., Zakaria, N., Mokhtar, M., Jalal, S. F., Pati, K. M., & Rahmat, N. H. (2023). Exploring students' fatigue: Is there a relationship between outcome with effort and performance? *International Journal of Academic Research in Business and Social Sciences*, *13*(9). https://doi.org/10.6007/IJARBSS/v13-i9/17731

Yao, S., Lu, H., Zhang, L., Liu, F., Ma, F., & Chi, A. (2025). Acute Exercise Fatigue Impairs Cognitive Control: Neurophysiological Mechanisms Revealed by ERP and ERSP Analyses. *Biology*, *14*(12), 1688. https://doi.org/10.3390/biology14121688

Zeinollakizi, M. (2026). Publish or perish in an emerging research system: barriers, stress, and ethical risks among PhD candidates in Kazakhstan. *Front. Educ*. 11:1743473. https://doi.org/10.3389/feduc.2026.1743473

Zhang, X., Lian, J., Yu, Z., Tang, H., Liang, D., Liu, J., & Liu, J. K. (2024). Revealing the mechanisms of semantic satiation with deep learning models. *Communications Biology*, *7*(1). https://doi.org/10.1038/s42003-024-06162-0

Zhang, J., Meng, J., &Wen, X. (2025). The relationship between stress and academic burnout in college students: evidence from longitudinal data on indirect effects. *Front Psychol.* 16:1517920. https://doi.org/10.3389/fpsyg.2025.1517920

Zhang, S., Liu, R., Rao, F., Zhou, Q., & Xiong, Q. (2026). The relationship between sleep quality and physical learning engagement among Chinese college students: a variable centered and person centered analysis. *Front. Public Health* 14:1845627. https://doi.org/10.3389/fpubh.2026.1845627

Zou, Y., Kuek, F., Feng, W., & Cheng, X. (2025). Digital learning in the 21st century: Trends, challenges, and innovations in technology integration. *Frontiers in Education*, *10*, Article 1562391. https://doi.org/10.3389/feduc.2025.1562391

P26019

Early Warning Analysis of Student Performance and Re-Enrollment in Cross-Disciplinary AI Courses

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ABSTRACT

This study examines early warning indicators for student performance and re-enrollment behavior in cross-disciplinary artificial intelligence (AI) courses offered at a case university in Taiwan during 2024–2025. Using routinely collected administrative data from 970 students across nine colleges, two conditional inference tree (ctree) models were constructed to identify meaningful student subgroups and their decision structures. Model 1 found that Fall 2024 GPA z-score was the sole significant predictor of re-enrollment, with a threshold of −0.867 separating students with notably lower continuation rates (8.9%) from those with higher rates (25.1%). Model 2 identified four split points—primarily based on prior GPA—producing five terminal nodes that differed substantially in AI course performance, with college affiliation providing additional differentiation among higher-performing students. Results highlight the heterogeneous structure of student learning outcomes in cross-disciplinary AI education and support the development of data-driven early warning and stratified instructional support systems.

Keywords: Conditional Inference Tree; Cross-Disciplinary AI Courses; Early Warning; Re-Enrollment; Learning Analytics

Introduction

As artificial intelligence (AI) has been rapidly integrated into higher education, an increasing number of students from non-computer science disciplines have enrolled in cross-disciplinary AI courses (Southworth et al., 2023; Kong et al., 2021). Whether students continue into subsequent AI courses—compared to the rapid expansion of course offerings—has become a

critical issue for cross-disciplinary talent development. Prior research has focused primarily on AI literacy, curriculum design, or learning outcome evaluation (Kong et al., 2022; Ng et al., 2022), with relatively little attention paid to how students' initial course performance and background characteristics jointly influence re-enrollment decisions.

A preceding study based on 1,281 cross-disciplinary students found that initial course performance was the strongest predictor of re-enrollment, and that students from different academic disciplines showed distinct continuation patterns (Dika et al., 2016; Nadasen et al., 2016). However, that study estimated the average effects of individual predictors and could not reveal interaction effects among student background variables or the decision structures formed by different combinations of characteristics. As a result, educational practice lacks approaches that can identify heterogeneous student profiles to support differentiated interventions and early warning strategies (Alalawi et al., 2025a, 2025b).

The present study addresses this gap by examining how student background characteristics and initial course performance jointly shape re-enrollment decision patterns. Rather than estimating average effects, this study uses conditional inference trees (ctree) to conduct tree-based analysis, identify representative student profiles and their decision pathways, and provide evidence for curriculum design, student support, and instructional intervention in cross-disciplinary AI education. Two research questions guide the study:

RQ1. Do students' prior learning experiences influence their intention to re-enroll in subsequent AI courses (Spring 2025 and Fall 2025)?

RQ2. Do students' prior learning experiences and individual background characteristics jointly influence their learning performance in AI courses (2025)?

Literature Review

1. Learning Outcomes and Influencing Factors

Cross-context research consistently shows that student outcomes—whether predicting re-enrollment, academic achievement, or learning performance in AI-related courses—reflect the interaction of academic background, learning motivation, institutional context, and demographic characteristics. Prior academic achievement (e.g., GPA and accumulated credits) and gender are the most stable predictors, though their effects are often mediated or moderated by intrinsic motivation, self-regulated learning, self-efficacy, prior education, and work or financial pressures (Kocsis & Molnár, 2025). Multi-factor predictive models commonly integrate demographic, academic, and behavioral data to improve accuracy; among these

variables, engagement patterns and academic history are widely recognized as key early indicators for identifying at-risk students.

Research on motivation further shows that dynamic motivational profiles and intrinsic motivation not only predict academic achievement but also influence subsequent educational choices, with these relationships varying across gender and discipline (Polso et al., 2025). In addition, epistemic profiles, academic discipline, and gender jointly shape students' learning perspectives and academic success, highlighting that institutional structures, disciplinary differences, and demographic factors collectively construct learning outcomes and educational trajectories in contemporary higher education (Lonka et al., 2021; Stolk et al., 2021; Pilotti, 2021).

To theoretically ground the relationship between academic performance and re-enrollment, this study draws upon Bean's (1981) Student Attrition Model and Tinto's (1993) Student Integration Model. Bean's framework posits that student persistence is driven by a synthesis of academic performance (e.g., GPA) and psychological states, with prior academic achievement serving as one of the strongest direct determinants of continuation decisions. Furthermore, Bean (1981) highlighted that student background variables often display non-linear interaction effects across different student subgroups. Integrating Bean's attrition framework with modern Learning Analytics (LA) enables us to operationalize these theoretical constructs into actionable administrative metrics (Hafer, 2018).

2. Learning Outcome Framework and Statistical Modeling

Research in Learning Analytics (LA) and Educational Data Mining (EDM) has increasingly shifted from optimizing predictive accuracy alone toward integrated frameworks emphasizing explainability and course-level actionable interventions. Recent studies on Learning Analytics Interventions (LAIs) indicate that modern learning analytics systems must not only identify at-risk students accurately but also support instructional decision-making and pedagogical adjustment, translating predictive outputs into theoretically grounded intervention strategies (Alalawi et al., 2025a, 2025b). This reflects a broader shift from single-model prediction toward integrated prediction–decision–intervention frameworks.

This study uses the conditional inference tree (ctree) algorithm (Hothorn et al., 2006). Ctree is a non-parametric recursive partitioning method that constructs decision tree models within a conditional inference framework, automatically identifying nonlinear relationships and interaction effects without pre-specifying functional forms. It is therefore well suited to exploring key determinants and subgroup structures in student re-enrollment behavior

(Hothorn et al., 2006; Venkatasubramaniam et al., 2017). Compared with traditional CART, ctree selects splitting variables using permutation-based significance tests before determining split points, reducing selection bias toward variables with more categories or potential splits, and applies Bonferroni correction to control familywise Type I error rates (Hothorn et al., 2006; Strobl et al., 2009). This study therefore adopts ctree to build a re-enrollment decision model, identify representative student subgroups, and provide a basis for curriculum design and instructional intervention.

Method

Data

This study used a secondary administrative dataset from a national university. All data were de-identified prior to analysis to protect research ethics and data privacy. The sample comprised 970 students enrolled in AI-related courses, including 602 males (62.1%) and 368 females (37.9%). Regarding high school background, 802 students (82.7%) graduated from public schools and 168 (17.3%) from private schools.

The sample covered nine colleges and academic units—Management, Information & Technology (IT), Biomedical Sciences, Engineering, Humanities, Earth Sciences, Science, Hakka Studies, and Sustainability—reflecting the cross-disciplinary nature of the data.

For academic performance variables, 869 students had valid Fall 2024 individual GPA z-scores ($M = -0.01$, $SD = 0.70$); AI course semester GPA z-scores were available for all 970 students ($M = -0.04$, $SD = 0.95$). Descriptive statistics are presented in Table 1.

Table 1: Descriptive Statistics of Study Variables (N = 970)

Variable	***n***	**% or μ (SD)**
Gender		
Male	602	62.1%
Female	368	37.9%
High School Type		
Public	802	82.7%
Private	168	17.3%
Re-Enrollment		

Variable	*n*	% or μ (SD)
Yes	225	23.2%
No	745	76.8%
College		
Management	381	39.3%
Information & Technology (IT)	164	16.9%
Engineering	104	10.7%
Humanities	91	9.4%
Science	80	8.2%
Earth Sciences	57	5.9%
Biomedical Sciences	57	5.9%
Hakka Studies	32	3.3%
Sustainability	4	0.4%
GPA z-score (Fall 2024)	869	−0.01 (0.70)
GPA z-score (AI course semester)	970	−0.04 (0.95)

Note. Valid sample for Fall 2024 GPA z-score is n = 869 due to missing data. All other variables have N = 970.

Conditional Inference Tree

This study constructed two predictive models using conditional inference trees (ctree; Hothorn et al., 2006). Ctree uses permutation tests as the basis for variable selection and split termination, avoiding the selection bias of traditional CART toward variables with more categories or levels, and applies Bonferroni correction to control the familywise Type I error rate without requiring post-hoc pruning.

Model 1 (fit1) used re-enrollment status (0 = non-re-enrollment, 1 = re-enrollment) as the binary outcome, with high school type (0 = public, 1 = private) and Fall 2024 individual GPA z-score as predictors (N = 970), aiming to identify the prior academic performance threshold that distinguishes re-enrollment decisions.

Model 2 (fit2) used AI course semester individual GPA z-score as the continuous outcome,

with five predictors: Fall 2024 GPA z-score, re-enrollment status, college affiliation, gender (0 = female, 1 = male), and high school type (N = 970). The aim was to identify heterogeneous student subgroups in AI course performance to support differentiated instructional resource allocation. All analyses used a significance threshold of $\alpha = .05$ for the conditional independence tests.

Results

RQ1: Effect of Fall 2024 Background Variables on AI Course Re-Enrollment

A conditional inference tree was used to examine the predictive effect of prior academic performance on re-enrollment behavior. The analysis treated re-enrollment status as the outcome, with high school type and Fall 2024 individual GPA z-score as predictors (N = 970). The conditional independence test for GPA z-score was significant (p = .002) and was the only significant splitting variable. High school type was not significant (p = .900) and did not enter the model, indicating that public versus private school background did not differentiate re-enrollment behavior when prior academic performance was held constant.

Using $z = -0.867$ as the cut point, the model produced two terminal nodes. Students with GPA z-scores at or below −0.867 (Node 2, n = 112) had a re-enrollment rate of 8.9%; those above −0.867 (Node 3, n = 858) had a rate of 25.1%—a difference of approximately 16 percentage points. These results suggest that students with substantially below-average prior academic performance are considerably less likely to continue into subsequent semesters.

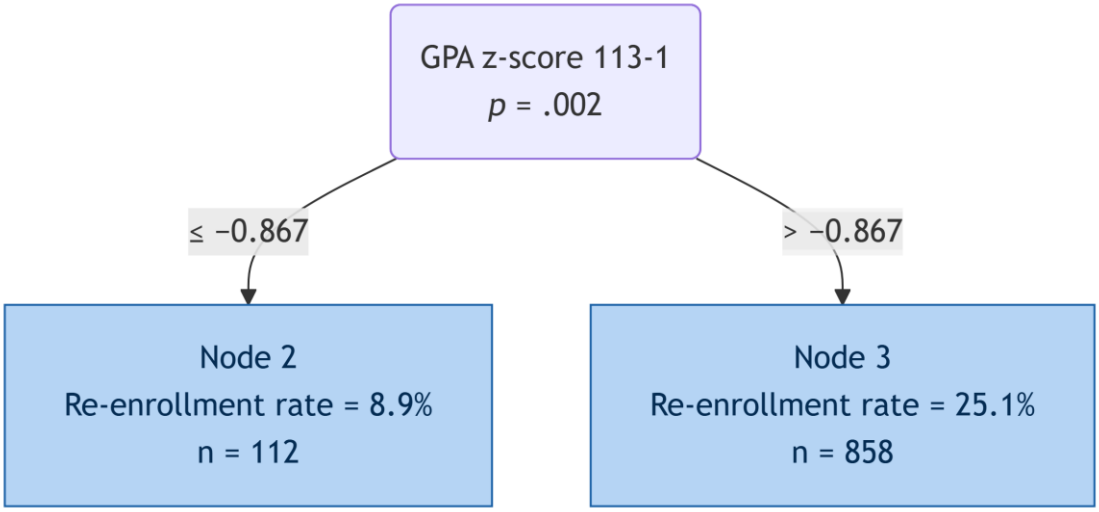


Figure 1: Conditional Inference Tree Results for Predicting Student Re-Enrollment Behavior.

Note. Predictors are individual GPA z-score (Fall 2024) and high school type; outcome is re-enrollment status (N = 970). Bar charts in terminal nodes display proportions of re-enrolled (1) and non-re-enrolled (0) students. Significance threshold for conditional independence tests set at α = .05.

Table 2: Terminal Node Statistics: Predicting Re-Enrollment (N = 970)

Node	Split Condition	*n*	Non-Re-Enrollment Rate	Re-Enrollment Rate
2	$z \leq -0.867$	112	91.1%	8.9%
3	$z > -0.867$	858	74.9%	25.1%

As shown in Table 2 and Figure 1, the conditional inference tree for re-enrollment identified a single split on Fall 2024 GPA z-score at a threshold of −0.867 (p = .002). Students with a GPA z-score at or below −0.867 (Node 2, n = 112) had a re-enrollment rate of 8.9%, compared to 25.1% among students above this threshold (Node 3, n = 858), a difference of approximately 16 percentage points. Students with substantially below-average prior academic performance are considerably less likely to continue into subsequent semesters.

Beyond confirming the predictive power of prior academic performance, the conditional inference tree reveals a non-linear threshold effect (z = -0.867) that clarifies the psychological mechanism driving student re-enrollment decisions. Grounded in Bean's Student Attrition Model (Bean, 1981; Bean & Metzner, 1985), prior GPA serves as a primary proxy for students' academic integration and sense of academic competence (Hafer et al., 2018). When prior performance falls below the critical cutoff of z = -0.867 (Node 2, representing the lower 11.5% of the sample), students experience a structural breakdown in academic confidence. In Bean's theoretical framework, this degradation of academic self-efficacy directly triggers a strong "intent to leave" (or non-continuation), resulting in a striking drop in re-enrollment rate to only 8.9% (compared to 25.1% for those above the threshold). Rather than a continuous, linear decline in persistence, ctree captures a distinct "competence failure threshold," demonstrating that early warning mechanisms must target this specific sub-population before academic frustration solidifies into program withdrawal.

RQ2: Effect of Student Background Variables on AI Course Performance

A conditional inference tree was used to examine factors influencing student AI course performance in Semesters Spring 2025/Fall 2025. The analysis treated AI course individual GPA z-score as the outcome, with Fall 2024 GPA z-score, re-enrollment status, college affiliation, gender, and high school type as predictors (N = 970).

The tree produced four splits and five terminal nodes. Fall 2024 GPA z-score was the splitting variable at the first three levels (all *p*s < .001), with cut points of −1.340, −0.595, and 0.213 dividing students by prior academic performance. Among students with above-average prior performance ($z > 0.213$), college affiliation produced an additional significant split ($p < .001$), separating Engineering, Humanities, Earth Sciences, Hakka Studies, and Science colleges from Sustainability, Biomedical Sciences, IT, and Management colleges. Gender ($p = .059$), high school type ($p = .926$), and college affiliation at the root node ($p = .070$) did not reach significance and were excluded from the model.

The five groups, ordered from lowest to highest AI course performance, are described below with sample-wide percentile ranks for reference.

Severely Behind Group (Node 2, n = 48, 4.9%). This group had Fall 2024 GPA z-scores below −1.340 (below the 9th percentile). AI course GPA z-score averaged −1.51 (*SD* = 1.70), corresponding to the 7th percentile—the lowest among all five groups. With severe underperformance in both periods, this group is the highest priority for instructional support.

Behind Group (Node 5, n = 125, 12.9%). This group had Fall 2024 GPA z-scores between −1.340 and −0.595 (9th to 28th percentile). AI course GPA z-score averaged −0.45 (*SD* = 1.05), corresponding to the 33rd percentile. Performance remained below the sample mean in both periods; this group is a secondary target for instructional support.

Average Group (Node 6, n = 381, 39.3%). This group had Fall 2024 GPA z-scores between −0.595 and 0.213 (28th to 58th percentile). AI course GPA z-score averaged −0.08 (*SD* = 0.75), near the 47th percentile. As the largest subgroup, performance was relatively stable.

Above-Average Engineering/Humanities Group (Node 8, n = 140, 14.4%). This group had Fall 2024 GPA z-scores above 0.213 (above the 58th percentile) and was enrolled in Engineering, Humanities, Earth Sciences, Hakka Studies, or Science. AI course GPA z-score averaged 0.03 (*SD* = 0.89), near the 51st percentile. Although prior performance exceeded the sample mean, AI course performance declined to near the sample median, suggesting these students may face greater learning challenges in AI courses.

Above-Average Sustainability/Biomedical/IT/Management Group (Node 9, n = 276, 28.5%). This group had Fall 2024 GPA z-scores above 0.213 and was enrolled in Sustainability, Biomedical Sciences, IT, or Management. AI course GPA z-score averaged 0.41 (*SD* = 0.59), corresponding to the 66th percentile—the highest among all five groups. Performance remained consistently high across both periods, requiring the least instructional intervention.

A pivotal finding in RQ2 is the performance divergence among high-achieving students ($z > 0.213$) across different academic disciplines. While high prior performance generally shields

students from academic failure, students in Engineering, Humanities, Earth Sciences, Hakka Studies, and Science (Node 8, M = 0.03) performed noticeably lower than their counterparts in Sustainability, Biomedical Sciences, IT, and Management (Node 9, M = 0.41). This sub-group heterogeneity can be interpreted through two key constructs in Bean's Attrition Framework: "Perceived Practical Value of Education" and "Major/Career Certainty" (Bean, 1981), alongside Cognitive Load Theory. For students in Management, IT, Biomedical Sciences, and Sustainability (Node 9), AI competencies map directly onto their core disciplinary identity and market expectations, instilling high perceived utility and task value (Polso et al., 2025). Conversely, high-performing students in Engineering, Humanities, and Pure Sciences (Node 8) often encounter a double burden: they experience heightened interdisciplinary cognitive load when learning non-native computational frameworks, while simultaneously perceiving lower immediate relevance between generic AI coursework and their primary major trajectories. Consequently, despite their high foundational academic capability, their learning engagement in entry-level AI courses decelerates, causing their performance to regress toward the sample mean. This underscores that cross-disciplinary AI education cannot rely on a standard curriculum; instructional design must explicitly bridge AI techniques with domain-specific practical applications to sustain engagement among non-CS high achievers.

Together, the Severely Behind and Behind groups comprised 173 students (17.8% of the total sample), all with Fall 2024 GPA z-scores below −0.595 (below the 28th percentile). These students are the priority targets for instructional support in Semesters Spring 2025/Fall 2025 AI courses. The Above-Average Engineering/Humanities group, despite above-average prior performance, showed a relative decline in AI course performance and warrants secondary monitoring.

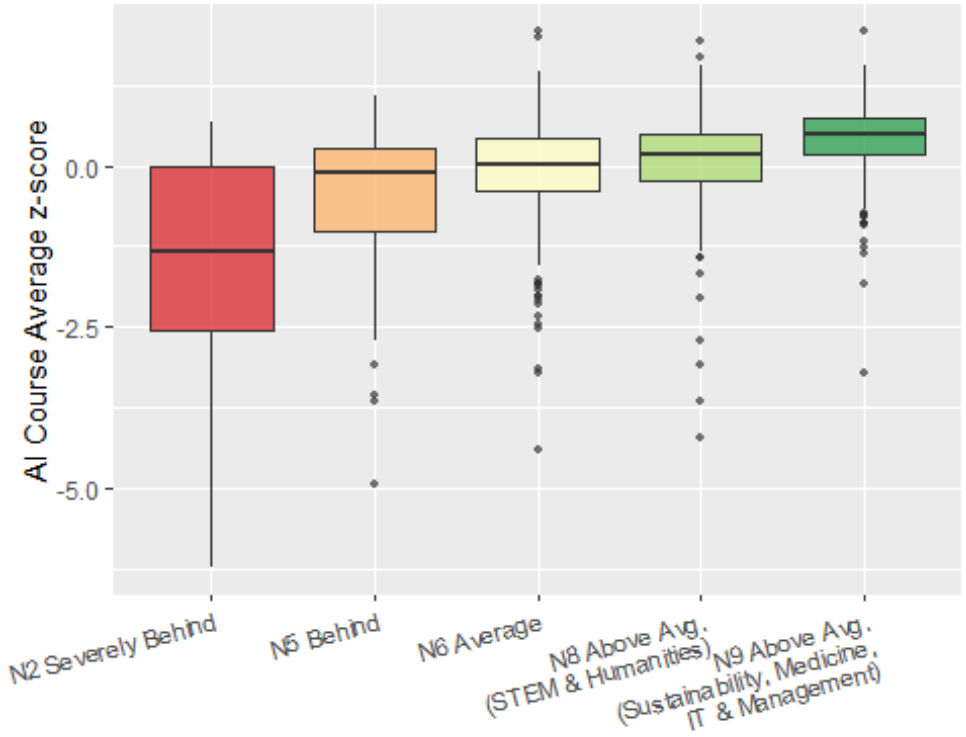


Figure 2: Five Subgroups Identified by the Conditional Inference Tree for AI Course Performance.

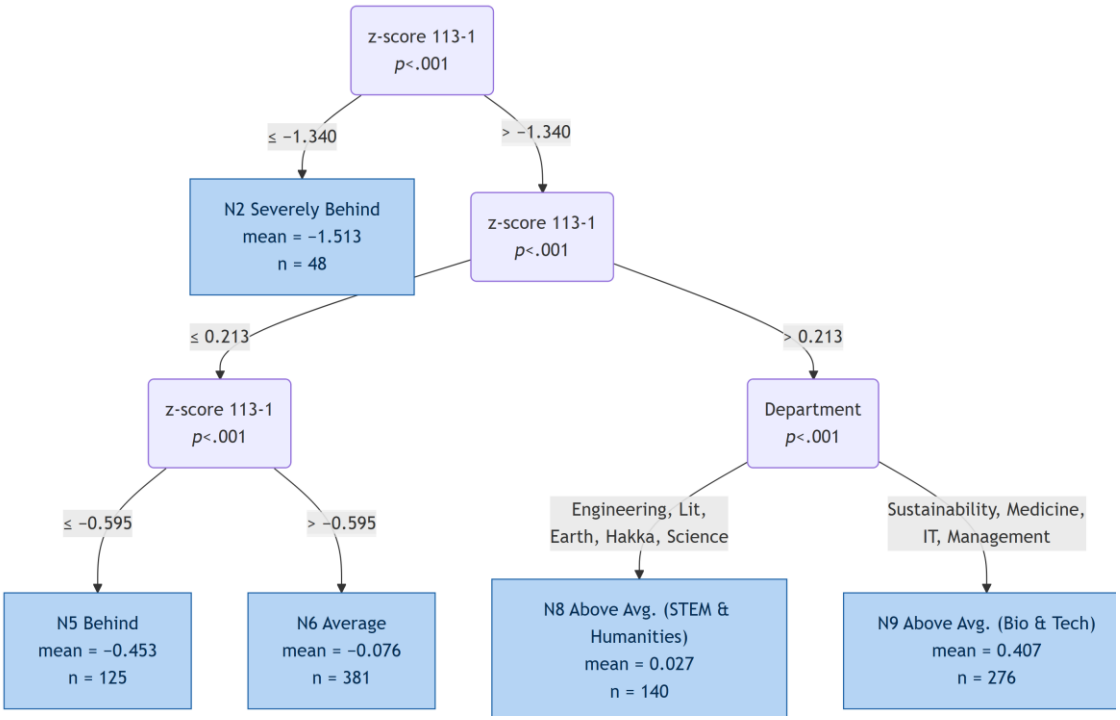


Figure 3: Conditional Inference Tree Results for Predicting Student AI Course Academic Performance.

Table 3: Terminal Node Statistics: Predicting AI Course Academic Performance (N = 970)

Node	Split Condition	*n*	*M*	*SD*	Percentile
2	$z \leq -1.340$	48	−1.51	1.70	7th
5	$-1.340 < z \leq -0.595$	125	−0.45	1.05	33rd
6	$-0.595 < z \leq 0.213$	381	−0.08	0.75	47th
8	$z > 0.213$, Eng., Hum., Earth, Hakka, Sci.	140	0.03	0.89	51st
9	$z > 0.213$, Sust., BioMed., IT, Mgmt.	276	0.41	0.59	66th

Note. z-scores represent standardized individual GPA from Fall 2024. Significance threshold for conditional independence tests set at α = .05. Eng. = Engineering; Hum. = Humanities; Earth = Earth Sciences; Hakka = Hakka Studies; Sci. = Science; Sust. = Sustainability; BioMed. = Biomedical Sciences; IT = Information & Technology; Mgmt. = Management.

As shown in Table 3, Figures 2 and 3, the conditional inference tree for AI course performance identified four splits and five terminal nodes. Fall 2024 GPA z-score served as the splitting variable across the first three levels (all *p*s < .001), with college affiliation further differentiating students with above-average prior performance ($z > 0.213$, $p < .001$). Gender, high school type, and re-enrollment status did not reach significance and were excluded from the model.

The five groups differed substantially in AI course GPA z-scores. The Severely Behind group (Node 2, $n = 48$) recorded the lowest AI course performance ($M = -1.51$, $SD = 1.70$), followed by the Behind group (Node 5, $n = 125$; $M = -0.45$, $SD = 1.05$) and the Average group (Node 6, $n = 381$; $M = -0.08$, $SD = 0.75$). Among students with above-average prior performance, those in Engineering, Humanities, Earth Sciences, Hakka Studies, and Science (Node 8, $n = 140$) performed near the sample mean ($M = 0.03$, $SD = 0.89$), whereas those in Sustainability, Biomedical Sciences, IT, and Management (Node 9, $n = 276$) recorded the highest AI course performance ($M = 0.41$, $SD = 0.59$). Taken together, prior academic performance was the strongest predictor of AI course achievement, with college affiliation providing additional differentiation among higher-performing students.

Results and Discussion

This study used conditional inference trees to analyze student learning performance and re-enrollment behavior in cross-disciplinary AI courses (2024–2025), based on routinely collected

administrative data, aiming to identify meaningful student subgroups and their decision structures.

Prior academic performance (GPA z-score in Fall 2024) was the strongest predictor of both AI course performance and re-enrollment behavior, with substantially greater explanatory power than demographic variables such as gender or college affiliation. The conditional inference tree identified statistically meaningful performance thresholds through permutation-based recursive partitioning, showing that student risk is not linearly distributed but concentrated below specific performance levels. In addition, students from different colleges showed differentiated AI course outcomes even under comparable prior performance conditions, suggesting that disciplinary context operates as an independent factor in cross-disciplinary AI learning.

Furthermore, background demographic variables—such as gender ($p = .059$) and high school type ($p = .926$)—did not enter the terminal decision tree models. This outcome aligns with the structural hierarchy of Bean's framework, which posits that the direct effects of distal background attributes are progressively mediated by proximal higher-education experiences and actual academic integration (Cabrera et al., 1993; Lonka et al., 2021). Once students enter the university environment, cumulative academic performance (GPA) becomes the dominant operational force, rendering secondary school origins and demographic backgrounds secondary in predicting university-level AI course outcomes and continuation behavior.

Practical Implications

These findings support developing data-driven early warning and stratified support systems. Institutions can identify at-risk students before course enrollment based on prior GPA thresholds, and provide timely interventions—remedial courses, academic advising, and targeted learning resources—to reduce the risk of failure and dropout. The observed disciplinary differences also suggest that cross-disciplinary AI courses should not follow a one-size-fits-all design; instructional approaches should account for the cognitive foundations and application contexts of different disciplines to improve adaptability and engagement among non-STEM students. The co-occurrence of low academic performance and low re-enrollment intention within the same subgroup identifies a structurally high-risk population, supporting integration of learning analytics with instructional support to shift from reactive remediation toward proactive intervention.

Theoretical Implications

This study extends the EDM and learning analytics literature by showing that statistical inference-based tree models not only provide data-driven subgroup identification but also

detect structurally meaningful split points through permutation tests and conditional independence testing, supporting a shift from aggregate-level inference toward the analysis of student heterogeneity and subgroup structures.

References

Alalawi, K., Athauda, R., & Chiong, R. (2025b). An extended learning analytics framework integrating machine learning and pedagogical approaches for student performance prediction and intervention. International Journal of Artificial Intelligence in Education, 35(3), 1239-1287.https://doi.org/10.1007/s40593-024-00429-7

Alalawi, K., Athauda, R., Chiong, R., & Renner, I. (2025a). Evaluating the student performance prediction and action framework through a learning analytics intervention study. Education and Information Technologies, 30(3), 2887-2916.https://doi.org/10.1007/s10639-024-12923-5

Bean, J. P. (1981). Student attrition calculation: A model for estimating the decision to drop out. *Higher Education*, 10(2), 129–163. https://doi.org/10.1007/BF00138311

Bean, J. P., & Metzner, B. S. (1985). A conceptual model of nontraditional undergraduate student attrition. *Review of Educational Research*, 55(4), 485–540. https://doi.org/10.3102/00346543055004485

Cabrera, A. F., Nora, A., & Castaneda, M. B. (1993). College persistence: Structural equations modeling validating an integrated model of student retention. *The Journal of Higher Education*, 64(2), 123–139. https://doi.org/10.2307/2960026

Dika, S. L., & D'Amico, M. M. (2016). Early experiences and integration in the persistence of first-generation college students in STEM and non-STEM majors. Journal of Research in Science Teaching, 53 (3), 368–383. https://doi.org/10.1002/tea.21301

Hafer, B. R., Rice, A., & St. Fleur, L. (2018). Predicting student retention in higher education: Integrating Bean & Metzner's model with self-determination theory. *Journal of College Student Retention: Research, Theory & Practice*, 20(3), 312–330. https://doi.org/10.1177/1521025116678853

Hothorn, T., Hornik, K., & Zeileis, A. (2006). Unbiased recursive partitioning: A conditional inference framework. Journal of Computational and Graphical Statistics, 15 (3), 651–674. https://doi.org/10.1198/106186006X133933

Kocsis, Á ., & Molnár, G. (2025). Factors influencing academic performance and dropout rates in higher education. Oxford Review of Education, 51(3), 414-432. https://doi.org/10.1080/03054985.2024.2316616

Kong, S. C., Cheung, W. M. Y., & Zhang, G. (2021). Evaluation of an artificial intelligence literacy course for university students with diverse study backgrounds. Computers and Education: Artificial Intelligence, 2, 100026. https://doi.org/10.1016/j.caeai.2021.100026

Kong, S. C., Cheung, W. M. Y., & Zhang, G. (2022). Evaluating artificial intelligence literacy courses for fostering conceptual learning, literacy and empowerment in university students: Refocusing to conceptual building. Computers in Human Behavior Reports, 7, 100223. https://doi.org/10.1016/j.chbr.2022.100223

Lonka, K., Ketonen, E., & Vermunt, J. D. (2021). University students' epistemic profiles, conceptions of learning, and academic performance. Higher education, 81(4), 775-793. https://doi.org/10.1007/s10734-020-00575-6

Nadasen, D., & List, A. (2016). Using community college prior academic performance to predict re-enrollment at a four-year online university. Online Learning, 20(2), 120-133. https://doi.org/10.24059/olj.v20i2.800

Ng, D. T. K., Lee, M., Tan, R. J. Y., Hu, X., Downie, J. S., & Chu, S. K. W. (2023). A review of AI teaching and learning from 2000 to 2020. Education and Information Technologies, 28(7), 8445-8501. https://doi.org/10.1007/s10639-022-11491-w

Pilotti, M. A. E. (2021). What Lies beneath Sustainable Education? Predicting and Tackling Gender Differences in STEM Academic Success. Sustainability 2021, 13, 1671. https://doi.org/10.3390/su13041671

Polso, K. M., Tuominen, H., Ihantola, P., & Niemivirta, M. (2025). Within-year stability and changes in adolescents' cross-domain motivational profiles: Predictions on academic achievement and educational choices. Journal of Educational Psychology.https://doi.org/10.1037/edu0000955

Southworth, J., Migliaccio, K., Glover, J., Glover, J. N., Reed, D., McCarty, C., Brendemuhl, J., & Thomas, A. (2023). Developing a model for AI Across the curriculum: Transforming the higher education landscape via innovation in AI literacy. Computers and Education: Artificial Intelligence, 4, 100127. https://doi.org/10.1016/j.caeai.2023.100127

Stolk, J. D., Gross, M. D., & Zastavker, Y. V. (2021). Motivation, pedagogy, and gender: Examining the multifaceted and dynamic situational responses of women and men in college STEM courses. International Journal of STEM Education, 8(1), 35. https://doi.org/10.1186/s40594-021-00283-2

Strobl, C., Malley, J., & Tutz, G. (2009). An introduction to recursive partitioning: Rationale, application, and characteristics of classification and regression trees, bagging, and

random forests. Psychological Methods, 14 (4), 323–348. https://doi.org/10.1037/a0016973

Venkatasubramaniam, A., Wolfson, J., Mitchell, N., Barnes, T., JaKa, M., & French, S. (2017). Decision trees in epidemiological research. Emerging Themes in Epidemiology, 14 , 11. https://doi.org/10.1186/s12982-017-0064-4

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The Role of AI in Implementing Deep Learning to Support Engaging and Enjoyable Learning Experiences

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ABSTRACT

The increasing complexity of global environmental challenges highlights the need for chemistry education that promotes conceptual understanding, environmental awareness, and sustainability-oriented learning. This study explored students' perceptions of the role of Artificial Intelligence (AI) in supporting Deep Learning experiences in Green Chemistry education. A qualitative phenomenological research design was employed with nine first-year students enrolled in a Green Chemistry course in the Chemistry Education Study Program at the Christian University of Indonesia. Data were collected through a ten-item open-ended questionnaire and analyse thematically, with NVivo used to support data organization, coding, and visualization. Four interconnected themes emerged: AI as a Facilitator of Deep Learning in Green Chemistry, AI-Engaging Learning Experiences, AI-Supported Critical Evaluation, and Enjoyable Learning Experiences. Participants reported that AI supported information exploration, conceptual clarification, brainstorming, and engagement with real-world environmental issues. They also described verifying information, comparing sources, and evaluating environmental claims, suggesting opportunities for critical engagement with AI-supported information. In addition, participants reported positive learning experiences characterized by interest, optimism, motivation, confidence, and enjoyment. The findings were interpreted through Fullan, Quinn, and McEachen's (2018) Six Global Competencies (6Cs), with the reported experiences most closely related to Critical Thinking, Character, and Citizenship. However, the 6Cs were not directly measured, and the findings therefore reflect students' reported perceptions and experiences rather than evidence of competency

development or the causal effectiveness of AI. The study suggests that AI may function as a potentially supportive learning partner in Green Chemistry when integrated with critical evaluation, authentic environmental contexts, and sustainability-oriented problem-solving. Given the small sample and single-institution context, the findings should be understood as exploratory and context-specific.

Keywords: Artificial Intelligence, Implementing Deep Learning, Green Chemistry, Engaging and Enjoyable Learning

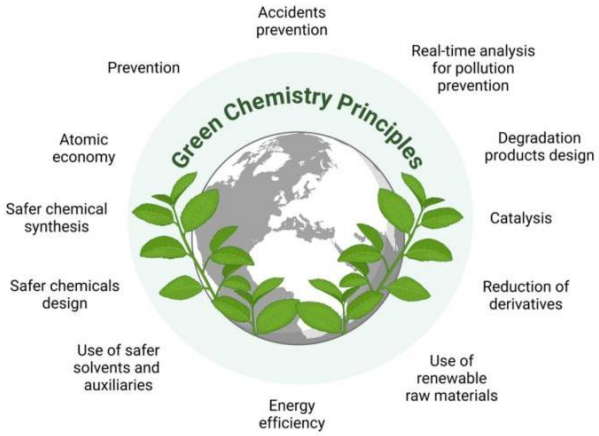
Introduction

The rise of various global environmental issues, such as pollution, climate change, and the use of chemicals that pose risk to health and the environment, drives the need for a transformation in chemistry education. One effort that can be made is to revitalize chemistry learning through the integration of Green Chemistry principles to foster awareness, responsibility, and sustainable behavior in students (Simangunsong et al, 2025). In the context of formal education, the essence of chemistry learning has shifted from merely transferring theories about the structure, characteristics, and reaction of substances into a means of shaping students ecological awareness. this learning emphasizes utilizing chemical science for human welfare while preserving nature. This very principle initiated the birth of the green chemistry concept, an approach that prioritizes early pollution prevention through the design of safe, efficient, and environmentally friendly chemical materials and processes (Ahmar & Azzajjad, 2024). The findings from observations revealed that the majority of students demonstrated interest and curiosity toward chemistry. However, these positive attitudes were accompanied by feelings of anxiety and the perception that chemistry is a challenging subject (Simanjuntak et al, 2026). Therefore, a specific approach is needed to ensure that students achieve a good level of conceptual understanding (Simanjuntak et al, 2023)

An understanding of Green Chemistry concepts is crucial for introductory chemistry students to recognize the environmental consequences of chemical activities. Through the study of green chemistry, students are encouraged to become more sensitive to the risks of using hazardous substances and the urgency of minimizing their negative impacts (Lane et al., 2023). The 12

principles of Green Chemistry, introduced by Paul Anastas and John Warner in 1998, provide a framework for designing chemical processes that reduce or eliminate the use of hazardous substances. The complete set of the twelve principles is presented in Figure 1. (Kurul et al., 2025)

Figure 1. The 12 principles of green chemistry (Kurul et al., 2025)



Preliminary findings reported by Azzajjad et al. (2024) indicate that students have limited understanding of Green Chemistry, particularly regarding the 12 principles (mean = 1.36) and the concept of upcycling (mean = 1.07), while their knowledge of environmentally friendly products was relatively good (mean = 3.07). These findings suggest that insufficient conceptual understanding may hinder students' ability to apply Green Chemistry principles in real-world contexts. Therefore, education must continuously adapt to societal and technological changes by adopting more innovative and effective learning approaches to improve both learning quality and student engagement. Therefore, innovative instructional strategies are needed to improve students' conceptual understanding while promoting meaningful engagement with Green Chemistry. To enhance the quality of learning and student interaction, educators and curriculum developers continue to strive to find new methods that are more innovative and efficient (Srimuliyani, 2023). One example is the use of virtual laboratories, which enable students to explore chemistry concepts, manipulate experimental variables, and analyze experimental results within a safe and efficient learning environment. (Simanjuntak, 2024)

The modern educational era demands accelerated innovation in teaching methods. One paradigm that is currently drawing widespread attention is utilization of Artificial Intelligence within the instructional ecosystem. The implementation of this technology is deemed capable

of transforming the learning process to make it more personalized, adaptive, and efficient (Shatila et al, 2025). The rapid advancement of digital technology has brought significant changes to various aspects of human life, including education. Artificial Intelligence (AI) has transformed the educational landscape by providing increasingly personalized, adaptive, and efficient tools and platforms, in contrast to traditional educational models that typically employ a one-size-fits-all approach. In the context of higher education, the integration of AI offers numerous benefits, including enhancing teaching and learning experiences for students, improving administrative efficiency for university management, and enabling more accurate assessment of student learning outcomes (younas et al., 2023).

Beyond improving learning efficiency, AI also supports the development of higher order thinking skills by facilitating inquiry based learning, problem solving, and critical reflection. In chemistry education, AI enables students explore complex scientific concepts through interactive learning experiences, immediate feedback, and authentic problem-solving activities, thereby making abstract concepts more accessible and meaningful. Previous studies have suggested that, when appropriately implemented, AI contributes to more engaging and enjoyable learning experiences while preparing students to address future scientific and environmental challenges (Gea et al., 2025; Neittaanmäki & Lehto, 2024). These characteristics position AI as a promising pedagogical tool for supporting the implementation of Deep Learning in Green Chemistry education.

According to Michael Fullan’s (2020), deep learning occurs when students are actively engaged in meaningful learning experiences, develop a sense of purpose, and connect their learning to authentic real-world contexts. These characteristics can foster a positive and enjoyable learning environment that supports students' motivation and engagement. Within the framework of New Pedagogies for Deep Learning, a joyful learning experience emerges when students develop global competencies (the sic Cs), which comprise character, citizenship, collaboration, communication, creativity, and critical thinking. The emergence of deep learning is fundamentally driven by rapid technological advancements, particulary the exponential growth of computational; power and the vast proliferation of big data. The rapid evolution of digital technology and artificial intelligence has accelerated the shift toward deep learning,

providing students with advanced tools to engage in meaningful and complex problem solving. (Fullan & Langworthy, 2013)

Although numerous studies have demonstrated that AI enhances personalized learning, student engagement, and learning effectiveness, most research has focused on the application AI within general educational contexts. In contrast, studies on Green Chemistry have primarily emphasized improving students conceptual understanding and promoting sustainability awareness, while investigations integrating AI as a facilitator of Deep Learning implementation in Green Chemistry education remain limited. Furthermore, little attention has been given to examining how AI can support the creation of engaging and enjoyable learning experiences while simultaneously fostering the development of the Six Global Competencies (6Cs) proposed by Fullan, Quinn, and McEachen (2018). Therefore, this study aims to explore students' perceptions of the role of AI in facilitating the implementation of Deep Learning to support engaging and enjoyable learning experiences in Green Chemistry education.

Methods

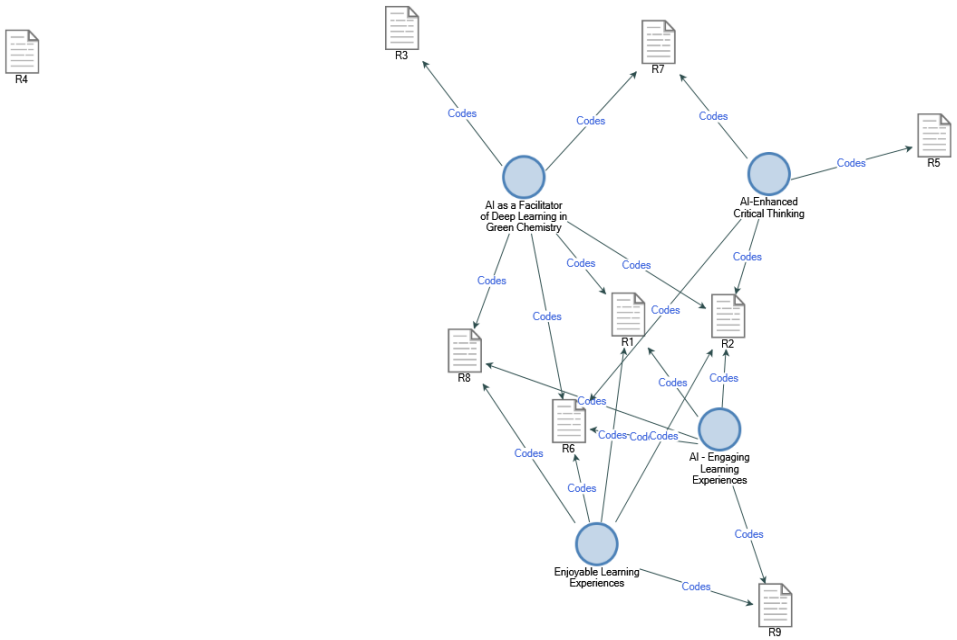
This study employed a qualitative phenomenological research design to explore students lived experiences and perceptions of using Artificial Intelligence (AI) in Green Chemistry learning and their perceived connections with Deep Learning. A phenomenological approach was selected because the study focused on understanding how students experienced, interpreted, and gave meaning to AI-supported learning within the specific context of Green Chemistry. The participants were nine first-year students enrolled in a Green Chemistry course in the Chemistry Education Study Program at the Christian University of Indonesia. Because all students enrolled in the course participated in the study, the study used an inclusive class-based recruitment approach rather than selecting a subset of students. Participation was voluntary, and respondents were anonymized using codes R1–R9. Data were collected through an open-ended questionnaire consisting of ten questions. The questionnaire was designed to allow participants to express their understanding, experiences, perceptions, reflections, and personal reasoning in their own words. The questions covered four interconnected aspects of Green Chemistry learning. first aspect concerned students' understanding of Green Chemistry and its relevance to environmental issues, addressed through Questions 1–2. The second aspect

explored students' application of Green Chemistry principles, environmental problem-solving, and sustainability-oriented decision making through Questions 3–6. The third aspect focused specifically on students' experiences with AI in Green Chemistry learning, including how AI encouraged information evaluation and supported environmental problem-solving, through Questions 7–8. The fourth aspect explored students' affective and learning experiences, including their feelings, engagement, and perceptions of meaningful learning, through Questions 9–10. Nvivo was used as a supporting tool to organize the qualitative data, facilitate coding, examine coding references, and visualize relationship among the emerging themes. Coding references were used descriptively to identify recurring patterns in data and to examine the relative occurrence of coded content across participant. Following the thematic analysis, the findings were interpreted using Fullan's Deep Learning framework, particularly the Six Global Competencies (6Cs): Character, Citizenship, Collaboration, Communication, Creativity, and Critical Thinking. The framework was used as an interpretive theoretical lens to examine how students' reported experiences with AI-supported Green Chemistry learning could be understood in relation to the competencies associated with Deep Learning. The 6Cs were not treated as directly measured outcomes of the study. Instead, the framework was used to interpret the meanings and patterns emerging from participants' experiences.

Results and Discussion

Analysis of student responses indicated that use of AI in Green Chemistry Learning provides various benefits that support the development of deeper and more meaningful learning experiences. The thematic analysis identifies five interconnected themes that explain students perceptions of the role of Artificial Intelligence (AI) in supporting the implementation of Deep Learning within Green Chemistry learning. These themes include (1) AI as a Facilitator of deep Learning in Green Chemistry, (2) AI-Engaging Learning Experiences, (3) AI-Enhanced Critical Thinking, and (4) Enjoyable Learning experiences. The consistency of these themes across participants suggests that students perceived AI as having a multifaceted role in supporting meaningful, engaging, and enjoyable learning experiences.

Figure 1. Overall Thematic Network



The aggregated NVivo network analysis identified four major interconnected themes that constitute a conceptual framework illustrating the role of artificial intelligence (AI) in facilitating the implementation of deep learning in Green Chemistry education. In contrast to the individual participant networks, the aggregated network highlights the dominant themes emerging across all participants, based on the frequency of coded references. This visualization demonstrates the relationships among the key themes and provides an overall representation of participants' shared experiences and perceptions regarding the integration of AI into Green Chemistry learning.

Based on the network connectivity, the themes are ordered according to their level of dominance as follows (Table 1)

Table 1. Themes, Sub-themes, supporting respondents

No	Theme	Interpretasi	Supporting Respondents
1	AI-Engaging Learning Experiences	The most dominant theme, suggesting that AI primarily promotes students engagement in the learning process	R1, R2, R6, R9
2	Enjoyable Learning	indicates that AI fosters positive learning	R1, R2, R6, R8

	Experiences	experiences and increases students motivation to learn.	
3	AI as an facilitator of deep learning in Green Chemistry	Emphasizes the role of AI in facilitating information exploration and fostering a deeper understanding of concepts	R1, R3, R6, R8
4	AI-Enhanced Critical Thinking	Demonstrates that AI contributes to the development of critical thinking skills by facilitating information evaluation and evidence-based decision-making.	R2, R5, R7

Table 2. Coding References Across the Four Emergent Themes

No	Themes	Sub-themes	References	$\sum Reference$
1	AI-Engaging Learning Experiences	Interactive Learning	6	29
		Learning Interest	8	
		Real-World Relevance	15	
2	Enjoyable Learning Experiences	Enjoyable Learning Experiences	8	28
		Learning Confidence	3	
		Learning Enjoyment	13	
		Positive Emotions	4	
3	AI as an facilitator of deep learning in Green Chemistry	Conceptual Understanding	11	40
		Information Exploration	19	
4	AI-Enhanced Critical Thinking	Evaluation of Environmental claims	8	24
		Evidence-Based Decision	3	

		Making		
		Information Verification	13	

The order of theme dominance reflects a coherent learning process in which AI first serves as a learning partner by supporting information exploration and conceptual understanding. This foundational role subsequently promotes student engagement through authentic real-world learning experiences, leading to more enjoyable learning experiences. Collectively, these experiences establish a supportive learning environment that nurtures critical thinking, particularly by encouraging information verification, evaluation of environmental claims, and evidence-based decision-making.

AI as a Facilitator of Deep Learning in green Chemistry

The first theme concerns the role of AI in supporting students exploration of information and understanding of Green Chemistry concepts. Students described AI as a readily accessible source of information that could help them clarify concepts, identify environmentally safer alternatives, and generate ideas for addressing environmental problems.

One participant explained that AI could be used to accelerate the development of environmentally friendly materials and processes:

> *"AI can accelerate the discovery of environmentally friendly materials and optimize industrial processes to minimize waste"* (R1)

Similarly, another participant emphasized the role of AI in generating and refining ideas for environmental problem-solving:

> "*AI helps me brainstorm solutions to environmental problems. What initially begins as a rough idea can be developed with the help of AI into clearer and more structured steps for addressing and solving environmental issues."* (R7)

These responses indicate that students perceived AI not merely as a source of factual information but also as a tool for information exploration, brainstorming, and conceptual

clarification. This is particularly relevant to Green Chemistry because many of its concepts require students to connect chemical principles with environmental consequences and possible technological solutions. However, the findings should not be interpreted as evidence that AI independently produced deeper learning. Rather, the responses suggest that AI may create conditions that support deeper engagement with learning content, particularly when students use it to explore ideas and develop questions.

AI-Engaging Learning Experiences

The second theme relates to students' perceptions of how technology and contextual learning activities could make Green Chemistry more engaging. The responses indicate that engagement was associated not only with AI itself but also with interactive activities, real-world cases, practical experiences, and visual learning resources. For example, one participant suggested:

> *"Using interactive simulations or simple and safe experiments, relating concepts to real-life cases in the surrounding environment, and creating collaborative projects, such as competitions for developing environmentally friendly products" (R2)*

Another participant emphasized the importance of practical and authentic experiences:

> *"It should involve real-world experiences, or ideally, direct field experience"* (R5)

A further response highlighted the importance of connecting Green Chemistry with everyday contexts:

> *"Green Chemistry learning would be more engaging if it included practical experiments and examples of cases closely related to everyday life."* (R4)

These responses suggest that students associated engagement with opportunities to connect theoretical concepts with authentic environmental problems. AI can potentially contribute to

this process by providing simulations, generating problem scenarios, supporting brainstorming, and helping students explore possible solutions. Nevertheless, students' responses indicate that AI should be integrated with other pedagogical strategies rather than treated as a replacement for practical or contextual learning.

The importance of real-world relevance is particularly significant in Green Chemistry because the discipline itself emphasizes the prevention of environmental harm through the design of safer chemical products and processes. Therefore, contextualizing learning through local environmental issues, practical activities, and authentic cases may help students perceive the relevance of chemistry beyond the classroom

AI-Enhanced Critical Thinking

The third theme represents one of the clearest patterns in the data. Several students reported that AI encouraged them to question information, compare sources, verify claims, and evaluate environmental statements rather than accepting information automatically. For example, one participant described an experience involving plastic recycling:

> "*AI encouraged me to evaluate the information by presenting the fact that only some types of plastic can actually be recycled effectively. This made me more critical of information sources*" (R2)

Another participant described how AI prompted critical evaluation of a biodegradable product claim:

> "*This experience taught me not to accept environmental claims (green claims) at face value, but rather to always verify them by questioning the conditions, context, and underlying scientific data*" (R3)

Other students also reported using AI to compare information from different sources. One response stated:

> "*AI helps me compare multiple sources, making me more critical when evaluating information about chemicals and their impacts*" (R4)

These responses are particularly important because they demonstrate that students did not always describe AI as an unquestioned authority. Instead, AI sometimes became a starting point for verification and evaluation. This finding is closely related to Fullan et al.'s (2018) Critical Thinking competency. Students' reported behaviors—questioning claims, comparing information, checking sources, and considering scientific evidence—can be interpreted as manifestations of critical engagement with information. At the same time, these findings should be interpreted cautiously. The study did not directly assess students' critical-thinking abilities through a validated test or performance task. Therefore, the results indicate students' reported experiences of critical evaluation, rather than demonstrating measurable development of critical-thinking competency. This distinction is important in the context of AI-supported learning. The educational value of AI may depend less on its ability to provide immediate answers and more on whether students are encouraged to question, verify, compare, and critically evaluate those answers.

Enjoyable Learning Experiences

The fourth theme concerns students' emotional responses to Green Chemistry learning. Students generally described positive emotions, including interest, enjoyment, optimism, motivation, and increased awareness of environmental issues.

One participant stated:

> *"I feel optimistic and motivated because Green Chemistry shows that chemistry can be a solution, rather than merely a source of problems."* (R2)

Another participant simply described the learning experience as:

> *"I feel happy because Green Chemistry is one of the topics in chemistry that I enjoy." (*R1)

A further response connected positive feelings with the lecturer's approach to explaining difficult concepts:

> *"Honestly, I feel happy. Our lecturer explains the material to us using simple examples. Although it initially seems difficult, Our lecturer always encourages us to understand, generate ideas, and solve problems."* (R3)

The responses indicate that enjoyment was not necessarily attributed to AI alone. Instead, positive learning experiences appeared to emerge from a combination of interesting content, understandable explanations, environmental relevance, practical examples, and opportunities to solve problems. One participant also expressed both concern and optimism:

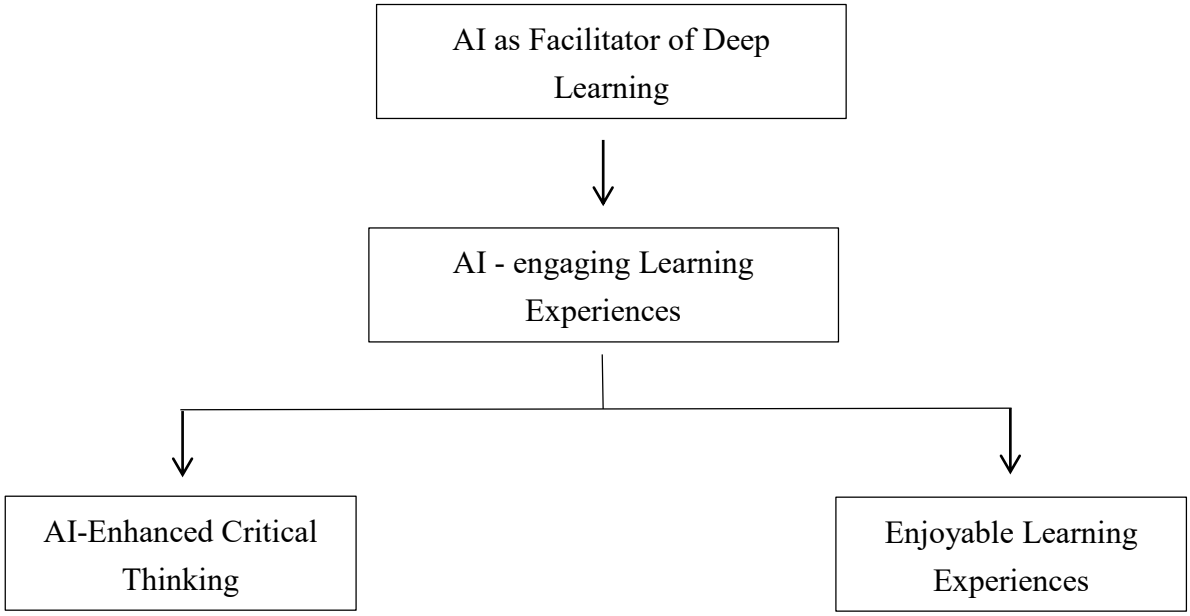
> *"On the one hand, I feel concerned when I realize how significant the negative impacts of conventional chemical industries are on the environment. On the other hand, I feel optimistic and encouraged because I know that sustainable scientific solutions are real and can be implemented."* (R4)

This response suggests that enjoyable learning in Green Chemistry does not necessarily mean that students experience only positive emotions. Awareness of environmental problems can initially generate concern, while knowledge of possible scientific solutions can contribute to optimism and motivation. Thus, enjoyable learning may be understood as an affective condition that supports meaningful engagement, rather than simply an outcome produced by AI technology.

Integration of Themes : A Conceptual Model of AI-Supported Deep Learning

The network analysis reveals that the four themes are not independent constructs but are interconnected within a coherents conceptual pathway. the relationships among these themes can be interpreted as follows :

Diagram 1. A Conceptual Model of AI-Supported Deep Learning



This Pathway demonstrates that AI first facilitates knowledge exploration and conceptual understanding. Increased engagement subsequently encourages students to think critically through information verification and evidence-based reasoning. These cognitive experiences generate positive emotions and confidence, ultimately leading to deeper conceptual learning and stronger awareness of environmental sustainability. Rather than functioning solely as an information provider, AI becomes an educational facilitator that integrates cognitive, affective, and metacognitive, affective, and metacognitive dimensions of learning.

The four theme indicate a possible relationship among information exploration, engagement, critical evaluation, and positive learning experiences. AI-supported information exploration may help students access explanations, generate questions, and brainstorm possible solutions. These opportunities may contribute to grater engagement when learning is connected to authentic environmental problems. At the same time, students' experiences suggest that AI can stimulate critical evaluation when students are encouraged to verify information and question environmental claims. The relationship should, however, be interpreted as a pattern emerging from students' accounts rather than a causal pathway. The qualitative data do not establish that AI caused engagement, enjoyment, or the development of Deep Learning competencies. A possible interpretive pattern is therefore:

AI-supported information exploration → conceptual clarification and brainstorming → greater engagement with authentic Green Chemistry problems → opportunities for critical evaluation → potentially more meaningful and enjoyable learning experiences. This pattern emphasizes that the educational contribution of AI depends on how it is pedagogically used. When students simply receive answers from AI, opportunities for critical inquiry may be limited. In contrast, when AI is used as a starting point for questioning, comparison, reflection, and problem-solving, it may function as a potentially supportive learning partner.

Interpretation through Fullan's Six Global Competencies

The findings were further interpreted using Fullan et al.'s (2018) Six Global Competencies: Critical Thinking, Communication, Collaboration, Creativity, Character, and Citizenship.

Among the six competencies, Critical Thinking was the most explicitly represented in the students' responses. Students described verifying information, comparing sources, questioning environmental claims, and considering scientific evidence before accepting information generated or supported by AI. These behaviors are consistent with critical engagement with information.

a. Character was reflected in students' reported awareness of responsibility toward the environment and consideration of the consequences of chemical use. For example, students discussed choosing environmentally safer products, reducing waste, and considering the long-term consequences of environmental pollution. These responses suggest that Green Chemistry learning may provide opportunities for students to reflect on responsible decision-making.

b. Citizenship was also evident in students' concerns about pollution, human health, ecosystem protection, and sustainability. Several responses connected Green Chemistry with responsibilities toward society and future generations. These patterns can be interpreted in relation to the concept of ecological citizenship, in which environmental responsibility extends beyond individual choices toward concern for broader social and ecological well-being.

c. Creativity appeared primarily through brainstorming and the generation of possible environmental solutions. One participant described AI as helping transform an initial

rough idea into more clearly structured steps for addressing an environmental problem. This suggests a potential connection between AI-supported brainstorming and creative problem-solving, although creativity was not directly assessed.

d. Communication and Collaboration were less directly represented in the dataset. One participant suggested collaborative projects such as an innovation competition, but the questionnaire responses primarily reflected individual experiences of learning and interaction with AI. Therefore, the present study provides limited evidence for interpreting AI-supported Green Chemistry learning in terms of these two competencies.

Implications for AI-Supported Green Chemistry Learning

The findings have several pedagogical implications. AI can be incorporated into Green Chemistry learning as a supportive learning partner rather than as a replacement for teachers, practical activities, or scientific sources. Its role may include helping students explore concepts, generate questions, brainstorm solutions, and examine environmental problems. AI-supported activities should deliberately include verification and critical evaluation tasks. For example, students can be asked to identify an environmental claim generated or retrieved through AI, verify it using scientific literature, identify possible limitations, and explain whether the claim is consistent with Green Chemistry principles. Green Chemistry learning can become more meaningful when AI is combined with authentic environmental contexts, such as pollution, waste management, biodegradable materials, industrial processes, or local environmental problems. Students' responses repeatedly emphasized the value of practical activities, real cases, and direct experience. Finally, enjoyable learning should not be considered merely an entertainment-oriented objective. The students' responses suggest that enjoyment may emerge when learners understand the relevance of chemistry, feel capable of solving problems, and recognize that chemistry can contribute to environmental solutions.

Conclusion

This exploratory study suggests that Artificial Intelligence (AI) can function as a potentially supportive learning partner in Green Chemistry education. Based on the thematic analysis of responses from nine first-year students, four interconnected themes emerged: AI as a Facilitator

of Deep Learning in Green Chemistry, AI-Engaging Learning Experiences, AI-Enhanced Critical Thinking, and Enjoyable Learning Experiences. Participants reported that AI supported information exploration, conceptual clarification, brainstorming, and engagement with real-world environmental issues. They also described using AI-supported information as a starting point for verifying information, comparing sources, and evaluating environmental claims.

The findings suggest a potential relationship among these reported experiences. AI-supported information exploration and conceptual clarification may contribute to students engagement with Green Chemistry topics, particularly when learning activities are connected to authentic environmental problems. At the same time, students reported practices of information verification and evaluation indicate opportunities for critical engagement with AI-generated information verification and evaluation indicate opportunities for critical engagement with AI-generated information. Positive emotions, learning confidence, and enjoyment were also evident in students' responses, although these experiences appeared to be associated with multiple factors, including teaching approaches, contextual examples, and the relevance of Green Chemistry to environmental issues. When interpreted through Fullan, Quinn, and McEachen's (2018) Deep Learning framework, the students' responses were most closely related to Critical Thinking, Character, and Citizenship. Critical Thinking was reflected in information verification, comparison of sources, and evaluation of environmental claims. Character and Citizenship were interpreted through students' reported environmental awareness, responsibility, and consideration of the broader consequences of chemical practices. Creativity was present to a lesser extent through brainstorming and environmental problem-solving, whereas Communication and Collaboration were less directly represented in the data. Importantly, these competencies were not directly measured in the present study; the 6Cs were used as an interpretive framework for understanding students' reported learning experiences.

The study therefore provides a contextual contribution to the emerging discussion of AI-supported Green Chemistry education by illustrating how students perceive AI as a potential support for information exploration, engagement, critical evaluation, and sustainability-oriented learning. Rather than demonstrating the effectiveness or causal impact of AI, the findings indicate that AI may provide meaningful learning opportunities when its use is

accompanied by critical verification, reflective inquiry, authentic environmental contexts, and appropriate pedagogical guidance.

References

Ahmar, D. S., & Azzajjad, M. F. (2024). Recent Trends in Green Chemistry: A Bibliometric Analysis of Materials and Innovations: Tren Terkini dalam Green Chemistry: Analisis Bibliometrik Materi dan Inovasi. *SEARCH: Science Education Research Journal*, *2*(2), 57-72.

Azzajjad, M. F., Ahmar, D. S., & Kilo, A. K. (2024). Pemahaman Mahasiswa tentang Keberlanjutan dalam Kimia: Kajian Pengembangan pada Proyek Green Chemistry. Jambura Journal of Educational Chemistry, 6(1), 11-20.

Fullan, M., Quinn, J., & McEachen, J. (2017). Deep learning: Engage the world change the world. Corwin Press.

Fullan, M., Quinn, J., & McEachen, J. (2018). Deep learning. California Bookwatch.

Fullan, M., Quinn, J., & McEachen, J. (2018). Deep Learning: Engage the World Change the World

Gea, N., Nehe, I., Zalukhu, L., Telaumbanua, M., & Bawamenewi, A. (2025). Dampak Artificial Intelligence (Ai) Dalam Pendidikan: Peluang Dan Tantangan Di Era Digital. *Jurnal Education and Development*, *13*(1), 637-644.

Kurul, F., Doruk, B., & Topkaya, S. N. (2025). Principles of green chemistry: building a sustainable future. Discover Chemistry, 2(1), 68.

Lane, M. K. M., Rudel, H. E., Wilson, J. A., Erythropel, H. C., Backhaus, A., Gilcher, E. B., ... & Zimmerman, J. B. (2023). Green chemistry as just chemistry. Nature Sustainability, 6(5), 502-512.

Neittaanmäki, P., & Lehto, M. (2024). Finland's AI-Supported Digital Social Welfare and Healthcare and School System 2030. Informaatioteknologian tiedekunnan julkaisuja, (104/2024).

Rojabi, M. A. (2025). Pengantar Artificial Intelligence (AI). Afdan Rojabi Publisher.

Shatila, A. G., Buchori, A., & Purwosetiyono, F. D. (2025). Analisis Kebutuhan Desain Pembelajaran Inovatif Berbasis Media AI Untuk Meningkatkan Kemampuan Pemecahan Masalah. Teorema: Teori Dan Riset Matematika, 10(1), 75-82.

Simangunsong, A. D. B., & Darmana, A. (2025). Revitalisasi Pembelajaran Kimia dalam Meningkatkan Kontribusi Menuju Green Chemistry. Jurnal Pendidikan Sains dan Komputer, 5(02), 423-429.

Simanjuntak, F. N., Ditasona, C., Sitohang, S. R. I., & Situmorang, A. P. (2026). Students' Perceptions of Green Chemistry in a Project-Based Learning (PjBL) Model Integrated with Local Culture. EduMatSains: Jurnal Pendidikan, Matematika dan Sains, 10(4), 37-45.

Simanjuntak, F. N., Harefa, N., Azahra, S. F., Sumiyati, S., Simatupang, N. I., Sormin, E., & Purba, L. S. L. (2024). Student Perceptions Regarding The Utilization of Virtual Laboratory to Increase Interest in Learning Chemistry at SMAN 3 Mataram. Journal of Chemistry Education Research, 8(1), 54-58.

Simanjuntak, F. N., Utomo, S. W., Sika Ery Seda, F. S., Budhi Soesilo, T. E., & Sumiyati, S. (2023). Learning Chemistry, Connecting Ecological Citizenship and Environmental Sustainability:"A Plate of Food" as a Learning Medium. ECNU Review of Education, 20965311231179737.

Srimuliyani, S. (2023). Menggunakan Teknik Gamifikasi untuk Meningkatkan Pembelajaran dan Keterlibatan Siswa di Kelas. EDUCARE: Jurnal Pendidikan Dan Kesehatan, 1 (1), 29–35.

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Enhancing On-Task Academic Engagement of Students with Emotional and Behavioral Disorders through the Good Behavior Game: Implications for AI-Ready Inclusive Classrooms

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ABSTRACT

One strategy found to increase the on-task academic behavior of students with emotional and behavioral disorders is the utilization of the Good Behavior Game, an evidence-based, interdependent class-wide intervention designed to reduce negative behavior and promote positive behavior through the provision of feedback and consequences. This study was conducted to provide insights into the game's effectiveness in improving on-task engagement of students in self-contained classrooms, contributing to a better understanding of how the game works across different contexts. Additionally, the study validated the indicators used to measure on-task academic engagement, establishing their potential suitability for integration into artificial intelligence-supported tools that can provide real-time feedback while monitoring students' observable behaviors during participation in the Good Behavior Game. Utilizing the one-group pretest-posttest quasi-experimental design, the study involved the participation of 27 grade school students with emotional and behavioral disorders in the Good Behavior Game intervention. Pretest observations on the dimensions – visual attention and manipulation of materials – indicated a "low" level of performance. Posttest assessments showed "very high" levels, with some "high" levels in the self-regulatory dimensions. A paired t-test showed that this improvement was statistically significant, rejecting the null hypothesis. The low standard deviations suggested a homogeneous class-wide effect, confirming the game's strength as seen through the operant conditioning and social learning theories that provided the grounding of the study. These findings provided an opening to explore how artificial intelligence can be integrated into the game to function as a decision-support and implementation tool, enhancing the efficiency of Good Behavior Game as a behavior management intervention for inclusive classrooms.

Keywords: *Good Behavior Game, on-task academic engagement, emotional and behavioral disorders, special education, AI-supported behavior monitoring*

Introduction and Rationale

Among the more challenging learners in inclusive classrooms are those with emotional and behavioral disorders (EBD) whose responses in school differ notably from appropriate norms, leading to impairments in educational progress, social relationships, self-care, classroom behavior, or performance (O'Brien et al., 2019). Students with EBD exhibit maladaptive behaviors towards adults or peers, aggression, classroom disruption, depression, excessive phobias, fears, and impulsive or obsessive behavior, posing challenges for special education professionals who must develop tailored programs to address their needs. Their display of physical and verbal aggression negatively impacts their ability to navigate successful relationships with adults and peers. Their difficulty studying has been shown to affect academic achievement (Blackwell et al., 2019; Maxwell & Adaugo, 2019). Since traditional classroom management strategies may not adequately address students' unique needs, teachers use a mix of affective and environmental support, along with academic support. At times, the highly maladaptive behaviors displayed by students with EBD necessitate specialized instruction in self-contained classrooms or special education settings, as noted in the Philippines (Peras et al., 2024).

Students with EBD in self-contained classrooms face challenges that make standard GBG protocols harder to apply. Their difficulties are usually more severe and persistent, requiring intensive, individualized supports beyond what typical interventions can provide (Gersib & Mason, 2023). They also need frequent, immediate feedback from teachers to learn and sustain appropriate behaviors (Cohen & Martin, 2022). These demands can overwhelm teachers already juggling multiple tasks while teaching academic content (Bradshaw et al., 2020).

Yet, recent advances in artificial intelligence (AI) now make it possible to analyze student behavior and engagement in real time (Valdes-Ramirez et al., 2026). These digital tools could reshape how evidence-based practices like GBG are implemented and monitored, especially in special education settings. They can facilitate data-driven decision-making and evaluate the effectiveness of interventions for both individual students and entire groups (Moore et al., 2021; Leidig et al., 2022),

However, for AI to truly support instructional decisions for learners with EBD, empirical research must first validate observable indicators of engagement. The issue expands from whether AI can monitor engagement while students participate in the Good Behavior Game to whether the indicators are theoretically meaningful and empirically associated with engagement. Despite the number of research studies on GBG and on AI-assisted classroom monitoring, the two have not been studied together. Furthermore, little work has examined the

full potential of artificial intelligence in real-time feedback or multimodal data (Futterer, 2025).

Thus, this study has two important directions. First, while GBG has shown promise in improving engagement or on-task behavior, evidence of its impact on students with EBD in self-contained classrooms is limited. Second, advances in AI open new opportunities to observe and analyze classroom behavior in real time. Yet, for AI to be effective, it must rely on empirically validated and theoretically sound behavioral indicators of on-task behavior.

Theoretical-Conceptual Framework

The study explored the effectiveness of the Good Behavior Game (GBG) based on Skinner's operant conditioning theory and Bandura's social learning theory.

Operant conditioning is a behavioral pattern in which an individual's response to a given situation is changed as a result of the effect of the response (McLeod, 2025; Guoli, 2024). Also known as instrumental conditioning, it has major elements such as reinforcement, punishment, extinction, and spontaneous recovery. Reinforcement learning principles embedded in the GBG design contribute to its value as an approach for students to learn goal-directed sequences of behaviors based on reward signals (Humphrey et al., 2018). In particular, GBG uses a group-oriented contingency management approach in which students learn that appropriate behavior leads to desirable outcomes (Tingstrom et al., 2006). Over repeated sessions, students adjust their behavior based on the consequences they experience.

Additionally, the study drew on Social Learning Theory (Alnoaim, 2022) to examine how behavior change and educational engagement can be facilitated. Although Operant Conditioning is the primary theory underlying GBG, Social Learning Theory also underpins several aspects of the game's design (Joslyn et al., 2019). The theory posits that individuals learn through observation of others and the consequences of their behavior through modeling and reinforcement. Individuals learn through vicarious experiences, acquiring new behaviors by observing the consequences of others' actions. Positive reinforcement, an integral component of the GBG game, plays a crucial role in shaping the desired behavior.

Given the integration of both theories in the design of the GBG game and based on the findings found in the literature reviewed, it is assumed that a behavior intervention utilizing the game will generate positive outcome in the on-task academic engagement of students. The diagram below represents this relationship.

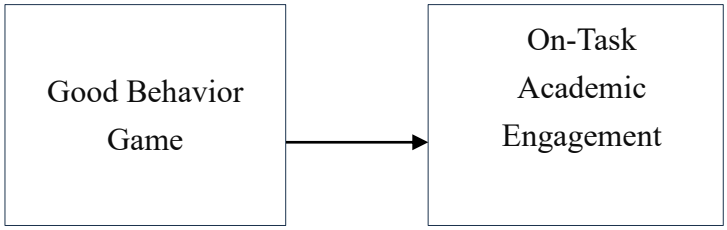


Figure 1: Illustration of how Good Behavior Game affects on-task academic engagement

On-task academic engagement in the classroom refers to the time a student is focused on the learning task. In studying key patterns of student behavior as a manifestation of learning engagement, Lomholt and Qvortrup (2025) grouped two analytical categories of behavioral engagement: task-related behaviors (on-task and off-task) and disruptive behaviors (severe withdrawal of effort). Under on-task behaviors, they identified (1) compliant behaviors such as active listening, and (2) self-initiating behaviors that usually occur when students begin working on a task.

Closely associated with active listening is visual attention. The latter is a more observable and defensible indicator of active listening and can be measured by student behaviors for a specified period. Visual Attention is operationally defined as a cognitive process by which students selectively and effectively focus their visual perception to sustain their attention on academic materials. Associated with self-initiating behavior is manipulation, which refers to what a student does independently when interacting with learning materials. The latter is an observable manifestation of self-initiation, as students begin to engage with materials independently. Materials manipulation is operationally defined as the physical interaction with and handling of academic materials, which allows the teacher to foster active engagement.

Given the features and reinforcement mechanisms of the Good Behavior Game, which is anchored in operant conditioning and social learning theories, it is hypothesized that implementing GBG as an intervention strategy will improve on-task academic engagement among students with emotional and behavioral disorders. This is manifested by both visual attention and materials manipulation.

Research Questions

The study aimed to examine changes in the on-task academic engagement of students with emotional and behavioral disorders (EBD) following the implementation of the Good Behavior Game (GBG) in a self-contained classroom and to identify potential implications of the

observed engagement indicators for AI-assisted monitoring and data-informed behavioral and instructional decision-making. Specifically, it endeavored to answer these questions:

1. What are the levels of EBD students' on-task academic engagement in terms of visual attention and materials manipulation before and after the Good Behavior Game intervention?

2. Is there a significant difference in the levels of on-task academic engagement among the EBD students before and after the Good Behavior Game intervention?

3. How can the findings be translated into AI-assisted monitoring approaches that support behavioral and instructional decision-making for students with EBD?

Methodology

Research Design

The study adopted the one-group pretest-posttest design to explore the effects of the Good Behavior Game intervention on the on-task academic engagement of students with emotional and behavioral disorders. Utilizing a validated researcher-developed observation scale, on-task academic engagement was measured by two indicators: (1) visual attention; and (2) materials manipulation.

This design was chosen because the intervention had to be carried out within an existing self-contained classroom, and the researchers did not have the option of setting up a separate comparison or control group. As a result, the changes observed in the students' on-task academic engagement were understood as differences between the pretest and posttest periods during the GBG implementation, rather than as definitive proof that the intervention alone caused those improvements.

Participants and Sampling

This quasi-experiment was conducted at Schoenbar Middle School in the Ketchikan Gateway Borough School District in Alaska, USA, where class sizes range from three to 13 middle schoolers. The school utilizes the Unique Learning System for mathematics and Language Live for literacy intervention. From this school, 27 students with EBD (14 in Grade 7 and 13

in Grade 8) in self-contained classrooms categorized as "with non-intensive needs" were purposively selected as study participants.

A post hoc power analysis was conducted based on the observed paired-samples effect sizes – Cohen's d_z, calculated as $t/\sqrt{n}$, was 8.16 for visual attention and 6.54 for manipulation of materials. At a two-tailed significance level of $\alpha=.05$, these effects yielded estimated statistical power exceeding 99.9%, indicating that the sample of 27 participants was more than adequate to detect the observed pre-test-to-post-test differences.

Data Gathering Procedure

Teachers or experiment facilitators who participated in selecting students were trained on the procedures and principles of the GBG intervention and on completing the rating sheets. Teachers revisited the features of the Unique Learning System of Schoenbar Middle School, as much of the Mathematics sessions' content was patterned after its modules. The teachers likewise received training on the rules, consequences, rewards, and strategies for GBG implementation.

Teachers assessed participants' on-task academic performance using a researcher-made observation sheet validated by ten special education and general education teachers. The pretest ratings, which provided baseline data, came from observations conducted before the intervention. The posttest ratings were generated from the recorded observations during the last multiple GBG sessions. Although observations followed the established procedures, inter-rater reliability was not formally calculated among the observers.

Participants were randomly grouped into teams and provided with a set of verbal and written GBG rules to follow during Mathematics class sessions. The researchers explained goals and expectations, focusing on the behavioral indicators being observed. A tally system monitored rule-breaking behaviors. Teams received penalty points for inappropriate behaviors during each session or game, and the team with the fewest penalty points won. Rule compliance after each session was rewarded immediately to strengthen the connection between outcome and behavior. The reward system consisted mostly of tangible rewards, but sometimes included mystery prizes.

Internal Validity and Bias

Several threats to internal validity were considered in interpreting the pretest-posttest findings. To reduce these risks, the study relied on clearly defined behavioral indicators,

standardized rating criteria, trained observers, and the same observation tool for both pretest and posttest. Students were also kept in the same classroom context and instructional setting, which helped ensure consistency. Even with these safeguards, however, the researchers acknowledged that factors beyond GBG may still have contributed to the changes observed.

Data Analysis

Data collected from the observations were collated in a Microsoft Excel sheet and presented and analyzed using descriptive and inferential statistics. SPSS facilitated hypothesis testing, particularly by measuring the significant difference between pretest and posttest ratings using a paired t-test. Cohen's *d* was calculated following the paired t-test to quantify the effect size of the mean difference, complementing the test's determination of statistical significance.

Ethical Considerations

The "informed consent" served as the cornerstone of ethical practice in this study. Students signed this agreement individually after being informed about the research purpose, the data to be collected, how the data would be collected and reported, and the potential risks. They confirmed that they understood their right to withdraw at any time, that their consent was freely given, and that they understood the research implications. Furthermore, confidentiality and anonymity were maintained to protect participants from potential harm. Observation data did not include their names and were identified only by their participant number.

Results and Discussion

Visual Attention

Table 1 presents the results of the assessment of visual attention of students with EBD before and after the GBG intervention.

Table 1: Visual attention to work materials before and after GBG intervention

Sub-Indicators	Before Intervention			After Intervention		
	Mean	SD	Interpretation	Mean	SD	Interpretation
Examining and using visual information to complete the assigned task	2.44	0.847	Low	4.63	0.492	Very High

Maintaining visual attention on relevant work materials while ignoring unrelated distractions	2.33	0.785	Low	4.63	0.492	Very High
Keeping visual attention on the assigned task or work materials for the duration of the activity	2.15	0.718	Low	4.67	0.480	Very High
Shifting visual attention appropriately between teacher, work materials, and related instructional sources	2.15	0.662	Low	4.59	0.501	Very High
Redirecting visual attention to the appropriate work materials when task instructions or classroom activities change	2.26	0.813	Low	4.41	0.501	High
Overall	2.27	0.765	Low	4.59	0.493	Very High

The pretest shows that students performed “low” before the intervention across all sub-indicators (overall M = 2.27). The finding is in consonance with broader literature describing learners with EBD as having problems staying on task. They experience intense emotions, which can be overwhelming and can interfere with their capability to focus on academic tasks (Sciarra et al., 2022; Murphy et al., 2020). They may have feelings of anxiety, lose self-control (Gonzales, 2020; Cohen et al., 2022) and struggle with impulsivity, leading to loss of interest in work materials and disruption of their ability to attend to tasks effectively (Hogstrom et al., 2019).

The uniformity of the "low" rating across all sub-indicators further suggests that the deficit in visual attention was not isolated to a single behavioral dimension but pervasive across the range of behaviors assessed. However, it must be noted that while the mean assessment was “low,” the standard deviation of 0.765 suggests moderate dispersion. This indicates that there are students with EBD who may have higher visual attention, representing a realistic scenario of heterogeneity within groups as found in the studies of Djamnezhad et al. (2025) and Leidig et al. (2022).

Meanwhile, the posttest results demonstrate that students with EBD improved to a generally “very high” level (overall M = 4.59). The students had “very high” visual attention across nearly all the sub-indicators. The results suggest a meaningful improvement in visual attention among the students after the GBG intervention, similar to findings of other studies concerning GBG-based programs. For instance, Leidig et al. (2022) revealed a significant increase in academic achievement among at-risk primary schoolers and Hier et al. (2024) reported

improvements in academic achievement in remote classroom instruction. However, the behavior of *redirecting visual attention*, which was not fully achieved by all, appears to require more behavioral support. Del Vecchio et al., (2024) likewise found that redirecting attention to task demands tend to be more difficult to teach as it is a self-regulatory behavior.

The posttest standard deviation of 0.493 shows a significant decrease in variability when compared to the pretest, indicating that students' visual attention became more uniform after the GBG implementation. This behavioral homogeneity is similar to what was found by Leidig et al. (2022) about consistent improvements across diverse individual profiles, and by Dadakhodjaeva et al. (2020) who observed class-wide improvements rather than individual gains after GBG implementation in kindergarten. It appears that a group game results to a positive, convergent change as a cohort, an outcome that finds support in social learning theory.

Materials Manipulation

The results of the assessment of materials manipulation before and after the GBG intervention are presented in Table 2.

The pretest results reveal that the students with EBD performed at a "low" level across all sub-indicators of material manipulation. This finding finds support from literature reporting how inherent characteristics of EBD, such as the lack of self-management skills (Moohr et al., 2021), lead to difficulty in initiating tasks and sustaining engagement. Without scaffolds or teacher prompting, students may struggle with interacting meaningfully with learning materials (Flores & Hinton, 2022). In addition, as students with EBD experience heightened frustration when they perceive that tasks are beyond their capabilities, they can exhibit avoidance behaviors towards their work materials, disrupting their capability to engage with learning tasks (Gersib & Mason, 2023).

The average standard deviation of 0.691 suggests low-to-moderate variability or a homogeneity of responses. This means that difficulties associated with materials manipulation are not isolated to individual students but are similarly experienced across the group of students with EBD, consistent with typical characteristics associated with EBD (Zaheer et al., 2019; Sutherland et al., 2020).

The level of materials manipulation after the intervention – a direct, observable indicator of task engagement – reflected the behavioral change that GBG was designed to produce. Findings show that students improved on their on-task academic engagement in materials manipulation, observed as "very high" in three sub-indicators. Joslyn et al. (2019) pointed out

that the social features of the game encourage students to remain positively engaged in the tasks. As what the social learning theory proposes, students learn appropriate behaviors by observing, imitating, and receiving reinforcement from others. In addition, consistent with the operant conditioning theory, GBG improved student behavior through reinforcement of positive behaviors and reduction of disruptive ones. However, while it appears that students' participation in GBG encouraged them to become organized in materials manipulation, they experienced challenges with self-regulatory behaviors such as independent and immediate use of materials (observed as merely "high").

Table 2: Manipulation of work materials before and after the GBG intervention

Sub-Indicators	Before Intervention			After Intervention		
	Mean	SD	Interpretation	Mean	SD	Interpretation
Appropriately handling the assigned learning materials	2.33	0.734	Low	4.67	0.480	Very high
Demonstrating more than one appropriate way of using the work materials	2.19	0.682	Low	4.67	0.480	Very high
Selecting and using the work materials needed to complete the assigned task	2.29	0.734	Low	4.59	0.501	Very high
Independently continuing work with the assigned materials	2.37	0.688	Low	4.37	0.492	High
Immediate utilization of the work materials after the teacher's instructions	2.22	0.698	Low	4.41	0.501	High
Overall	2.27	0.691	Low	4.54	0.491	Very high

The low average standard deviation of 0.491 indicates a homogeneous distribution of behavior in terms of materials manipulation after the GBG intervention. This means that improvement was not only evident in a subset of students with EBD, but it was achieved across the entire cohort. This is consistent with the findings of Dadakhodjaeva et al. (2020) who demonstrated that the effect of GBG is evident across students rather than on particular individuals.

Difference in the Levels of On-Task Academic Engagement

Table 3 presents the results of a paired samples t-test examining whether the GBG intervention produced statistically significant differences in visual attention and manipulation of materials.

The negative mean differences reflect that pre-test scores of the indicators were lower than post-test scores, indicating a positive behavioral shift after the GBG intervention.

H_O1: There is no significant difference in students' visual attention before and after the GBG intervention.

The paired mean difference of -2.32 (SD = 0.284, SEM = 0.055) indicates a substantial and consistent increase in visual attention following the intervention. This is supported by a narrow 95% confidence interval of [-2.43, -2.21] that does not cross zero. Furthermore, the t-value of -42.38 at 26 degrees of freedom, with a two-tailed significance of p = 0.000, indicates that the probability of observing this difference by chance alone is virtually zero, thereby leading to the rejection of the hypothesis.

Table 3: Paired samples t-test for significant difference between pre-test and post-test means

	Paired Differences								
				95% Confidence Interval					
Indicators	Mean	SD	Standard Error Mean	Lower	Upper	t	df	Significance (two-tailed)	Decision on Hypothesis
Visual attention	-2.32	0.284	0.055	-2.43	-2.21	-42.38	26	0.000	Reject
Manipulation of materials	-2.27	0.346	0.067	-2.404	-2.129	-34	26	0.000	Reject

The low SD of 0.284 suggests a highly homogeneous improvements in visual attention among the participants, indicating that the effect was not isolated to a few individuals but observed across the sample. This is consonant with findings reported by Leidig et al. (2022), who attributed behavior improvement to the game's interdependent group contingency structure, which creates shared behavioral incentives that promote sustained attentional focus across all group members.

The paired-samples *t*-test revealed a significant difference between pre-test and post-test scores for visual attention, $t(26) = -42.38$, $p < .001$. The magnitude of the difference was exceptionally large, with a paired-samples effect size of Cohen's $d_z = 8.17$. At a two-tailed significance level of $\alpha = .05$, the effect yielded an estimated statistical power exceeding 99.9%, indicating that the sample of 27 participants was more than adequate to detect the observed pre-test to post-test differences and that the participants' paired differences are very consistent.

The data provide strong statistical evidence of a significant difference between students' pretest and posttest ratings of visual attention following the period of GBG implementation. However, because the study employed a one-group pretest-posttest design without a comparison group, the observed improvement cannot be attributed exclusively to GBG.

H_O2: There is no significant difference in students' materials manipulation before and after the GBG intervention

The results likewise led to the rejection of the hypothesis. This decision is supported by the paired mean difference of -2.27 (SD = 0.346, SEM = 0.667), with a 95% confidence interval of [-2.404, -2.129], which suggest an increase in task-related material engagement post-intervention. The t-value of -34 (df = 26, p = 0.000) further confirms the significant improvement, as it falls far below the 0.05 alpha threshold required for rejecting the null hypothesis. These findings align with those of Murphy et al. (2020), who reported that GBG sessions conducted for students with EBD resulted to class-wide increases in engagement with academic materials. Joslyn et al. (2019) and Groves et al. (2022) likewise demonstrated that GBG reduced off-task behavior and improved material engagement, highlighting the strength of the intervention's effect in EBD populations.

The significant pretest-posttest difference in materials manipulation indicates substantial improvement in students' observable engagement with learning materials following GBG implementation. While the magnitude and consistency of the improvement are noteworthy, other factors occurring during the intervention period may have contributed to the observed change.

A significant difference was found for manipulation of materials, $t(26) = -34.00$, $p < .001$, with an exceptionally large paired-samples effect size of Cohen's $d_z = 6.56$. At a two-tailed significance level of $\alpha = .05$, these effects yielded estimated statistical power exceeding 99.9%, indicating that the sample of 27 participants was more than adequate to detect the observed pre-test to post-test differences. A very large $d_z$can occur when participants' paired differences are unusually consistent.

Overall, the rejection of both hypotheses proves that the Good Behavior Game produced statistically significant improvements in both dimensions of on-task academic engagement – visual attention and materials manipulation– for students with EBD. These results are congruent with broader literature reporting the effectiveness of GBG in modifying behavior of students in the classroom. The low standard deviations across both indicators further confirm

the strength of GBG's behavioral effects that were class-wide, and not specific to learners who may be high-functioning.

The large Cohen's d_z values indicate substantial changes in students' on-task academic engagement following the implementation of the Good Behavior Game. However, these effect sizes should be interpreted cautiously because the study employed a single-group design without a control or comparison group; consequently, the observed changes cannot be attributed exclusively to the GBG and may also reflect other factors.

Relevance to AI-Assisted Engagement Monitoring

The significant impact of GBG on students' on-task engagement—seen in both visual attention and materials manipulation—points to the value of these behaviors as clear, observable indicators for AI-supported classroom monitoring. Their responsiveness to GBG shows that they can capture meaningful shifts in how students stay engaged with tasks. They are outward behaviors that can be defined, observed, and recorded systematically, making them promising foundations for future applications of artificial intelligence, especially computer-vision and video-based analytics, to help teachers track engagement. Thus, AI systems could be trained to recognize specific on-task engagement patterns, such as focusing on instructional materials or using learning tools appropriately, and then provide teachers with additional insights into student engagement.

Recent work in computer vision has shown that deep learning models—like YOLO detectors and CNN+LSTM temporal networks—can achieve high accuracy in identifying student attention and behavioral states in real classrooms (Trabelsi et al., 2023; Alawneh et al., 2025; Abbes et al., 2025). These systems analyze cues such as eye gaze, head position, facial expressions, and posture. Such indicators align closely with the dimensions of visual attention and materials manipulation highlighted in this study, offering teachers objective, real-time data that would otherwise require intensive direct observation.

Another technology is a hybrid approach that combines deep learning models (MobileNet, VGG16, ResNet50) with machine learning algorithms for automated student engagement detection (Leidig et al., 2022). Notably, a study used a YOLOv4-based approach for student engagement detection, demonstrating the feasibility of real-time behavior recognition in classroom settings (Pillai, 2022). Another study on advanced AI systems for behavior analysis is the multimodal engagement analysis of classroom facial videos, which showed that combining visual, temporal, and contextual information improves detection accuracy (Sümer, 2021). Likewise, an automated learning analytics system designed to assist teachers by analyzing student behavior, engagement, and psychological state parameters and providing

actionable feedback shows promise (Khalid et al., 2025). These multimodal systems capture interactions in the classroom and individual student responses – i.e., data that are relevant to the successful implementation of the Good Behavior Game.

Therefore, a potential initiative is the development of an AI-enhanced Good Behavior Game for students with EBD that preserves the behavioral principles grounding the game while integrating AI monitoring capabilities. This is supported by Fattah (2023), in which an AI-based behavioral disorder management strategy improved outcomes among third-grade primary students. Literature has also shown that AI platforms and tools can monitor behavior and be calibrated to GBG parameters, providing real-time feedback for potential rewards and generating alerts for students at risk of disengagement.

Conclusion and Recommendations

The findings indicate that implementing the Good Behavior Game was associated with substantial improvement in observable on-task academic engagement among students with emotional and behavioral disorders in the participating self-contained classrooms. Both visual attention and materials manipulation increased from low pretest levels to high or very high posttest levels, with statistically significant pretest-posttest differences observed for both indicators. These findings provide preliminary evidence supporting the potential utility of GBG as a classroom-based behavioral management strategy for students with EBD.

These effects confirm the theoretical propositions of operant conditioning and social learning. The group reward feature of GBG facilitated the shaping of prosocial and task-oriented behaviors, while the cooperative format provided opportunities for students to observe, imitate, and internalize on-task academic behaviors. However, some sub-indicators were self-regulatory in nature and did not readily respond to group contingency. This points out that while GBG may be effective, it has limitations in improving self-directed engagement skills that rely on individualized teacher scaffolding.

This study contributes in two key ways. First, it strengthens the evidence base for GBG by demonstrating its effectiveness in a self-contained EBD classroom—a context that has received less attention in prior research. Second, it defines on-task academic engagement through clear, measurable behaviors that align well with computer vision-based AI monitoring systems. Methodologically, future studies should include a control or comparison group to better establish causality and determine whether improvements in engagement are due specifically to GBG rather than to maturation, instructional changes, or other contextual factors.

Translational Implications

The findings have direct implications for classroom practice, particularly for using structured, evidence-based behavioral interventions to improve students' academic engagement. In AI-enabled classrooms, teachers may complement these interventions with carefully selected AI tools that help them differentiate tasks, provide multiple means of representation and engagement, and monitor patterns of learner participation. This supports a model where teachers retain a central role in behavioral and instructional decision-making while AI enhances their ability to provide individualized support.

In higher education policy, the results indicate that institutions require programs to integrate evidence-based behavioral and instructional interventions into student training. Specifically, teacher education and special education programs include GBG and other game-based approaches in their coursework and faculty professional-development programs, linking this approach to Universal Design for Learning, assistive technology, and AI-based tools. This is particularly important as schools become more diverse and instructional services are increasingly supported by technology.

Limitations of the Study

The findings of this study should be interpreted with caution in light of several methodological limitations. First, the one-group pretest-posttest design, without a comparison or control group, limits the extent to which changes in students' on-task academic engagement can be attributed specifically to the Good Behavior Game. Second, expectations about behavioral improvement may have influenced the ratings, consciously or unconsciously. In addition, the present study did not assess inter-rater reliability; therefore, it could not empirically establish the consistency of behavioral ratings across independent observers. Third, the purposive selection of participants and the specific educational setting limit the generalizability of the findings to students with different levels of support needs, other disability groups, grade levels, school settings, or inclusive classrooms. Finally, the study examined only two observable dimensions of on-task academic engagement—visual attention and manipulation of work materials.

These limitations suggest that the findings should be regarded as preliminary evidence of behavior improvement associated with GBG implementation rather than definitive evidence of a causal intervention effect. Future studies using randomized or matched comparison groups, independent or blinded observers, multiple measurement methods, and larger, more diverse samples would provide stronger evidence on the effectiveness, generalizability, and

sustainability of GBG for students with emotional and behavioral disorders.

Declaration of AI Assistance

The authors used generative artificial intelligence (ChatGPT) and SciSpace research assistant to search for relevant literature on selected topics. The suggestions generated by the tools were critically evaluated and verified prior to their use.

Reference List

Abbes, A. C., Khanouche, M. E., Attal, F., Tari, A., & Chibani, A. (2025). Internet of behaviors-based focus state classification for enhancing educational engagement. *IEEE 37th International Conference on Tools with Artificial Intelligence (ICTAI)*, 1117-1123. doi: 10.1109/ICTAI66417.2025.00163

Alawneh, Y. J., Al-Khateeb, R. H., Salah, L. A. F., Khazen, D., Salman, F. N., & Hole, S. (2025). Using computer vision and AI for monitoring student attention in classrooms. *IEEE 5th International Conference on ICT in Business Industry and Government (ICTBIG)*, 1-6. doi: 10.1109/ICTBIG68706.2025.11323999

Alnoaim, J. (2022). "Sociocultural and social cognitive theories: Historical and cultural practices for students with emotional and behavioral disorder (EBD)", *Information Sciences Letters; An International Journal, 11*(6), 1859-1870. http://dx.doi.org/10.18576/isl/110601.

Ashworth, E., Humphrey, N., & Hennessey, A. (2020). Game Over? No main or subgroup effects of the Good Behavior Game in a randomized trial in English primary schools. *Journal of Research on Educational Effectiveness*, *13*(2), 298–321. https://doi.org/10.1080/19345747.2019.1689592

Blackwell, W., Duran, J.B. & Buss, J. (2019). Students with emotional and behavioral disorders and special education due process in the United States. *International Journal of Special Education*, *34*(1), 129-151. https://eric.ed.gov/?id=EJ1237120

Bradshaw, C.P., Marchese, D. & Hardee, S. (2020). Optimizing implementation of the Good Behavior Game in the classroom: Recommendations and lessons learned. In: Reschly, A.L., Pohl, A.J., Christenson, S.L. (eds.) *Student Engagement*. Springer, Cham. https://doi.org/10.1007/978-3-030-37285-9_9

Cohen, G. & Martin, N. (2022). High-tech classroom management: Effects of the use of an app on disruptive and on-task classroom behaviors for students with emotional and behavioral disorder. *Behavioral Sciences*, *13*(1). doi:10.3390/bs13010023

Dadakhodjaeva K., Radley K.C., Tingstrom D.H., Dufrene B.A. & Dart E.H. (2020). Effects of daily and reduced frequency implementation of the Good Behavior Game in kindergarten classrooms. *Behav Modif*. *44*(4), 471-495. doi: 10.1177/0145445519826528

Del Vecchio, M. L., Crosland, K., & Fuller, A. (2024). The effects of self-monitoring with I-Connect to increase on-task behavior of students with or at-risk for emotional and behavioral disorders. *Journal of Positive Behavior Interventions*, *27*(1), 12-25. https://doi.org/10.1177/10983007241268784

Djamnezhad, D., Bergström, M., Delfin, C. & Hofvander, B. (2025). Classroom effects of a preventive behavioral management program: A pragmatic cluster-randomized trial of Good Behavior Game. *PLOS Mental Health*. https://doi.org/10.1371/journal.pmen.0000487

Fattah, N.E.E.A. (2023). Effectiveness of using the artificial intelligence in behavioral disorders management among the third-grade primary students. *Eurasian Journal of Educational Research 101*, 33-48. doi: 10.13140/RG.2.2.11712.14081

Flores, M.M. & Hinton, V.M. (2022). Use of the concrete–representational–abstract instructional sequence to improve mathematical outcomes for elementary students with EBD. *Beyond Behavior*, *31*(1), 16-28. https://doi.org/10.1177/10742956211072421

Futterer, T., Goldberg, P., Buhler, B., Sikimic, V., Trautwein, U., Gerjets, P., Sturmer, K., & Kasneci, E. (2025). Artificial intelligence in classroom management: A systematic review on educational purposes, technical implementations, and ethical considerations. [Pre-print]. doi: 10.31219/osf.io/wfazn

Gersib, J. & Mason, S. (2023). A meta-analysis of behavior interventions for students with emotional-behavioral disorders in self-contained settings. *Behavioral Disorders*, *48*(4), 269–283. doi: 10.1177/01987429231160285

Gonzales, M. (2020). Supporting students with emotional and behavioral disorder. In: *Systems Thinking for Supporting Students with Special Needs and Disabilities*. Springer, Singapore. https://doi.org/10.1007/978-981-33-4558-4_15

Groves, E.A., May, R.J., Rees, R.E. & Austin, J.L. (2022). Adapting the Good Behavior Game for special education classrooms. *Psychology in the Schools*, *59*(5), 1015–1031. https://doi.org/10.1002/pits.22496

Guoli, Y. (2024). Operant conditioning. In: Kan, Z. (eds), *The ECPH Encyclopedia of Psychology*. Springer, Singapore. https://doi.org/10.1007/978-981-97-7874-4_337

Hier, B.O., MacKenzie, C.K., Ash, T.L., Maguire, S.C., Nelson, K.A., Helminen, E.C., Watts, E.A., Matsuba, E.S., Masters, E.C., Finelli, C.C., Circe, J. J., Hitchings, T. J., Goldstein, A.R. & Sullivan, W.E. (2024). Effects of the Good Behavior Game on students' academic engagement in remote classrooms during the COVID-19 pandemic. *Journal of Positive Behavior Interventions, 26*(1). https://doi.org/10.1177/10983007231168400

Hogstrom, J., Nordh, M., Larson, L., Taylor, E., Serlachius, E. & Kleberg, J.L. (2019). Visual attention to emotional faces in adolescents with social anxiety disorder receiving cognitive behavioral therapy. *PLOS One, 14(*11). doi: 10.1371/journal.pone.0225603.

Humphrey, N., Hennessey, A., Ashworth, E., Frearson, K., Black, L., Petersen, K., Wo, L., Panayiotou, M., Lendrum, A., Wigelsworth, M., Birchinall, L., Squires, G. & Pampaka, M. (2018). Good Behavior Game: Evaluation report and executive summary. https://eric.ed.gov/?id=ED617332

Jornevald, M., Pettersson-Roll, L., & Hau, H. (2024). The Good Behavior Game for students with special educational needs in mainstream education settings: A scoping review. *Psychology in the Schools, 61*(3), 861–886. https://doi.org/10.1002/pits.23086

Joslyn, P.R., Donaldson, J.M., Austin, J.L. and Vollmer, T.R. (2019), The Good Behavior Game: A brief review. *Journal of Applied Behavior Analysis, 52(3),* 811-815. https://doi.org/10.1002/jaba.572

Khalid, M. I., Komal, A., Wushishi, U. J., Hussain, A., Hussain, N., & Hussain, S. A. (2025). An integrated deep learning framework for real-time monitoring of student engagement in smart classrooms. *ICCK Journal of Image Analysis and Processing*, *1*(4), 172-183. https://www.icck.org/article/abs/jiap.2025.377388

Leidig, T., Casale, G., Wilbert, J., Hennemann, T., Volpe, R., Briesch, A. & Grosche, M. (2022). Individual, generalized, and moderated effects of the Good Behavior Game on at-

risk primary school students: A multilevel multiple baseline study using behavioral progress monitoring. *Frontiers in Education, 7.* doi: 10.3389/feduc.2022.917138

Lomholt, R. & Qvortrup, A. (2025). Categorizing student behaviors as manifest indicators of learning engagement: A contextual approach. *European Journal of Psychology of Education, 40*(121). https://doi.org/10.1007/s10212-025-01034-5

Maxwell, E. & Adaugo, B. (2019). Influence of emotional behavioral disorder on academic performance of junior secondary students in Rivers State. *International Journal of Innovative Psychology and Social Development*, *7*(2), 114-121. Available from: www.seahipaj.org.

McLeod, S. (2025). Operant conditioning: What it is, how it works, and examples. [website] *Simply Psychology*. https://www.simplypsychology.org/operant-conditioning.html

Moohr, M. L., Balint-Langel, K., Taylor, J. C., & Rizzo, K. L. (2021). Practicing academic independence: Self-regulation strategies for students with emotional and behavioral disorders. *Beyond Behavior, 30*(2), 85-96. https://doi.org/10.1177/10742956211020666

Moore, T. C., Gordon, J. R., Williams, A., & Eshbaugh, J. F. (2022). A positive version of the Good Behavior Game in a self-contained classroom for EBD: Effects on individual student behavior. *Behavioral Disorders, 47*(2), *67-83*. https://doi.org/10.1177/01987429211061125

Murphy, M.J., Hawkins, R.O. & Nabors, L. (2020). Combining social skills instruction and the Good Behavior Game to support students with emotional and behavioral disorders. *Contemporary School Psychology*, 24(2), 228–238. https://doi.org/10.1007/s40688-019-00226-3.

O'Brien, K.M., Brunsting, N.C., Nelson, C., Bettini, E., Cumming, M.M., Ragunathan, M. & Sutton, R. (2019). Special educators' working conditions in self-contained settings for students with emotional or behavioral disorders: A descriptive analysis. *Exceptional Children, 86*(1), 40-57. https://eric.ed.gov/?id=EJ1229460

Peras, G.M., Castro, J.C. & Mantog, JR A. (2024). Mitigating students' disruptive behavior through operant conditioning. *International Journal of Advance Research and Innovative Ideas in Education,* 9(3), 4795-4809. https://l1nq.com/xyosrpj

Pillai, A.S. (2022). Student engagement detection in classrooms through computer vision and deep learning: A novel approach using YOLOv4. *Sage Science Review of Educational Technology*, *5*(1). https://journals.sagescience.org/index.php/ssret/article/view/144

Sciarra, D., Austin, V. & Biennia, E. (2022). Working with students with emotional and behavioral disorders: A guide to K-12 teachers and service providers. *Series in Education,* Vernon Press. https://sl1nk.com/crq29la

Sümer, Ö., Goldberg, P., D'Mello, S., Gerjets, P., Trautwein, U., & Kasneci, E. (2021). Multimodal engagement analysis from facial videos in the classroom. *IEEE Transactions on Affective Computing*, *14*(2), 1012-1027. doi: 10.1109/TAFFC.2021.3127692

Sutherland, K. S., Conroy, M. A., & Granger, K. L. (2020). A tier-2 program for children with and at-risk for emotional/behavioral disorders. In *Handbook of Research on Emotional and Behavioral Disorders*. https://doi.org/10.4324/9780429453106-15

Tingstrom D.H., Sterling-Turner H.E. & Wilczynski S.M.. The Good Behavior Game: 1969-2002. (2006). *Behavior Modification*, *30*(2):225-53. doi: 10.1177/0145445503261165

Trabelsi, Z., Alnajjar, F., Parambil, M., Gochoo, M., & Ali, L. (2023). Real-time attention monitoring system for classroom: A deep learning approach for students' behavior recognition. *Big Data and Cognitive Computing*, *7*(1), 48. https://doi.org/10.3390/bdcc7010048

Valdes-Ramirez, D., Beltran-Sanchez, J.A., Conant-Pablos, S.E., Lopez, R.P., Dominguez, A., Camacho-Zuñiga, C. & Zavala, G. (2026). A deep learning approach to estimating interaction levels in face-to-face lessons. *Computers and Education: Artificial Intelligence* 10, (2026): 100528. https://doi.org/10.1016/j.caeai.2025.100528

Zaheer, I., Maggin, D., McDaniel, S., McIntosh, K., Rodriguez, B. J., & Fogt, J. B. (2019). Implementation of promising practices that support students with emotional and behavioral disorders. *Behavioral Disorders, 44*(2), *117-128.* https://doi.org/10.1177/0198742918821331

P26022

The Roles of Special Education Teachers in Promoting the Potential of Students with Special Needs in Inclusive Schools

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Abstract

Background and Objectives. Inclusive education in complex metropolitan contexts faces significant challenges regarding curricular accessibility and social adaptation. Special education teachers must pivot from passive aides to proactive change agents. This study aimed to investigate the proactive roles of special education teachers in enhancing the potential of students with special needs in inclusive classrooms under the Bangkok Metropolitan Administration, focusing on three core dimensions: classroom participation, self-help skills, and peer social interaction.

This study employed a descriptive qualitative research design grounded in a phenomenological approach. Data were collected using focus group discussions and in-depth interviews with a total of 15 participants, purposively selected from schools located in the eastern area of Bangkok (covering Min Buri, Nong Chok, Lat Krabang, and Saphan Sung districts). The key informants comprised: 1) five special education teachers from schools under the Bangkok Metropolitan Administration (BMA), 2) five special education teachers from schools under the Office of the Basic Education Commission (OBEC), and 3) five special education teachers from schools under the Office of the Private Education Commission (OPEC). The research instrument was a semi-structured interview guide with predetermined questions. Audio recordings were conducted during all interview sessions, data triangulation was applied to ensure trustworthiness, and the collected data were analyzed using qualitative content analysis.

Findings revealed three major themes: (1) Classroom Participation: Special education teachers proactively serve as "co-designers of learning" and "curricular bridges" by modifying the core curriculum, recommending reduced task volumes, and initiating flexible oral assessments. (2)

Self-Help Skills: Teachers transition from service providers to "scaffolders," utilize task analysis and pre-train daily living skills in resource rooms, while providing preventive consultation to general teachers on reducing physical classroom distractions. (3) Peer Social Interaction: Teachers act as "social engineers" and "in-situ social coaches" by cultivating peer-mediated interventions based on shared interests, combined with subtle, strategic prompting to preserve students' self-esteem and prevent school bullying.

The proactive roles of special education teachers extend beyond individual student support to institutional transformation. Collaborative and preventive consultation with general teachers is paramount to establishing an ecosystem of inclusion and educational equity in urban school settings.

Keywords: special education teachers, inclusive education; classroom participation, self-help skills, peer social interaction

Introduction

Inclusion education, a global benchmark, is central to the development goals (SDGs), specifically Goal 4. This strategy aims to break down barriers to equitable access to quality education for students with special needs, including those with general needs and those with special needs. In Thalland, the number of students per regular classroom is high, with regular school councils and social schools at the school level. The number of students with special needs integrated into regular schools exceeds 400,000 nationwide. The proportion of inclusive education in municipal schools (BMA) is 60% of all schools (Office of the Education Council, 2024). The system needs to address the issue of teacher recruitment, focusing on special education teachers and special education universities, with a ratio of 1:15 for special needs students exceeding the standard for inclusive care (Office of the Basic Education Commission [OBEC], 2023).

Under the constraints of limited human resources and the environment in capital schools, "special education teachers" no longer function merely as instructors in segregated classrooms or resource rooms. They need to adapt their competencies and practices to a "proactive role" as academic leaders and systemic supporters (Nampolsaen, 2021; Puangsomit et al., 20:22). However, in reality, special education teachers often bear overlapping workloads and face misconceptions about inclusive education. Therefore, understanding best practices and approaches to addressing psychological and social problems in the classroom is crucial to

translating top-down policy implementation into bottom-up practice within the classroom context.

Considering the key indicators of success in inclusive education at the primary level, three interconnected behavioral dimensions can be identified. The first dimension is promoting classroom participation. Evidence in typical classrooms often shows that students with special needs are merely "students placed in the classroom" who sit but cannot access the lessons because the core curriculum content is too difficult and complex for their abities. Modern special education teachers must therefore elevate their role from simply accompanying children to becoming "co-designers of learning" and "curricular bridges" to adapt, extract, and simplify content so that learners have the opportunity to participate in activities with their classmates according to their true potential (Zagona et al, 2021; Marod & Witchawut, 2023). The second dimension is promoting self-help skills in the classroom, which is a crucial foundation for building sustainability in learners. This is because learners with special needs often have limitations in self-regulation and tend to strictly adhere to established instructions, lacking flexibility in real world situations. Special education teachers must therefore utize task analysis processes to systematically train life skills, daily routine skills, and emal management in supplementary learning rooms before placing children in regular classsrooms. This includes providing preventative counseling to general education teachers on seating arrangements and environments that minimize distractions (Takala et al., 2020). The final dimension is promoting peer social interaction to address the challenges of bullying and stigmatization in primary schools, where general children often lack awareness. Special. education teachers must thus assume the role of "social engineer" and "social skills coach in real-life situations" to create a peer support system and foster a positive perspective on diversity within the organizational culture (Messiou, 2024; Saengkaew, 2023).

Despite some attempts to study the role of special education teachers in Thai society, most research employs quantitative methods, often presenting findings as averages or policy-oriented statistics. These figures tend to overshadow the reality, feelings, subtle strategies employed, and the highly specific contextual conditions of schools in metropolitan areas like. Bangkok. Therefore, a qualitative research approach focusing on accessing the realism and essence of experience through phenomenological methods is the most suitable way to answer this question. This approach allows practicing special education teachers to reflect on their collaborative work processes, psychological compromises with regular teachers, and supportive techniques hidden beneath structural limitations.

Therefore, this qualitative research on the proactive role of special education teachers in fostering the potential of students with special needs in inclusive schools under the Bangkok Metropolitan Administration was conducted to fill this academic gap. The knowledge extracted from focus groups and in-depth interviews will not only reveal effective practical models in all three key dimensions but will also provide crucial empirical findings and institutional insights for school administrators, policymakers, and researchers in the Southeast Asian region, enabling them to contribute to the advancement of inclusive education systems towards true equity and inclusivity.

Research Objective:

To investigate the proactive roles of special education teachers in promoting the potential of students with special needs in inclusive classrooms across various affiliations in eastern Bangkok, focusing on three core dimensions: classroom participation, self-help skills, and peer social interaction.

To synthesize practical recommendations for enhancing the roles of special education teachers in promoting inclusive education within an urban context.

Literature Review

Takala, Pirttimaa, & Tomaen (2020) studied "Inclusive education in Finland: The changing role of special education teachers in elementary schools" with the objective of examining the changing role of special education teachers in Finnish elementary schools. The research employed a qualitative survey and work diaries of special education teachers. Key findings indicated that the work of special education teachers in Finland has shifted towards a more consultative and preventive role. Special education teachers now dedicate up to one third of their working time to consulting general teachers, enabling these teachers to effectively manage and provide early learning opportunities for children with special needs in regular classrooms.

Zagona, Kurth, & MacFarland (2021) studied "Teachers' views of their roles and preparation for inclusive education for students with significant disabilities in elementary settings" with the aim of examining the perspectives and preparations of special education teachers in promoting inclusive education for students with significant disabilities at the elementary level. The qualitative research was conducted using focus groups categorized by teachers' experience levels. The findings indicated that teachers reflected their most challenging role was acting as a "curricular bridge," meaning breaking down complex core curriculum into basic skills that children with cerebral palsy or multiple disabilities can learn and participate within a regular

classroom. Teachers emphasized that university training should include skills in collaborating with parents and other professionals (such as occupational therapists).

Messiou (2024) studied "Collaborating with special education teachers to promote inclusion in primary schools: Voices from the field" with the objective of exploring field feedback on the collaboration of special education teachers in driving inclusion in primary schools. The study employed qualitative action research in collaboration with teachers from leading primary schools. The findings revealed that the most powerful role of special education teachers is to be advocates for student voices. These teachers interviewed and collected data on the feelings of special needs children regarding their learning preferences, and then presented this information at principal meetings to adjust policies and classroom arrangements. This fostered a genuine sense of belonging for special needs children within the school.

De Vroey, Struyf & Petry (2023) studied “The role of special education teachers in supporting elementary school staff towards inclusive education: A qualitative multiple case study” with the objective of examining the role of special education teachers in supporting and coaching elementary school staff towards inclusive education. The study used a qualitative multiple case study approach in four elementary schools transitioning to inclusive education. The findings indicated that the role of special education teachers had evolved from that of instructors to that of inclusion coaches/school-wide supporters. These teachers conducted workshops within the school, advised administration on scheduling, and provided psychological support to general teachers experiencing burnout or stress from managing inclusive education. This resulted in a more accepting and inclusive organizational culture.

Puangsomjit et al. (2022) studied the role of special education teachers in inclusive education for children with special needs in primary schools under the Office of the Basic Education Commission (OBEC). The objective was to examine the roles and operational guidelines of special education teachers in managing inclusive education for children with special needs in primary schools under the OBEC. The research employed a qualitative approach using in-depth interviews with special education teachers and school administrators in leading inclusive schools, and focus group discussions with experts. The findings revealed that the main roles of special education teachers can be divided into four areas: 1. Developing Individualized Education Plans (lEPs), 2. Managing teaching and behavior modification, 3. Coordinating and providing counseling to homeroom teachers and parents, and 4. Providing media and assistive technologies.

Marod & Witchawut (2023) conducted a qualitative study on the collaborative process between special education teachers and classroom teachers in promoting inclusive education at the

primary school level. The objective was to examine the content and collaborative processes between special education teachers and classroom teachers in promoting inclusive education at the primary school level. The research employed a qualitative approach using grounded theory. Key informants were 14 special education teachers and classroom teachers from a renowned primary school known for inclusive education. Data was collected through semi-structured. interviews and observation. The results showed that successful collaborative work stemmed from three main factors: mutual trust, open communication, and clear role assignment. Special education teachers acted as content designers and adapters, while classroom teachers implemented the content in the main classroom. This seamless coordination reduced anxiety among classroom teachers and enabled special needs children to learn happily in inclusive environments.

Nampolsaen (2021) studied "The Role and Competencies of Modern Special Education Teachers in Inclusive Primary School Classrooms: A Phenomenological Qualitative Research." The objective was to examine the roles and competencies of modern special education teachers in organizing inclusive primary school classrooms. The research employed a phenomenological approach, selecting eight experienced special education teachers with significant experience in inclusive primary schools as participants. The research tools included in-depth interviews and field notes. The results indicated that the competencies of modern special education teachers extend beyond simply teaching in the resource room. They must also play a *"proactive role** as "Inclusive academic leaders," providing internal supervision, introducing Universal Design for Learning (UDL) to general teachers, and driving technolocical innovations and assistive devices in schools.

Aphiradee Saengkaew (2023) studied "Guidelines for Promoting Inclusive Learning Abilities of Autistic Students in Primary Schools through the Work Process of Special Education Teachers: A Multiple Case Study." The objective was to investigate approaches to promoting inclusive learning abilities of autistic students in primary schools through the work process of special education teachers. The research employed a multiple case study approach in three primary schools, collecting data through interviews, observation of autistic children's behavior in the classroom, and analysis of Individualized Education Plan (IEP) documents. Key findings indicated that special education teachers play a crucial role in promoting inclusive learning abilities of autistic children through the **"Scaffolding and Transition Model****. This begins with preparation in the academic enrichment classroom focusing on social skills and self-control before placing the children in regular classrooms. Special education teachers then observe, adapt the physical environment, and create short behavioral guides for regular teachers

to use in managing the learning process. This effectively increases the time achievable by autistic children in the classroom (Time on Task).

A qualitative literature review, both domestic and international, clearly reflects that the role of special education teachers in inclusive primary schools has evolved from being solely tutors in resource rooms to proactive leaders and systemic supporters driving holistic inclusive education. This can be synthesized into three key dimensions of research supporting this topic. The first dimension is the role of systemic support and consultation, aligning with the concepts of Takala et al. (2020) and De Vroey et al. (2023), who found that special education teachers have transitioned to becoming inclusion coaches and focus on preventative consultation with regular teachers for up to one-third of their working time. This direction directly connects to Thai research by Puangsomjit et al. (2022) and Nampolsaen (2021), which indicates that modern special education teachers must play a "proactive role" as academic leaders in inclusive education, coordinating and advising stakeholders. The second dimension is the role of frontline collaboration and bridging the curriculum. (Collaborative Practice & Curicular Bridge) Research by Marod & Witchawut (2023) indicates that success arises from assigning roles to special education teachers as designers and adapters of content, which are then passed on to regular teachers for application. This concretely explains the collaborative mechanism and aligns with the perspective of Zagona et al. (2021), who emphasize the challenge for teachers to act as a "curricular bridge" to break down and streamline the core curriculum so that children with severe disabilities can access it. The final dimension is the role of supporting student potential and feedback (Scaffolding & Student Advocacy). Research by Saengkaew (2023) proposes a "Scaffolding and Transition Mode!" to prepare and modify students' behavior before entering the regular classroom. This is a practical process that aligns with and complements the goals of Messiou's (2024) research which focuses on being an advocate for student voices so that policy adjustments and classroom arrangements can truly create a sense of belonging for children with special needs. In summary, integrating the roles of special education teachers as systemic consultants, co-curriculum designers, and advocates of student rights is a key mechanism that both Thai and international research recognize as the most effective factor in creating sustainable inclusive education at the primary level.

Research Methodology

This study adopted a qualitative research approach, utilizing focus group discussions and in-depth interviews to synthesize practical recommendations for enhancing the roles of special education teachers in promoting inclusive education. To obtain in-depth insights from

practitioners with direct experience, the research participants comprised primary-level special education teachers teaching in inclusive schools within the eastern area of Bangkok (covering Min Buri, Nong Chok, Lat Krabang, and Saphan Sung districts). A total of 15 key informants were selected across three school affiliations: 1) 5 special education teachers from 5 schools under the Bangkok Metropolitan Administration (BMA), 2) 5 special education teachers from 3 schools under the Office of the Basic Education Commission (OBEC), and 3) 5 special education teachers from 5 schools under the Office of the Private Education Commission (OPEC). For data collection, the researcher coordinated with the respective schools to seek formal permission. Upon approval, the study's objectives were clarified, informed consent for data collection was obtained, and schedules and locations for the interview sessions were formally arranged.

***Interview Procedure*:**

The researcher conducted interactive interviews in person, introducing themselves, explaining the purpose of the interview, and requesting permission to record data using a voice recorder. Interviewees were given the opportunity to express their opinions and answer questions freely. The researcher reviewed key information or points to verify mutual understanding with the interviewees. Each interview lasted 45-60 minutes. After obtaining the data, field notes were compiled and the interview transcripts were transcribed. The content, meaning, grouping of meanings, and connections between different concepts were recorded.

***Informants*:**

The key informants were selected using criterion sampling to ensure the inclusion of individuals directly experiencing the context and capable of providing rich, experiential data (Oumtanee, 2010). The ideal participants were primary-level special education teachers working in inclusive schools across various affiliations in eastern Bangkok (covering Min Buri, Nong Chok, Lat Krabang, and Saphan Sung districts). A total of 15 participants were selected across three school affiliations: 1) 5 special education teachers from schools under the Bangkok Metropolitan Administration (BMA), 2) 5 special education teachers from schools under the Office of the Basic Education Commission (OBEC), and 3) 5 special education teachers from schools under the Office of the Private Education Commission (OPEC). The specific inclusion criteria for participant selection comprised: (a) currently working in a primary inclusive school, (b) having at least three years of teaching experience, (c) directly working with students with special needs, and (d) voluntarily agreeing to participate in the study.

Table 1 Summary of Key Informants Context

Participant Code	Affiliation	District Area (Eastern Bangkok)	Teaching Experience (Years)
ST-01 – ST-05	BMA	Min Buri, Lat Krabang, Saphan Sung	ST-01 = 20 years ST-02 = 25 years ST-03 = 28 years ST-04 = 18 years ST-05 = 15 years
ST-06 – ST-10	OBEC	Min Buri, Nong Chok	ST-06 = 23 years ST-07 = 24 years ST-08 = 12 years ST-09 = 25 years ST-10 = 8 years
ST-11 – ST-15	OPEC	Min Buri, Nong Chok, Lat Krabang, Saphan Sung	ST-11 = 22 years ST-12 = 14 years ST-13 = 5 years ST-14 = 2 years ST-15 = 18 years

****BMA:** Bangkok Metropolitan Administration

****OBEC:** Office of the Basic Education Commission

****OPEC:** Office of the Private Education Commission

Data Collection Tools and Processes:

The researcher focused on focus groups and in-depth individual interviews. Three key question areas were developed based on the research objectives and framework. The in-depth interview process emphasized open-ended questions, allowing for freedom of information sharing among similar groups, with some adjustments to pronouns and context. Lessons learned were also incorporated.

Data Analysis:

Interpret and decode data from focus group transcripts and in-depth interviews, perform descriptive comparisons using phenomenological principles, and conduct content analysis.

Research Findings

The informants reflect that special education teachers play a crucial role in promoting inclusive learning abilities for students with special needs. They act as facilitators, fostering collaboration between students, classroom teachers, parents, and relevant personnel to support students in adapting, participating in learning activities, and effectively incorporating them into mainstream learning. Data analysis reveals the key roles of special education teachers as follows:

1. Promoting Classroom Participation

The role of special education teachers is not just to sit and observe children, but to act as co-designers of learning so that children with special needs can access the core curriculum lessons. They also act as a curriculum bridge, extracting and simplifying the lesson plans of regular teachers to adapt the content to the abilities of children with special needs, while still teaching the same material as their classmates. Furthermore, they design participation techniques, suggesting ways for regular teachers to help organize activities that allow children with special needs to answer questions or act according to their abilities. For example, having children with special needs assist their peers in holding presentation signs, or assigning specific tasks in the classroom to foster pride and boost confidence in the classroom.

Sometimes I would advise homeroom teachers/subject teachers on teaching techniques that would help students with special needs feel included in the class, such as group presentation situations. I would suggest that homeroom teachers/subject teachers assign simpler tasks for students with special needs, or assign tasks appropriate to their ability level, so that students with special needs do not feel isolated or that they are not being included in group work. (Key informant ST-03)

I once suggested that teachers assign tasks appropriate to the ability level of children with special needs. For example, if a typical child is assigned 10 tasks, the tasks for a child with special needs could be fewer, perhaps five to eight, depending on how much the child with special needs con learn. (Key informant ST-07)

Before inclusive classroom learning, I always teach children with special needs that if they fall behind or don't understand a lesson, they should immediately inform the teacher or ask the classmate sitting next to them. If they fall behind, they shouldn't skip that lesson or con consult a special education teacher after the lesson. (Key informant ST-14)

I have previously informed teachers who teach students with special needs to add methods for assessment. If a student with special needs is unable to write a written answer or explanation, I would like the teacher to allow them to respond orally to express their thoughts or use spoken words to explain what they are trying to convey, instead of assessing them through written reports. (Key informant ST-04)

I often tell subject teachers that if there's anything a student needs to review further, they can inform the student's parents or the special education teacher so they can coordinate with the parents. (Key informant ST-01)

When homeroom teachers/subject teachers observe any problems, whether behavioral or academic, please inform the special education teacher directly so that they can be addressed promptly. (Key informant ST-13)

Sometimes, when my students fall behind in their lessons, I summarize certain sections to help them understand better. Sometimes, I need to provide various examples to help them grasp the material, including certain skills like teasing. My students often misunderstand the meaning of teasing; they tend to think their friends are always criticizing them. (Key informant ST-08)

I always ask my homeroom teacher to inform us of the daily activities in advance because some students with special needs may lack confidence of they don't know the activities beforehand, which can cause them anxiety. (Key informant ST-10)

2. Promoting Self-Help Skills in the Classroom

The role of special education teachers must shift from being a doer to a supporter and gradually reducing assistance to build behavioral sustainability. Break down classroom activities (Task Analysis), such as homework assignments or scheduling, so children can follow each step. Gradually reduce assistance to enable children to become self-reliant. Collaborate with the homeroom teacher to create a classroom environment that minimizes distractions (Visual Supports) and establishes quiet corners. Implement positive behavior agreements to help children manage stress. Provide preparatory training and practice essential skills in the academic enrichment room before introducing children to real-world classroom situations.

Before sending them to co-educational settings, I need to make sure they can take care of themselves in daily life, such as using the restroom, dressing, and managing their emotions at a basic level. (Key informant ST-15)

I always emphasize to my students with special needs that if a friend bullies them or does something they don't like, they should immediately inform their homeroom teacher. They should not retaliate by hitting or pinching their friend. (Key informant ST-11)

I will train the children to recognize their own class schedules and know where the different laboratories are located, such as where the computer room is, where the library is, or if students can't find their classrooms, they can come to the special education teacher in the academic enrichment room at any time. (Key informant ST-05)

It's crucial to always emphasize to students that if they need to leave the classroom, such as to go to the restroom or get a drink of water, they should inform their homeroom teacher.

Alternatively, if the teacher/homeroom teacher isn't in the classroom, they can tell their seated classmate. Children with special needs tend to be very particular about following instructions; they won't go to the restroom unless they see their homeroom teacher. Therefore, it's always important to have a second option and inform them. In some cases, children may be too shy to communicate directly with the teacher, so they can inform a friend instead, as this is a more comfortable communication method. (Key informant ST-03)

I always inform the homeroom teacher before placing students in co-educational classes about the limitations of each student. Some students are easily distracted if they sit near a door or window, or in the play area. I usually ask the homeroom teacher to place students with special needs near the teacher or near a classmate who can help and support them. (Key informant ST-14)

I train students to ask for help in sensitive matters, such as if they have trouble dressing or not being able to put their shirt in or unzip their pants, they only ask the teacher for help. You shouldn't ask for help from friends when it comes to your own body. (Key informant ST-06)

3.Promoting Peer Social Interaction

The role of special education teachers is to be social engineers, not only training children with special needs but also preparing them for the social context surrounding them. Special education teachers act as social bridges, designing classroom activities or games that encourage pairing or group work using a peer-mediated intervention system. They select and nurture typical students to understand how to approach, help, and play appropriately with their special needs peers. They coach social skills in real-life situations and observe and prompt special needs children at appropriate times, such as during lunch breaks or group work. They teach them how to ask to join play, wait in line, or share toys. They organize activities or provide education to teachers and students in the school to create awareness and positive attitudes towards diversity, which will help reduce bullying and stigmatization in the long term.

We cannot prevent bullying in schools, especially among elementary school children who don't understand about children with special needs. We're not asking young children to learn about special needs, but rather to foster a better understanding of them and to prevent them from seeing their friends as inferior. For example, I often point out the positive qualities of students with special needs to my classmates. In art class, I would highlight the abilities of a child with special needs, saying that even if they aren't academically gifted, they're good at painting, and suggesting they paint together. (Key informant ST-07)

I always teach my children that if they see a friend's pencil, eraser, or pencil case they like, they should always ask their friend's permission before touching it. Because students themselves don't like it when others play with their things, right? Friends feel the same way. When you want to look at a friend's belongings, ask first if you can touch or look at them. Because our special needs children, when they see something they like, they will pick it up and examine it. It's not typical for elementary school children to be possessive of their things. (Key informant ST-03)

I often ask students about their feelings, their studies, and other matters during lunchtime because I don't want to visit students with special needs in regular classrooms. This might make them feel like they can't take care of themselves and always need a special education teacher nearby. I also don't want other students in the class to perceive students with special needs as incapable of self-care and therefore requiring frequent visits from a special education teacher. (Key informant ST-09)

Sometimes I'll help guide my classmates on how to play and approach students with special needs without making them feel interfered with or manipulated. For example, I once told a student that their friend also likes playing Minecraft, and suggested they ask them about it. (Key informant ST-02)

Often, teachers have to help create play situations so that students with special needs can interact with their peers by initiating relationships. For example, they can encourage students to start conversations with friends about shared interests, such as cord games, their favorite cartoons, or playing sports together during lunchtime. (Key informant ST-08)

Discussion of Results

1. Promoting Classroom Participation:

The findings clearly demonstrate that special education teachers do not merely perform duties as passive monitors or individual safety supervisors in the classroom. Instead, they elevate their role to "co-designers of learning." In metropolitan schools under the Bangkok Metropolitan Administration (BMA), characterized by densely populated classrooms and high teacher workloads, special education teachers serving as "curricular bridges" significantly alleviate the burden on general education teachers from creating separate instructional materials or exams. This facilitates greater acceptance of inclusive education among general educators. By extracting, modifying, and adapting core curriculum lesson plans, special education teachers

align instructional content with the functional abilities of students with special needs, enabling these students to learn the same topics alongside their peers.

This role in breaking down curricular barriers strongly aligns with the framework of Zagona, Kurth, and MacFarland (2021), who emphasized that modern special education teachers must act as curricular bridges, simplifying complex lessons into foundational skills to afford students with disabilities access to general education classrooms. Similarly, this reflects the research of Marod and Witchawut (2023), who highlighted the critical role of special education teachers as "adapters" who modify instructional content for seamless implementation by general teachers. This is evident in the empirical findings, where special education teachers suggested reducing task volume based on individual student capabilities (e.g., reducing from 10 items to 5–8 items) to mitigate excessive cognitive overload and task-induced distress.

Furthermore, the results highlight a "proactive role" in providing consultative support and promoting social inclusion during group activities. Special education teachers offer technical guidance to general teachers on structuring inclusive tasks that allow students with special needs to demonstrate their potential. This includes assigning suitable responsibilities within group work to prevent feelings of alienation or designating students as sign-holders during presentations to foster self-pride and confidence. These scaffolding processes align with Nampolsaen (2021), who asserted that special education teachers must demonstrate academic leadership by supervising and guiding general educators to design activities that embrace diversity.

Regarding student preparation and collaborative coordination, special education teachers play a prominent role in cultivating proactive learning behaviors in students (e.g., encouraging them to communicate with teachers or peers when falling behind). They also act as a central coordination hub between subject teachers and parents to address behavioral or learning issues promptly. Additionally, special education teachers assist by summarizing supplementary content, providing varied concrete examples to resolve student misinterpretations (such as understanding peer teasing), and requesting daily activity schedules in advance to reduce student anxiety. These findings are consistent with Puangsomchit et al. (2022), who identified that the essential roles of special education teachers encompass developing Individualized Education Programs (IEPs), managing instruction and behavior, and offering collaborative consultation to general teachers and parents. This extends to recommending flexible assessment alternatives (e.g., requesting oral responses instead of written essays) to ensure that educational evaluations accurately, validly, and equitably reflect the actual knowledge of students with special needs.

2. Promoting Self-Help in the Classroom:

The research findings reflect that in fostering students' life skills and learning within inclusive classrooms, special education teachers have shifted their roles from "providers doing everything" to "systematic scaffolders and fading-support facilitators," focusing on long-term behavioral maintenance and ultimate self-reliance. Special education teachers utilize task analysis to break down classroom activities into step-by-step procedures, such as schedule reading, combined with training in basic life skills (e.g., dressing, restroom use, and emotional regulation) within the resource room. This practice builds mastery and self-confidence before transitioning students into real inclusive classroom settings.

This process aligns with the "Scaffolding and Transition Model" proposed by Saengkeow (2023), which emphasizes that structured, step-by-step preparation of foundational skills and behaviors in resource rooms significantly reduces emotional stress and increases learning attention span when students integrate with their general peers. Furthermore, the findings reveal the proactive role of special education teachers in designing physical environments and implementing flexible alternative thinking systems. For instance, to assist students who exhibit rigid adherence to initial commands, teachers introduce secondary communication alternatives, such as allowing a student who cannot find the class teacher to inform a close desk mate before going to the restroom. This strategy addresses the student's reluctance to communicate with adults due to greater comfort with peers. Special education teachers also establish physical safety protocols by teaching students to protect their rights and seek assistance regarding sensitive matters (e.g., clothing or zipping) exclusively from teachers rather than peers, thereby preventing potential physical complications. These findings are consistent with Puangsomchit et al. (2022) regarding instructional management and behavior modification roles aimed at reducing challenging behaviors and daily functional limitations.

In terms of collaborative and consultative prevention, special education teachers proactively coordinate with general class teachers prior to student placement. They communicate individual limitations, such as susceptibility to distraction, and request physical environmental adaptations to minimize sensory triggers—a necessity in dense urban school settings. Examples include shifting student seating away from doors, windows, or noisy, chaotic toy corners, and placing them closer to the teacher's desk or alongside supportive peers. This proactive approach perfectly aligns with the Consultative and Preventive Role concept by Takala, Pirttimaa, and Törmänen (2020), which asserts that high-impact special education teachers dedicate time to coach and consult general educators in advance. This enables general teachers to recognize vulnerabilities, adapt environments, and handle challenging behaviors appropriately from the

outset, ultimately creating a psychologically safe classroom that sustainably supports self-reliance among students with special needs in a metropolis like Bangkok.

3. Promoting Peer Interaction:

The findings explicitly indicate that the role of special education teachers extends beyond assisting the individual student; they act as "social engineers" and "social bridges" who structure and prepare the surrounding social context. Utilizing Peer-Mediated Intervention (PMI), teachers recruit, cultivate, and guide general education students to naturally approach, play with, and assist peers with special needs. They leverage shared interests embedded in urban youth culture (e.g., digital gaming such as Minecraft, trading card games, or digital animations) to help special education students initiate relationships and break down social barriers in highly diverse classrooms. These findings echo Zagona, Kurth, and MacFarland (2021), who emphasized that to foster effective social interactions in inclusive classrooms, special education teachers must act as social context modelers, facilitating mutual learning and acceptance between general and special education students.

Additionally, special education teachers serve as real-time social skills coaches through subtle, well-timed observation and guidance. They address common primary school social challenges, such as asking for permission before touching others' belongings, by fostering empathy to resolve natural egocentric and possessive behaviors. Crucially, a highly sophisticated strategy identified in this context is the teachers' spatial and psychological awareness. Teachers choose to observe, debrief, or coach social skills during recess or extracurricular times rather than accompanying students during regular instructional periods. This avoids making special education students feel incompetent and prevents classmates from stigmatizing them as requiring constant supervision. This nuanced approach strongly supports Marod and Witchawut (2023), who stated that social scaffolding by special education teachers must be applied flexibly and discreetly to preserve students' self-esteem and promote independence in educational settings.

Regarding bullying prevention and building a culture of inclusion, the findings highlight that preventing peer bullying in primary schools is challenging due to students' developing maturity and diverse family backgrounds in an urban environment. Special education teachers employ asset-based reframing by highlighting the unique strengths and talents of students with special needs rather than focusing on deficits. For example, by praising a student's artistic ability in art class and encouraging peers to collaborate with them, teachers foster positive attitudes toward diversity and reduce devaluation. This aligns directly with Nampolsaen (2021) and Puangsomchit et al. (2022), who collectively stressed that successful inclusion relies not solely

on the adaptation of the student with special needs, but on the teacher's role in creating an "ecosystem of inclusion" and transforming institutional attitudes to dismantle stigma and foster equal acceptance within the urban context of Bangkok.

Recommendations

Recommendations from the research:

1. Recommendations for the application of research findings (Implications for Practice & Policy)

School Level: Promote a model where special education teachers co-design learning, This should involve allocating time for special education teachers and regular teachers to collaboratively extract and break down curriculum content, as well as arranging seating and physical environments to minimize distractions for students in advance of the school year. Classroom Level: Encourage teachers to adapt flexible assessment methods, such as oral assessments instead of written descriptions, and the use of peer-mediated interventions, connecting students through shared interests (e.g., games or group activities) to create positive interactions and reduce bullying in schools.

Individual Level: Emphasize the practice of self-help skills and emotional management in the resource room, alongside teaching proactive social skills to build students' confidence and self-reliance when entering inclusive classrooms.

2. Recommendations for Future Research:

Quantitative or experimental research should be conducted to test the effectiveness of peer-mediated systems or scaffolding withdrawal models on the self-reliance capabilities of children with special needs in urban school contexts. Policy impact assessment research or studies on competency development for general classroom teachers in managing inclusive education should be conducted to reduce workload and create sustainable collaboration between general classroom teachers and special education teachers.

References

De Vroey, C., Struyf, E, & Petry, K (2023). The role of special education teachers in supporting elementary school staff towards inclusive education: A qualitative multiple case study. Teacher Development, 27(4), 487-505. https://doi.org/10.1080/1364530.2023.2190835

Nampolsaen, K (2021). Roles and competencies of modern special education teachers in organizing inclusive classrooms at the primary education level: A phenomenological qualitative research. Journal of Educational Research, Faculty of Education, Srinakharinwirot University, 16(2), 78-92. https://ejournals.swu.ac.th/index.php/jedu/article/view/13952

Marod, B, & Witchawut, S. (2023). A qualitative study on the collaboration process between special education teachers and homeroom teachers in promoting inclusive education at the primary level. Journal of Clinical Psychology and Counseling, 15(1), 45-61. https://so05.tci-thaijo.org/index.php/JCPC/article/view/261048

Messiou, K (2024). Collaborating with special education teachers to promote inclusion in primary schools: Voices from the field. Journal of Research in Special Educational Needs, 24(1), 54-65. https://doi.org/10.1111/1471-3802.12612

Office of the Basic Education Commission. (2023). Statistical report on special and inclusive education management for the academic year 2023. Karn Sasana Press.

Office of the Education Counal. (2024). State of Thai education 2023/2024: Guidelines for educational reform to reduce inequality in urban society. 21st Century.

Oumtanee, A. (2010). Qualitative research in nursing. Chulalongkorn University Printing House.

Puangsomit, C., Suksai, M., & Trakulthone, P. (2022). The roles of special education teachers in managing inclusive education for children with special needs in primary schools under the Office of the Basic Education Commission. Journal of Education, Naresuan University, 24(3), 112-125. https://so06.tci-thaijo.org/index.php/EDUNU/article/view/254132

Saengkaew, A. (2023). Guidelines for promoting the inclusive education capability of autistic students in primary schools through the working process of special education teachers: A multiple case study. Journal of Education, Rajabhat Maha Sarakham University, 20(2), 210-225. https://so05.tci-thaijo.org/index.php/RMU-JED/article/view/259874

Takala, Mi, Pirtimaa, R., & Tormanen, M. (2020). Inclusive education in Finland: The

changing role of special education teachers in elementary schools. Scandinavian Journal of Educational Research, 64(5), 701-715. https://doi.org/10.1080/00313831.2019.1595718

Zaqona, A. L. Kurth, J. A, & MacFarland, S. Z.(2021), Teachers' views of their roles and preparation for inclusive education for students with significant disabilities in elentany settings. Research and Practice for Persons with Severe Disabilities, 46(2), 99-115. https://doi.org/10.1177/15407969211014167

P26027

Effectiveness of a Communicative-Based Learning Module in Reducing Fear of Negative Evaluation in Speaking Among Freshman College Students

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ABSTRACT

Fear of Negative Evaluation (FNE) is a significant psychological barrier that limits students' oral communication, classroom participation, and speaking confidence in higher education. This study evaluated the effectiveness of a Communicative-Based Learning (CBL) module in lowering FNE among freshmen college students at Community College, Misamis Oriental, Philippines. An embedded mixed-methods design was employed with 119 freshmen college students. Quantitative data were collected using the Brief Fear of Negative Evaluation (BFNE) Scale developed by Leary (1983), administered before and after the implementation of the CBL module. Qualitative data were obtained through classroom observations and group interviews to provide deeper insights into students' learning experiences. Results showed a significant decline in BFNE scores from M = 3.17 (SD = 0.62) to M = 2.50 (SD = 0.73), indicating the effectiveness of the CBL module. Qualitative findings corroborated the quantitative results and generated three themes emerged: collaborative group activities reduced speaking anxiety, peer support strengthened students' confidence, and authentic, real-life communication tasks fostered meaningful classroom interaction. The findings demonstrate that Communicative-Based Learning is an effective learner-centered instructional approach for enhancing communication competence and enhancing students' confidence in oral communication. The findings provide empirical support for integrating Communicative-Based Learning into oral communication instruction to foster supportive learning environments, increase speaking confidence, and enhance student participation in higher education.

Keywords: Communicative-Based Learning, Fear of Negative Evaluation, Oral Communication, Speaking Confidence, Communicative Language Teaching

Introduction

Oral communication is a fundamental competency in higher education, enabling students to participate actively in classroom discussions, collaborate effectively with peers, and communicate confidently in academic and professional settings. As higher education increasingly adopts learner-centered and communication-oriented pedagogies, students are expected to articulate ideas clearly and engage in meaningful interactions. Nevertheless, many students continue to experience apprehension during speaking activities, limiting their classroom participation and communication development.

Among the psychological factors influencing oral communication, Fear of Negative Evaluation (FNE) has been recognized as one of the most significant barriers to students' communication. Students with high levels of FNE often anticipate criticism, embarrassment, or unfavorable judgment from peers and instructors, resulting in heightened speaking anxiety, reduced self-confidence, avoidance of speaking opportunities, and decreased willingness to communicate. Recent studies consistently support this relationship, showing that students with higher FNE experience greater anxiety and lower participation during oral communication activities, particularly when required to respond spontaneously. Conversely, collaborative learning, interaction with familiar peers, and supportive classroom environments reduce apprehension, strengthen learners' confidence, and encourage greater willingness to communicate. In the Philippine context, fear of making mistakes and negative evaluation similarly discourages learners from participating in classroom discussions. Collectively, these findings suggest that effective oral communication instruction should address both students' communicative competence and the psychological factors that influence their participation.

Communicative Language Teaching (CLT) has been widely recognized as an effective learner-centered approach for developing communicative competence while fostering supportive learning environments. By emphasizing authentic communication, learner interaction, and meaningful collaborative tasks, CLT enables students to develop speaking skills while reducing Fear of Negative Evaluation, minimizing speaking anxiety, and promoting greater willingness to communicate. Studies have shown that communicative activities such as pair work, role-playing, interviews, and collaborative problem-solving, improve learners' speaking performance and confidence through meaningful interaction.

This study is anchored on the communicative competence framework of Richards and Rodgers (2014), which emphasizes meaningful communication as the foundation of language learning. It is further supported by Vygotsky's Sociocultural Theory, which posits that learning occurs through social interaction, collaboration, and shared experiences. Together, these frameworks

explain how meaningful interaction and collaborative learning facilitate both communicative competence and reductions in learners' Fear of Negative Evaluation

Despite substantial evidence supporting Communicative Language Teaching in improving speaking proficiency, limited research has examined the effectiveness of a structured Communicative-Based Learning (CBL) module in reducing Fear of Negative Evaluation among first-year college students in Philippine community colleges using an embedded mixed-methods design.

To address this gap, the present study developed a Communicative-Based Learning (CBL) module integrating collaborative learning, authentic communication tasks, peer interaction, interviews, role-playing and problem-solving activities to promote meaningful communication in a psychologically supportive classroom environment. Guided by the study's theoretical framework, it is hypothesized that sustained engagement in these communicative learning experiences enhances students' confidence and participation in speaking activities, thereby reducing Fear of Negative Evaluation.

Accordingly, this study aimed to evaluate the effectiveness of a Communicative-Based Learning (CBL) module in reducing Fear of Negative Evaluation during speaking activities among freshmen college students at Community College, Misamis Oriental, Philippines. Specifically, it sought to:

1. Determine the students' level of Fear of Negative Evaluation before and after the implementation of the Communicative-Based Learning module;
2. Determine whether a significant reduction in Fear of Negative Evaluation occurred following the implementation of the Communicative-Based Learning module; and
3. Explore students' experiences regarding how the Communicative-Based Learning module influenced their confidence during speaking activities.

Guided by these objectives, the study tested the following null hypothesis:

H_0: There is no significant difference in the Fear of Negative Evaluation of first-year college students before and after the implementation of the Communicative-Based Learning module.

This study contributes to language education by providing empirical evidence on the effectiveness of a Communicative-Based Learning module in reducing Fear of Negative Evaluation while improving students' oral communication competence. The findings may guide language teachers, curriculum developers, and higher education institutions in implementing learner-centered instructional strategies that foster confidence and meaningful

communication. Unlike previous studies focusing primarily on communicative competence, this study demonstrates that a structured Communicative-Based Learning module also addresses the psychological barrier of Fear of Negative Evaluation through collaborative and authentic communicative experiences.

Methodology

This study employed an embedded mixed-methods intervention design, in which quantitative data served as the primary source of evidence and qualitative data provided complementary insights into students' learning experiences. The quantitative component utilized a one-group pretest–posttest design to determine changes in students' Fear of Negative Evaluation (FNE) before and after the implementation of the Communicative-Based Learning (CBL) module. The qualitative component consisted of focus group discussions that explored students' perceptions of how the intervention influenced their confidence during speaking activities.

The study involved 119 freshmen college students enrolled in the Purposive Communication course at Community College, Misamis Oriental, Philippines, during the School Year 2021–2022. Participants were selected through purposive sampling. Following the intervention, 17 students voluntarily participated in focus group discussions to provide richer insights into their learning experiences.

The primary quantitative instrument was the Brief Fear of Negative Evaluation (BFNE) Scale (Leary, 1983), which was adapted with minor contextual modifications for the study and pilot-tested, yielding acceptable internal consistency (Cronbach's $\alpha = .751$). The intervention consisted of a researcher-developed Communicative-Based Learning (CBL) module, validated by experts and pilot-tested prior to implementation. The module incorporated authentic communicative tasks, collaborative learning, role-playing, interviews, pair work, and problem-solving activities based on the principles of Communicative Language Teaching.

Data collection consisted of administering the BFNE pretest, implementing the CBL module, conducting the posttest, and facilitating focus group discussions. Quantitative data were analyzed using a paired-samples t-test to determine significant differences between pretest and posttest FNE scores, while qualitative responses were analyzed through thematic analysis. Ethical standards, including institutional approval, informed consent, voluntary participation, confidentiality, and anonymity, were observed throughout the study.

Results and Discussion

The findings demonstrate that the Communicative-Based Learning (CBL) module effectively reduced students' Fear of Negative Evaluation (FNE) during speaking activities. Before the intervention, participants exhibited a moderate level of FNE (M = 3.17), with the greatest concerns centered on being judged by others and making mistakes while speaking. Following the implementation of the CBL module, the mean FNE score decreased to 2.50, indicating a slight level of Fear of Negative Evaluation. The significant decline suggests that repeated exposure to collaborative speaking opportunities gradually reduced students' fear of being negatively judged. This finding supports Vygotsky's Sociocultural Theory, which emphasizes that social interaction promotes confidence and learning through shared experiences.

This finding corroborates the studies of Valencia et al. (2021) and Garni and Almuhammadi (2019), who likewise reported that communicative learning environments enhanced speaking confidence. It also extends previous research by demonstrating that a structured Communicative-Based Learning module can reduce Fear of Negative Evaluation among Philippine community college students.

The paired-samples t-test further confirmed that this reduction was statistically significant ($t(118) = 12.03$, $p < .001$), providing evidence that the intervention positively influenced students' speaking confidence.

The qualitative findings reinforced the quantitative results by explaining how the CBL module contributed to the reduction of Fear of Negative Evaluation. Three interconnected themes emerged from the focus group discussions: (1) collaborative group activities reduced speaking anxiety, (2) peer support and constructive feedback enhanced students' confidence, and (3) authentic, real-life communicative tasks promoted meaningful engagement and active participation. Students consistently reported feeling more comfortable expressing their ideas when working in supportive groups, receiving encouragement from classmates, and participating in communicative activities grounded in real-life situations.

Overall, the integration of quantitative and qualitative findings indicates that the Communicative-Based Learning module not only significantly reduced students' Fear of Negative Evaluation but also fostered a supportive learning environment that enhanced confidence, participation, and willingness to communicate. These findings support the principles of Communicative Language Teaching and Sociocultural Theory, emphasizing that meaningful interaction, collaboration, and authentic communication experiences contribute to the development of both communicative competence and learners' psychological readiness to speak.

Conclusion

The study contributes empirical evidence that a structured Communicative-Based Learning module can serve as an effective pedagogical intervention for reducing Fear of Negative Evaluation while fostering communicative competence among tertiary students.

Recommendations

The Communicative-Based Learning module may be integrated into tertiary oral communication courses as an instructional intervention to promote speaking confidence and reduce Fear of Negative Evaluation. Future studies should validate its effectiveness using larger and more diverse samples, longer implementation periods, and comparative or experimental research designs across different higher education settings.

References

Banagbanag, R. A. (2020). ESL teachers' attitudes and competence on Communicative Language Teaching (CLT) methodology. *Universal Journal of Educational Research, 8*(6), 2534–2541.

Barrot, J. S. (2017). Exploring the implementation of Communicative Language Teaching in the Philippines: A tertiary teacher's perspective.

Camacho, C. H., Valencia, J. C., & Villacis, C. H. (2021). Speaking skills development through Communicative Language Teaching techniques. In *Proceedings of the 5th International Conference on Education and Multimedia Technology*.

Creswell, J. W. (2007). *Qualitative inquiry and research design: Choosing among five approaches* (2nd ed.). Sage Publications.

Dawadi, S., Shrestha, S., & Giri, R. A. (2021). Mixed-methods research: A discussion on its types, challenges, and criticisms. *Journal of Practical Studies in Education, 2*(2), 25–36. https://doi.org/10.46809/jpse.v2i2.20

Feng, E., Wang, Y., & King, R. B. (2023). Achievement goals, emotions, and willingness to communicate in EFL learning: Combining variable- and person-centered approaches. *Language Teaching Research, 30*(1). https://doi.org/10.1177/13621688221146887

Garni, S. A., & Almuhammadi, A. H. (2019). The effect of using Communicative Language Teaching activities on EFL students' speaking skills at the University of Jeddah. *English Language Teaching, 12*(6), 72–86. https://doi.org/10.5539/elt.v12n6p72

Gunawan, I. D. (2025). Speaking anxiety in EFL learners: A systematic review of causes, strategies, and pedagogical interventions. *EduLite: Journal of English Education, Literature and Culture*.

Hymes, D. (1972). On communicative competence. In J. B. Pride & J. Holmes (Eds.), *Sociolinguistics: Selected readings* (pp. 269–293). Penguin Books.

Jugo, R. R. (2020). Language anxiety in focus: The case of Filipino undergraduate teacher education learners. *Education Research International*, Article 7049837. https://doi.org/10.1155/2020/7049837

Kiger, M. E., & Varpio, L. (2020). Thematic analysis of qualitative data: AMEE Guide No. 131. *Medical Teacher, 42*(8), 846–854. https://doi.org/10.1080/0142159X.2020.1755030

Kurniawan, A. G., & Sumani. (2022). Communicative Language Teaching approach potential for English language teaching. *KnE Social Sciences*. https://doi.org/10.18502/kss.v7i7.10648

Lee, J. S., & Chiu, M. M. (2023). Modeling EFL learners' willingness to communicate: The roles of face-to-face and digital L2 communication anxiety. *Annual Review of Applied Linguistics, 43*, 64–87. https://doi.org/10.1017/S0267190523000090

Ogayon, I. V., Esmalde, V. S., & Tangalin, I. A. (2020). Communicative Language Teaching: Its effect on the speaking competence of Grade 11 learners. *International Journal of Management, 11*(9), 327–335.

Okyar, H. (2023). Foreign language speaking anxiety and its link to speaking self-efficacy, fear of negative evaluation, self-perceived proficiency, and gender. *Science Insights Education Frontiers, 16*(1). https://doi.org/10.15354/sief.23.or388

Richards, J. C., & Rodgers, T. S. (2014). *Approaches and methods in language teaching* (3rd ed.). Cambridge University Press.

Solhi, M. (2024). The impact of EFL learners' negative emotional orientations on (un)willingness to communicate in in-person and online L2 learning contexts. *Journal of Psycholinguistic Research, 53*, Article 26. https://doi.org/10.1007/s10936-024-10071-y

Sudina, E. (2023). Scale quality in second-language anxiety and willingness to communicate: A methodological synthesis. *Studies in Second Language Acquisition, 45*(5), 1427–1455.

Sudina, E. (2024). A scoping review of willingness to communicate in language education: Premises to doubt, lessons to learn, and future research questions to examine. *Language Testing in Asia, 14,* Article 9.

Tania, M., Danim, S., & Yensy, N. A. (2025). Foreign language speaking anxiety: A systematic literature review of research developments and practical implications. *TPM – Testing, Psychometrics, Methodology in Applied Psychology, 32*(3), 850–861.

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.

Wahyuni, Y., Susilo, S., & Sunggingwati, D. (2023). Willingness to communicate as a mediator variable to speaking anxiety amongst EFL university-level learners. *International Journal of Multidisciplinary Research and Growth Evaluation, 4*(2), 92–101.

P26028

Exposure to Brainrot Content and Its Relationship with Communication and Language Use among Senior High School Learners

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ABSTRACT

The rapid proliferation of short-form digital media has introduced brainrot content, a form of repetitive and entertainment-oriented online content that is increasingly encountered by adolescents. This study examined the level of exposure to brainrot content and its relationship with communication and language use among Senior High School learners. A descriptive-correlational quantitative research design was employed involving 150 Grade 11 students selected through stratified random sampling from six sections of a state university in Cagayan de Oro City, Philippines. Data were collected using an expert-validated structured questionnaire and analyzed using frequency counts, percentages, weighted means, standard deviations, Spearman's rho correlation coefficient, and the Kruskal–Wallis H test.The findings showed that respondents had a high level of exposure to brainrot content, with more than half reporting over six hours of daily social media use and TikTok as the most frequently used platform. Respondents were generally uncertain about the perceived effects of brainrot content on formal writing, grammar, vocabulary, and academic language, although they showed somewhat greater agreement regarding its influence on conversational style and internet slang. Spearman's rho revealed significant positive relationships between exposure to brainrot content and communication ($\rho = .4885$, $p < .001$), language use ($\rho = .3594$, $p < .001$), and overall perceived effects ($\rho = .4003$, $p < .001$). Exposure also differed significantly according to age ($p = .014$), but not across academic sections ($p = .185$). The findings indicate that greater exposure to brainrot content is associated with differences in students' reported communication and language use. The study highlights the relevance of digital literacy and responsible media engagement in supporting appropriate communication and language practices among Senior High School learners.

Keywords: Brainrot Content, social media, Communication, Language Use, Digital Literacy, Senior High School Students

Introduction

The rapid expansion of digital media has transformed how students communicate, learn, and interact. Among the emerging forms of online content is brain rot content, characterized by short-form, highly repetitive, entertainment-oriented digital content characterized by rapid consumption, recurring or low-substance themes, and informal or attention-grabbing communication patterns.

Excessive consumption of such content has been associated with declining cognitive functioning, reduced attention, and changes in communication patterns among adolescents (Ö zbay, 2026; Rosen et al., 2014; Carr, 2020). Conversely, responsible digital media use may enhance communication and socio-emotional skills (Uhls et al., 2014).

Recent studies indicate that digital media significantly influences students' communication and language use. Local research has shown that frequent social media exposure promotes the use of internet slang, abbreviated expressions, and informal language, potentially affecting formal language proficiency (Sibayan, 2025). Likewise, Donaldo (2025) found that excessive exposure to brain rot content was associated with reduced conversational engagement, limited vocabulary, and difficulties in formal speaking and writing. Although social media may support vocabulary development and learning, excessive use has also been linked to distraction and reduced attention (Batos, 2020).

International studies report similar findings. Excessive exposure to short-form digital content has been associated with fragmented communication, reduced critical thinking, cognitive fatigue, and diminished executive functioning (Aysi et al., 2025; Yousef et al., 2025). Other studies have shown that social media shapes young people's linguistic practices and communication patterns (Escarda & Mendoza, 2024; Eklund & Isotalus, 2024), while prolonged screen time has been linked to poorer psychological well-being and behavioral outcomes (Kwon et al., 2024).

Theoretical and Conceptual Framework

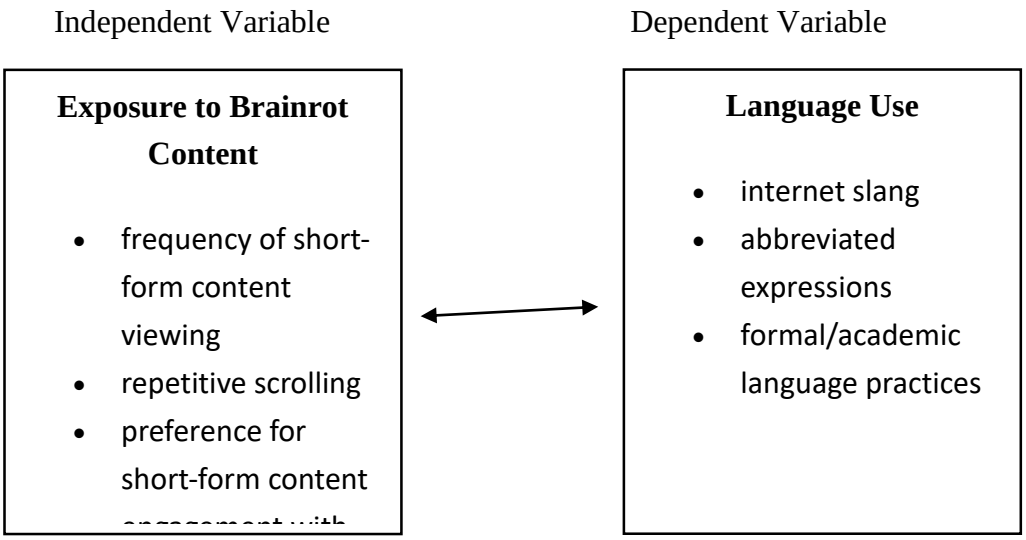
This study is anchored primarily on Media Ecology Theory and Social Learning Theory. Media Ecology Theory provides the broader perspective that communication technologies and media environments shape how individuals communicate, interact, and process information. In the context of this study, short-form digital media provides an increasingly influential communication environment in which Senior High School learners encounter recurring forms of language, expressions, and interaction.

Social Learning Theory provides a more specific explanation of how such exposure may relate to students' communication and language use. Through repeated observation of digital content and interaction with peers and online communities, learners may encounter and reproduce informal expressions, internet slang, abbreviations, and conversational patterns. Repeated exposure may therefore be associated with the incorporation or normalization of such forms in students' reported communication practices.

Taken together, the two theories provide a focused explanation for examining the relationship between exposure to brainrot content and students' communication and language use. Media Ecology Theory explains the role of the digital environment, while Social Learning Theory explains the possible process through which observed communication patterns may be reflected in learners' own language practices.

Accordingly, the conceptual framework of the study focuses on three measurable constructs: (1) exposure to brainrot content, represented by students' reported patterns of engagement with short-form and repetitive digital content; (2) communication, referring to students' reported communication practices; and (3) language use, referring to their reported use of linguistic forms in communication, including informal and academic language practices.

The framework therefore proposes that exposure to brainrot content is associated with students' reported communication and language use. Because the study employs a descriptive correlational design, the framework does not assume a causal relationship but examines whether a statistically significant association exists between the variables.



Despite the growing literature on social media and adolescent communication, empirical research specifically examining exposure to brainrot content and its relationship with

communication and language use among Senior High School learners in the Philippine context remains limited. This study addresses this gap by examining brainrot content as a distinct form of short-form, repetitive, and entertainment-oriented digital media exposure and by relating students' exposure to their perceived communication and language practices.

The study contributes to educational research in three ways. First, it provides empirical evidence on the association between a specifically operationalized form of short-form digital media exposure and two communication-related outcomes among Philippine Senior High School learners. Second, it extends existing discussions of social media and language use by focusing specifically on an emerging form of digital content that is increasingly embedded in students' everyday media consumption. Third, it highlights an educational concern relevant to teacher education and higher education: the development of students' capacity to shift appropriately between informal digital communication and the formal language practices required in academic and professional contexts. Thus, the findings may inform digital literacy, media evaluation, and communication-oriented educational interventions for learners transitioning to higher education.

Existing research has established that social media and short-form digital media can shape young people's communication practices, including the use of informal expressions, internet slang, and abbreviated language. Other studies have primarily examined cognitive, psychological, behavioral, or general media-use outcomes. However, these strands of research do not fully address how exposure to the emerging form of repetitive, entertainment-oriented short-form content commonly described as brainrot content relates specifically to learners' communication and language use.

A further limitation in the existing literature is the tendency to examine social media exposure broadly rather than distinguish particular forms and patterns of digital content consumption. This makes it difficult to determine whether emerging short-form content practices are associated with communication and language outcomes beyond general social media use. In addition, empirical evidence examining this relationship among Philippine Senior High School learners remains limited. The present study addresses these gaps by examining brainrot content exposure as a potentially associated with communication/language patterns and empirical relationship tested.

Research Questions

This study investigates the influence of brain rot content on the communication and language use of Senior High School students. Specifically, it seeks to answer the following questions:

1. What is the respondents' level of exposure to brain rot content?

2. What are the perceived effects of brainrot content on students' communication and language use?
3. Is there a significant relationship between exposure to brain rot content and students' communication and language use?
4. Is there a significant difference in the effects of brain rot content on students' communication and language use when respondents are grouped according to age, section, daily duration of social media use, and most frequently used social media platform?

Hypotheses

The study tested the following hypotheses:

$H0_1$: There is no significant relationship between students' level of exposure to brain rot content and their communication and language use.

Ha_1: There is a significant relationship between students' level of exposure to brain rot content and their communication and language use.

$H0_2$: There is no significant difference in the effects of brain rot content on students' communication and language use when respondents are grouped according to age, section, daily duration of social media use, and most frequently used social media platform.

Ha_2: There is a significant difference in the effects of brain rot content on students' communication and language use when respondents are grouped according to age, section, daily duration of social media use, and most frequently used social media platform.

Methodology

This study employed a descriptive-correlational quantitative research design to examine the relationship between students' exposure to brainrot content and their communication and language use. The descriptive component assessed the respondents' level of exposure and perceived effects, while the correlational component examined the relationship between exposure to brainrot content and communication and language use.

The participants were 150 Grade 11 Senior High School students selected from a population of 240 enrolled students at a state university in Cagayan de Oro City, Philippines, during the Academic Year 2025–2026. The sample size was determined using Slovin's formula with a

5% margin of error. Participants were selected through proportionate stratified random sampling to ensure representation across the six sections. The sample represented 62.5% of the accessible population and included students from all six sections.

Data were collected using an expert-validated structured questionnaire administered through Google Forms. The instrument consisted of four parts: (1) respondents' demographic profile, (2) level of exposure to brainrot content, (3) communication and language use, and (4) perceived effects of brainrot content on communication and language use. The questionnaire measured exposure to brainrot content through self-reported media-consumption behaviors, including the frequency and patterns of viewing short-form videos, repetitive scrolling, preference for short-form content, and related digital media behaviors. Communication and language use were assessed through indicators related to conversational style, communication practices, use of informal expressions, internet slang, abbreviations, and formal or academic language practices. The perceived-effects section assessed the respondents' overall perceptions of how exposure to brainrot content affects their communication and language use.

The instrument included eight items for each major construct, resulting in a total of 32 scale items, excluding demographic questions. Each item was rated using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Higher scores indicated a higher level of the measured construct. The questionnaire underwent expert validation to assess the relevance, clarity, and appropriateness of its items in relation to the study objectives. Six experts with backgrounds in psychology, communication, education, and research methodology reviewed the instrument. Their evaluation focused on the alignment of the items with the operational definitions of the constructs, clarity of wording, and suitability for the target respondents.

The internal consistency of the questionnaire was measured using Cronbach's alpha. The Exposure to Brainrot Content scale demonstrated good internal consistency ($\alpha = .85$), while the Communication ($\alpha = .82$), Language Use ($\alpha = .84$) and Perceived Effects ($\alpha = .86$) scales also demonstrated good internal consistency. These coefficients suggest that the items within each scale were sufficiently consistent in measuring their respective constructs.

The collected data were analyzed using frequency counts, percentages, weighted means, and standard deviations to describe the respondents' demographic profile and levels of exposure to brainrot content. Spearman's rank-order correlation was used to examine the relationship between exposure to brainrot content and students' communication and language use. The Kruskal–Wallis H test was employed to determine whether perceived effects of brainrot content differed across age groups and sections. All inferential analyses were conducted using

a significance level of $\alpha = .05$. Statistical significance was determined based on the obtained *p* values, with results considered statistically significant when $p < .05$.

The questionnaire was administered through Google Forms, and respondents were not required to provide personally identifying information unless necessary and ethically justified. All collected data were treated confidentially and used solely for academic research purposes. Access to the data was limited to the researchers, and appropriate measures were taken to protect the privacy and welfare of the participants.

Ethical Considerations

The study observed institutional requirements for research involving Senior High School learners. Permission to conduct the study was obtained from the principal. Because the respondents were Senior High School students, the researchers secured the required parental/guardian consent and student assent prior to participation. Participation was voluntary, and respondents were informed of the purpose of the study, their right to decline participation, and their right to discontinue without academic consequence. No personally identifying information was requested in the questionnaire. Responses were treated confidentially and were used solely for research purposes, with access to the collected data limited to the research team.

Results and Discussion

Most respondents were 17 years old (53.3%), with balanced representation across the six Grade 11 sections. More than half (51.3%) reported spending over six hours daily on social media, while TikTok (52.7%) was the most frequently used platform, indicating extensive engagement with short-form digital content. These findings support the Uses and Gratifications Theory and Media Ecology Theory, suggesting that students actively consume digital media, which gradually shapes their communication practices.

The findings further revealed a high level of exposure to brain rot content. Respondents frequently watched short-form videos, engaged in repetitive scrolling, and preferred short-form content over longer materials. These patterns suggest sustained exposure to algorithm-driven digital content that may influence students' communication and language behaviors.

Regarding language use, most respondents were uncertain whether brain rot content affected their formal writing, grammar, vocabulary, and academic language. Likewise, respondents expressed uncertainty regarding its influence on communication, although a slightly higher proportion agreed that brain rot content affects their conversational style and use of internet

slang. These findings are consistent with the Third-Person Effect Theory, which suggests that individuals often underestimate media effects on themselves, and the Social Network Theory, which explains how peer interactions normalize informal online language.

Although respondents likewise reported uncertainty regarding the broader effects of brain rot content on concentration, learning, and thinking, these findings suggest that any cognitive influences may be gradual and not immediately recognized by students.

The Kruskal–Wallis H test revealed a significant difference in exposure according to age ($p = .014$) but no significant difference across academic sections ($p = .185$), indicating that exposure varies with age but remains relatively similar across Grade 11 sections.

Spearman's rho revealed significant positive associations between exposure to brainrot content and communication ($\rho = .4885$, $p < .001$), language use ($\rho = .3594$, $p < .001$), and overall perceived effects ($\rho = .4003$, $p < .001$). These findings indicate that students who reported higher levels of exposure also tended to report higher scores on the communication and language-use measures. The magnitude of the associations suggests a meaningful relationship between the variables, particularly for communication.

Variables	Spearman's ρ	p-value	Interpretation
Exposure × Communication	.4885	< .001	Moderate positive association
Exposure × Language Use	.3594	< .001	Moderate positive association
Exposure × Overall Perceived Effects	.4003	< .001	Moderate positive association

Overall, the findings indicate that Senior High School student’s exhibit high exposure to brain rot content, and greater exposure is significantly associated with changes in communication and language use. These results highlight the importance of strengthening digital literacy and promoting responsible social media use among adolescents.

The positive association may be consistent with Social Learning Theory, as repeated exposure to linguistic patterns in digital environments may provide opportunities for observation and imitation. However, the relationship may also reflect broader patterns of social media engagement or peer communication. Because the study did not control for overall social media.

Limitations of the Study

The findings of this study should be interpreted in light of several limitations. First, the study employed a cross-sectional descriptive-correlational design; therefore, the significant relationships identified between exposure to brainrot content and communication and language use do not establish causal relationships. The findings indicate association at a particular point in time rather than evidence that exposure to brainrot content causes changes in students' communication or language practices.

Second, the study relied on self-reported questionnaire responses. Students' reports of their exposure to brainrot content, communication, and language use may be affected by recall difficulties, social desirability, or differences in how respondents interpret the items. The study also did not directly observe students' actual digital-media consumption or communication behavior.

Third, the study was conducted among 150 Senior High School learners from a single state university in Cagayan de Oro City. Although stratified random sampling was used across six sections, the single-site setting limits the extent to which the findings can be generalized to learners from other schools, institutions, geographic locations, or educational levels.

Fourth, the study did not control for potentially relevant factors such as overall social media use, age, academic achievement, peer interaction, or socioeconomic background. These variables may also be related to students' communication and language practices and may partly explain the observed associations.

Finally, the measurement of brainrot content exposure was based on students' reported engagement with short-form and repetitive digital content. Because brainrot content is an emerging and evolving form of digital media, differences in students' understanding of the term and in the types of content they consider as brainrot may introduce measurement uncertainty. Future studies should further refine and validate the construct and its measurement.

Conclusion

Senior High School learners in the study reported high exposure to brainrot content, particularly through short-form digital media. Although respondents were generally uncertain about several perceived effects on formal writing, grammar, vocabulary, and academic language, they reported somewhat greater agreement regarding conversational style and internet slang. Statistical analysis showed significant positive associations between exposure to brainrot content and reported communication and language use.

These findings suggest that brainrot content exposure is associated with students' reported communication and language practices; however, the results do not establish that such exposure causes changes in these practices. The observed relationships may also be influenced by other factors, including overall social media use, age, peer interaction, and individual differences in communication. The findings therefore highlight the relevance of digital literacy and critical media engagement while underscoring the need for further research using longitudinal, multivariable, or mixed-method approaches.

Recommendations

Based on the findings and limitations of the study, the following recommendations are proposed:

1. **For teachers:** Integrate short activities that help learners distinguish between informal digital language and formal academic communication. Students may be asked to transform internet slang, abbreviated expressions, or informal online messages into appropriate academic or professional forms. This recommendation responds to the finding that students reported somewhat greater agreement regarding conversational style and internet slang.
2. **For schools:** Rather than relying solely on general awareness seminars, schools may incorporate digital-media literacy into existing communication and language programs. Activities may focus on critical evaluation of short-form content, conscious media consumption, and appropriate language use across digital, academic, and social contexts.
3. **For teacher education and higher education institutions:** Develop transition-oriented digital communication initiatives that prepare learners to navigate the difference between informal online communication and the language practices expected in higher education and professional settings. This is particularly relevant because Senior High School represents a stage immediately preceding tertiary education.
4. **For parents and students:** Encourage awareness of patterns of digital-media engagement, particularly prolonged and repetitive consumption of short-form content. Guidance should focus not only on reducing screen time but also on helping learners make purposeful choices about the type of content they consume and how they use digital language.
5. **For future researchers:** Replicate the study across multiple schools and educational contexts to determine whether the observed relationships are consistent beyond the

single institutional setting. Future studies should also use larger and more diverse samples and examine relevant variables such as overall social media use, academic achievement, peer interaction, and socioeconomic background.

6. **For future research design:** Longitudinal or mixed-method studies are recommended to examine how digital-media exposure and communication practices develop over time and to complement self-reported data with interviews, observation, digital-use records, or other behavioral measures where ethically and practically appropriate.
7. **For measurement development:** Future researchers should further develop and validate an instrument specifically measuring exposure to brainrot content. Clearer operational dimensions and psychometric evidence would help distinguish brainrot-content exposure from general social media use and improve comparability across studies.

References

Bandura, A. (1977). *Social learning theory*. Prentice-Hall.

Carr, N. (2020). *The shallows: What the Internet is doing to our brains*. W. W. Norton & Company.

Chiossi, F., Haliburton, L., Ou, C., Butz, A. M., & Schmidt, A. (2023). Short-form videos degrade our capacity to retain intentions: Effect of context switching on prospective memory. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (pp. 1–15). https://doi.org/10.1145/3544548.3580772

Davison, W. P. (1983). The third-person effect in communication. *Public Opinion Quarterly, 47*(1), 1–15. https://doi.org/10.1086/268763

Donaldo, K. P. (2025). Scrolling into stagnation: A qualitative study on the perceived effects of brain rot among students' communication skills. *PPSDP International Journal of Education, 4*(2), 892–915. https://doi.org/10.59175/pijed.v4i2.823

Escarda, M. G., & Mendoza, R. C. (2024). *Navigating the influence of social media on translingual patterns of Cebuano youth in an ESL milieu*. ResearchGate.

Gerbner, G., & Gross, L. (1976). Living with television: The violence profile. *Journal of Communication, 26*(2), 172–194. https://doi.org/10.1111/j.1460-2466.1976.tb01397.x

Katz, E., Blumler, J. G., & Gurevitch, M. (1973). Uses and gratifications research. *Public Opinion Quarterly, 37*(4), 509–523. https://doi.org/10.1086/268109

McLuhan, M. (1994). *Understanding media: The extensions of man*. MIT Press. (Original work published 1964)

Milroy, L. (1987). *Language and social networks* (2nd ed.). Blackwell.

Oxford University Press. (2024, December 2). *Brain rot named Oxford Word of the Year 2024*. https://corp.oup.com/news/brain-rot-named-oxford-word-of-the-year-2024/

Owens, R. (2026). "It speaks to me in brain rot": Theorising brain rot as a genre of participation among teenagers. *Research on Youth and Media, 14*(2), 45–62.

Özbay, M. (2026). The effects of digital media consumption on cognitive abilities among adolescents. *Journal of Digital Learning, 12*(2), 45–60.

Rosen, L. D., Lim, A. F., Felt, J., Carrier, L. M., Cheever, N. A., Lara-Ruiz, J. M., Mendoza, J. S., & Rokkum, J. (2014). Media and technology use predicts ill-being among children, preteens, and teenagers. *Computers in Human Behavior, 35*, 364–375. https://doi.org/10.1016/j.chb.2014.01.036

Serenko, A. (2025). Brain rot—The 2024 Oxford English Dictionary Word of the Year: Why should technology leaders care? *IEEE Engineering Management Review, 54*(1), 14–20. https://doi.org/10.1109/EMR.2025.3583977

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Artificial Intelligence Literacy and Behavioral Intention of Pre-Service Teachers: Insights from the ABCE Framework and Constructivist Learning Theory

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ABSTRACT

Artificial intelligence (AI) has become increasingly integrated into educational settings, underscoring the need for future educators to develop adequate AI literacy to use technology effectively and responsibly. Guided by Constructivist Learning Theory and the Affective–Behavioral–Cognitive–Ethical (ABCE) framework, this study examined the self-reported AI literacy levels and behavioral intentions of pre-service teachers at the University of Science and Technology of Southern Philippines (USTP). Specifically, the study determined the respondents' AI literacy across the affective, behavioral, cognitive, and ethical dimensions; assessed their overall behavioral intention toward AI integration; examined differences in AI literacy according to course specialization, prior AI-related training, and frequency of AI tool use; and investigated the relationship between AI literacy and behavioral intention. A descriptive-correlational research design was employed involving 226 fourth-year pre-service teachers from seven teacher education programs. Data were collected using a modified Artificial Intelligence Literacy Questionnaire (AILQ) and analyzed using descriptive statistics, one-way analysis of variance (ANOVA), and Pearson product-moment correlation. Findings revealed that the respondents demonstrated a moderate level of overall AI literacy and a moderate behavioral intention toward AI integration. Among the AI literacy domains, ethical literacy obtained the highest rating, followed by the affective, behavioral, and cognitive domains. Results further showed no significant differences in AI literacy when respondents were grouped according to course specialization, prior AI-related training, and frequency of AI tool use. However, a very strong positive relationship was found between AI literacy and behavioral intention ($r(224) = .84$, $p < .001$), indicating that higher AI literacy levels were associated with stronger intentions to use AI technologies. These findings, specific to the pre-service teachers surveyed at USTP, suggest that structured learning experiences, practical applications, and ethical AI instruction may help strengthen self-perceived AI literacy within this teacher education context; because AI literacy and behavioral intention were measured through self-report, the findings should not be interpreted as evidence of actual competency or

classroom-ready pedagogical skill, and generalization beyond this institutional context should be made with caution.

Keywords: Artificial Intelligence (AI) Literacy, Constructivism, Pre-service Teachers, Behavioral Intention, ABCE Model, Technology Integration

Introduction

Artificial intelligence (AI) has rapidly evolved from a specialized technological innovation into a transformative force across education, reshaping how information is accessed, learning experiences are personalized, and instructional tasks are designed and delivered (Chen et al., 2020; Hwang et al., 2020; Laupichler et al., 2022). The widespread adoption of generative AI tools, such as ChatGPT, has further accelerated this transformation by providing educators and learners with new opportunities to support teaching, learning, assessment, and content creation (Shi, 2025). As AI becomes increasingly integrated into educational practice, teacher education institutions are expected not only to familiarize future educators with AI technologies but also to prepare them to use these tools critically, ethically, and pedagogically.

Central to this preparation is AI literacy, which extends beyond the ability to operate AI applications. Rather, it encompasses the knowledge, skills, attitudes, and ethical dispositions required to understand AI technologies, critically evaluate their capabilities and limitations, use them responsibly, and collaborate effectively with AI systems (Long & Magerko, 2020). Contemporary scholarship increasingly recognizes AI literacy as a multidimensional construct that integrates conceptual understanding, practical competence, critical evaluation, and ethical judgment rather than merely technical proficiency (Laupichler et al., 2022; Ng et al., 2024). Consequently, AI literacy has emerged as a key competency in higher education and teacher preparation, where future educators are expected to make informed decisions about integrating AI into teaching while fostering responsible AI use among their learners.

Despite the growing recognition of AI literacy as an essential competency, existing evidence suggests that many pre-service teachers remain inadequately prepared to integrate AI into educational practice. Lamanauskas (2025) reported that more than half of pre-service preschool and primary school teachers perceived themselves as unprepared to use AI because of limited knowledge, insufficient practical skills, and low confidence in the technology. Similarly, Dayagbil et al. (2025) found that although pre-service teachers acknowledged the instructional potential of AI, they also expressed concerns regarding algorithmic bias, inaccurate outputs,

contextual limitations, and the need for continuous human oversight. These findings underscore that access to AI technologies alone does not necessarily translate into meaningful AI literacy. Instead, developing AI literacy requires learning experiences that enable future educators to critically engage with AI, reflect on its educational implications, and apply it responsibly within authentic teaching contexts (Du et al., 2024).

Most existing research on pre-service teachers' AI literacy converges on the conclusion that AI literacy matters and should be strengthened, yet the field has not settled on a single way of conceptualizing or explaining it. Reviews of AI competence frameworks for educators have identified multiple, only partially overlapping models, organized around existing teacher-knowledge frameworks, new AI knowledge domains, competence levels, or the underlying AI system itself, with little empirical work reconciling these competing formulations (Mikeladze et al., 2024). International bodies have added further variation: UNESCO's AI competency framework for teachers, for instance, structures teacher AI competence around progression levels (understand, apply, create) and knowledge-skills-values dimensions rather than the affective-behavioral-cognitive-ethical structure adopted in the ABCE model (Miao & Cukurova, 2024). Findings on what actually predicts AI literacy or acceptance are similarly unsettled: some studies report that AI-related training courses and AI-TPACK significantly predict pre-service teachers' acceptance of AI (Runge et al., 2025), and a recent Philippine study found significant differences in AI literacy by academic discipline, gender, and internet connectivity (Balasa, 2025), while others, consistent with the present study, find no significant relationship between such background variables and AI literacy (Cetin & Celen, 2025). This unresolved empirical pattern points to a broader theoretical problem beyond simply applying one more instrument to one more population: it remains unclear whether AI literacy develops mainly through structured instruction and demographic exposure, as some acceptance-model studies imply, or through the quality of experiential engagement that constructivist accounts emphasize largely independent of formal training or specialization. In the Philippine setting specifically, a small but growing body of work has begun to examine pre-service teachers' AI literacy and readiness (Dayagbil et al., 2025; Lumanlan et al., 2025; Balasa, 2025), but this literature has largely relied on general readiness or acceptance measures, or on three-component cognitive-affective-behavioral instruments that omit an explicit ethical dimension (Lumanlan et al., 2025), and has concentrated on general education programs rather than technical-vocational teacher education. Relatively few studies have examined AI literacy as a four-dimensional construct using the Affective–Behavioral–Cognitive–Ethical (ABCE) framework developed by Ng et al. (2024) among pre-service teachers, and none, to the researchers' knowledge, have done so within technical-vocational and technology teacher education programs in the Philippines, where curricula, resource access, and institutional AI policy differ from both the general-education Philippine samples described above and the

international settings (e.g., Hong Kong, Turkey, Thailand) in which ABCE-based instruments have primarily been validated. Furthermore, limited empirical research has explored AI literacy among pre-service teachers through a constructivist perspective that explains how such competencies develop through active engagement, reflection, and authentic learning experiences, and Constructivist Learning Theory itself has rarely been used to generate specific, testable expectations about which predictors of AI literacy should or should not matter. Addressing this gap is important not only because understanding the strengths and weaknesses across the different dimensions of AI literacy can provide teacher education institutions with evidence to strengthen curriculum design, but also because a Philippine technical-vocational teacher education sample, examined through both the ABCE framework and constructivist theory, offers a test case for adjudicating among these competing explanations of how AI literacy develops.

To provide a theoretical lens for understanding how AI literacy develops, this study is anchored in constructivist learning theory, which views learning as an active process in which individuals construct knowledge through experience rather than passively receive information. Rooted in Piaget's (1970) theory of cognitive development and further advanced by Vygotsky's (1978) emphasis on social interaction, constructivism positions pre-service teachers as active learners who develop professional competence through authentic experiences, collaboration, and reflective practice. This perspective is particularly relevant to AI literacy because the competencies required to understand, evaluate, and use AI responsibly are developed progressively through meaningful engagement with emerging technologies rather than through passive knowledge acquisition (Chiu, 2025). The theoretical relationship between constructivism and AI literacy, together with the multidimensional framework adopted in this study, is discussed further in the succeeding section.

Guided by this perspective, the present study examines the AI literacy of pre-service teachers across the affective, behavioral, cognitive, and ethical dimensions of the ABCE framework. Rather than proposing a new theoretical model or measurement approach, the study's primary contribution is contextual: it extends the four-dimensional ABCE framework, together with a constructivist reading of its predictors, to a Philippine state university setting that combines general secondary and technical-vocational teacher education programs, a setting distinct from both the general-education Philippine samples in which pre-service teacher AI literacy has so far been studied (Balasa, 2025; Dayagbil et al., 2025; Lumanlan et al., 2025). By providing empirical evidence on AI literacy profiles in this underexamined combination of framework and population, the study seeks to contribute to the growing body of research on AI in teacher education and offer insights that may inform curriculum development, instructional planning,

and institutional initiatives aimed at preparing future educators for the responsible and effective integration of AI in educational practice.

Statement of the Problem

This study aims to determine the level of Artificial Intelligence (AI) literacy of pre-service teachers, using the Affective–Behavioral–Cognitive–Ethical (ABCE) model. Specifically, this study seeks to answer the following questions:

1. What is the level of AI literacy of pre-service teachers across affective, behavioral, cognitive, and ethical dimensions?
2. What is the level of overall behavioral intention toward AI integration for the pre-service teachers?
3. Is there a significant difference in the AI literacy level among pre-service teachers when grouped according to course specialization?
4. Is there a significant difference in AI literacy level among pre-service teachers when grouped according to prior AI-related training or coursework?
5. Is there a significant difference in the AI literacy levels of pre-service teachers when grouped according to their frequency of using AI tools?
6. Is there a significant relationship between AI literacy level and behavioral intention among pre-service teachers?

Framework of the Study

Constructivist learning theory provides the theoretical foundation for this study by explaining how pre-service teachers develop AI literacy through active engagement with learning experiences rather than through passive knowledge acquisition. According to Piaget (1970), learners build knowledge by integrating new information into their existing cognitive structures and modifying those structures when new experiences challenge their prior understanding. Vygotsky (1978) further extended this perspective by emphasizing that learning is socially mediated through interaction, collaboration, and dialogue. Applied to teacher education, constructivism positions pre-service teachers as active learners who continuously develop professional knowledge through coursework, field experiences, collaboration, and reflective practice rather than by acquiring a fixed body of competencies.

This perspective is particularly appropriate for artificial intelligence (AI) literacy because AI technologies continue to evolve rapidly, requiring future educators to continually refine their knowledge and instructional practices. Rather than viewing AI literacy as a static collection of technical skills, constructivism explains it as a developmental competency that is progressively built through authentic experiences, hands-on engagement with AI technologies, critical reflection, and meaningful social interaction. As pre-service teachers interact with AI tools, evaluate AI-generated outputs, and reflect on their educational applications and limitations, they actively construct deeper, more informed understandings of AI within authentic teaching and learning contexts. This developmental process is reflected in the study of Dilek et al. (2025), where educators gradually co-constructed their understanding of AI concepts, ethical considerations, and context-specific applications through collaborative, hands-on exploration rather than through direct instruction.

Constructivism also explains why AI literacy varies among pre-service teachers. Individual learners enter teacher education with different levels of technological experience, prior knowledge, beliefs, and exposure to AI, all of which influence how they interpret and integrate new learning experiences (Laru et al., 2025). Consequently, misconceptions, such as assuming that AI-generated outputs are always accurate or that AI systems operate without limitations, often represent learners' initial understandings rather than fixed beliefs (Dilling & Herrmann, 2024). Through authentic learning experiences, collaborative discussions, and reflective practice, these initial conceptions are continually examined, refined, and reconstructed, resulting in increasingly sophisticated AI literacy.

The constructivist perspective aligns closely with the Affective–Behavioral–Cognitive–Ethical (ABCE) model underlying the Artificial Intelligence Literacy Questionnaire (AILQ) developed by Ng et al. (2024), which serves as the conceptual framework for assessing AI literacy in this study. The ABCE model conceptualizes AI literacy as a multidimensional construct comprising four interrelated dimensions: affective, behavioral, cognitive, and ethical. Rather than representing isolated competencies, these dimensions develop simultaneously as learners engage with AI in meaningful educational contexts.

Within a constructivist perspective, the cognitive dimension develops as pre-service teachers actively construct conceptual understanding of AI by integrating new knowledge with prior experiences. The behavioral dimension is strengthened through repeated opportunities to explore, apply, and evaluate AI tools in authentic instructional situations. The affective dimension reflects learners' attitudes, confidence, and willingness to engage with AI, which are shaped through accumulated learning experiences rather than through direct instruction alone. Finally, the ethical dimension develops as learners critically examine issues such as fairness,

bias, accountability, privacy, and responsible use of AI while reflecting on the educational implications of AI technologies. Together, these four dimensions illustrate that AI literacy extends beyond technical competence and encompasses the knowledge, skills, attitudes, behaviors, and ethical judgment necessary for the responsible integration of AI into educational practice.

The convergence of constructivist learning theory and the ABCE model provides a strong theoretical foundation for the present study. Constructivism explains the learning processes through which AI literacy develops, whereas the ABCE model provides the multidimensional framework for assessing that development. Guided by these complementary perspectives, the study examines the AI literacy of pre-service teachers across affective, behavioral, cognitive, and ethical dimensions to generate evidence to inform teacher education programs and support the responsible integration of AI in future educational practice. Beyond serving as a general background lens, constructivism is used here to generate two specific, testable expectations that speak directly to the unresolved predictor debate identified in the literature review. First, because constructivist theory attributes literacy development to the quality of active engagement, reflection, and knowledge construction rather than to mere exposure or categorical membership, course specialization, prior training, and frequency of AI tool use were expected to be, at most, weak and inconsistent predictors of AI literacy, in contrast to acceptance-model studies that treat training and demographic categories as direct predictors (e.g., Runge et al., 2025; Balasa, 2025); group membership is, on this account, only a proxy for the learning experiences it may or may not have provided. Second, because constructivism treats affective, behavioral, cognitive, and ethical development as mutually reinforcing rather than independent, literacy and behavioral intention were expected to be closely associated, since the accumulated understanding captured by the ABCE dimensions should carry over into learners' willingness to act on that understanding. These two expectations are revisited directly in the Results and Discussion section, where the pattern of findings is read as evidence for or against the constructivist account rather than as a backdrop incidental to it.

Methodology

To determine the level of Artificial Intelligence (AI) literacy of the pre-service teachers in a state university, a total of two hundred twenty six (226) pre-service teachers from seven (7) education programs namely Bachelor in Secondary Education major in Mathematics (BSEd – Mathematics) and in Science (BSEd – Science), Bachelor of Technology and Livelihood Education major in Home Economics (BTLEd – HE) and in Industrial Arts (BTLEd – IA), and Bachelor in Technical-Vocational Teacher Education major in Computer Hardware Servicing (BTVTEd – CHS), in Fashion and Garments Technology (BTVTEd – FGT), and inFood

Service Management (BTVTEd – FSM). These pre-service teachers were in their last semester of the program and had already completed or were currently completing their practice teaching, depending on the program they were enrolled in. Fourth-year pre-service teachers have completed most of their professional education courses and often their practice teaching or field experiences. Assessing their AI literacy provides a gauge of how well teacher education programs have equipped them to bring emerging technologies into teaching practice (Hsu, 2026). Hsu (2026) emphasizes the need for teacher education programs to prepare future teachers with AI skills and the ability to use AI in instructional planning, assessment, and ethical decision-making.

A modified version of the Artificial Intelligence Literacy Questionnaire (AILQ), developed by Prof. Ng et al. (2024), was used to measure pre-service teachers' literacy, readiness, and attitudes toward Artificial Intelligence (AI), aligned with the ABCE framework. The instrument consisted of a 26-item Likert-scale survey administered via Microsoft Forms.

To ensure the reliability of the questionnaire, a pilot test was conducted with 30 undergraduate students from the same population, and the responses were analyzed using Cronbach's alpha to assess internal consistency. This statistical measure yielded an acceptable alpha value of 0.93, indicating that the instrument is reliable for the target group. Moreover, to support the validity of the modified instrument, content validity was assessed by three experts from the college. Their positive feedback confirmed that the instrument covered all relevant constructs and is both clear and relevant to the target group.

The participants completed the AILQ online over a specified period during the semester. Privacy in data collection was ensured to encourage honest responses. Online surveys in academic and professional research demonstrate their methodological acceptability (Maslovskaya et al., 2022). This data gathering technique is appropriate to this study since respondents are generally regular users of digital technologies (Maslovskaya et al., 2022) and assigned to different cooperating schools as part of their teaching internship, and become a dispersed population that is difficult to access simultaneously through face-to-face data collection (Zhao & Zhang, 2017).

The data collected were analyzed using descriptive statistics to obtain the frequency distribution, mean, and standard deviation of the participants' demographic characteristics. To examine the relationship between the AI Literacy level and other variables, a one-way ANOVA was used. This was used to determine whether the scores of the variables differ across groups. Furthermore, the Pearson product-moment correlation was used to examine the relationship between AI Literacy level and overall behavioral intention among pre-service teachers.

The researchers observed established ethical principles governing research involving human participants throughout the conduct of the study and complied with the applicable requirements of the University. Data collection proceeded under an institutional circumstance in which the University's Ethics Review Committee was undergoing organizational restructuring, resulting in a temporary limitation in its capacity to process ethics applications. Because a formal ethics review could not be completed before the study commenced, the Committee subsequently issued a waiver acknowledging the situation and the inability to conduct the review within the required timeframe. The researchers proceeded with the study in accordance with the University's applicable procedures and ethical standards for research involving human participants.

The study involved 226 fourth-year pre-service teachers from seven teacher education programs. Participation was voluntary, and informed consent was obtained from the participants prior to their completion of the modified Artificial Intelligence Literacy Questionnaire (AILQ). The questionnaire was administered online through Microsoft Forms, consistent with the dispersed nature of the participants during their teaching internship. Privacy was maintained during data collection to encourage honest responses.

The researchers took appropriate measures to protect the anonymity and confidentiality of the participants. Information collected through the survey was used solely for research purposes, and individual responses were treated confidentially and reported in aggregate form. Research data were securely stored and handled to prevent unauthorized access. Throughout the study, the researchers observed the principles of voluntary participation, informed consent, privacy, confidentiality, and responsible management of research data.

Results and Discussion

Participants' Demographics

The research study group consisted of 226 pre-service teachers from a state university in the Philippines for the academic year 2025-2026. Table 1 shows the distribution of respondents by demographic characteristics. Most of the respondents were female (f = 177, 78.30%), while only 49 (21.70%) were male. This result indicates a considerable superiority of female pre-service teachers in the sample. This finding is in line with the global trend in teacher education where females still dominate in teaching-related programs and the teaching profession (UNESCO, 2023). Similarly, Mogadime et al. (2024) found increased representation of women in teacher education programs and linked this to historical and sociocultural perceptions of teaching as a female profession.

Table 1: Demographic characteristics of pre-service teachers (n=226)

Variables	Feature	f	%
Sex	Male	49	21.70
	Female	177	78.30
Course	BSEd – Science	61	27.00
	BSEd – Math	29	12.80
	BTLEd – HE	77	34.10
	BTLEd – IA	16	7.10
	BTVTEd – CHS	8	3.50
	BTVTEd – FSM	23	10.20
	BTVTEd – FGT	12	5.30
Prior AI-related Training or Coursework	None	40	17.70
	Basic	95	42.00
	Moderate	87	38.50
	Extensive	4	1.80
Frequency of using AI Tools	Never	0	0.00
	Rarely	0	0.00
	Sometimes	58	25.70
	Often	118	52.20
	Very Often	50	22.10

The majority of the respondents were from BTLEd – HE (34.10%), followed by BSEd – Science (27.00%), BSEd – Mathematics (12.80%), BTVTEd – FGT (10.20%), BTLEd – IA (7.10%), BTVEd – FSM (5.30%), and the lowest was BTVTEd – CHS with only 3.50% of the total sample. This means that the respondents came from different fields of teacher education. The disciplinary diversity matters in research on AI literacy, since the pre-service teachers' technological knowledge and readiness to adopt emerging technologies may vary depending on their academic specialization. Previous studies have indicated that academic preparation affects pre-service teachers' AI-related knowledge, technology acceptance, and pedagogical use of AI in educational settings (Runge et al., 2025; Hsu, 2026).

Regarding prior AI-related training or coursework, most respondents reported basic (42.00%) or moderate (38.50%) exposure. On the other hand, 17.70% had no AI training whatsoever, while only 1.80% reported extensive training. These results indicate that although most pre-service teachers have been exposed to AI concepts, their exposure is primarily introductory or intermediate. This pattern reflects the current terrain of teacher education, where AI-related learning opportunities exist but have yet to be embedded broadly in teacher preparation programs. Previous studies have shown that pre-service teachers' knowledge of AI, perceived usefulness of AI, and intention to use AI in teaching are positively affected by their

participation in AI-related courses, highlighting the importance of providing more structured AI training in teacher education programs (Runge et al., 2025; Han, 2025).

Regarding the frequency of AI tool use, over half of respondents reported using them often (52.20%), while 22.10% reported using them very often and 25.70% reported using them sometimes. Notably, none of the respondents chose the "never" or "rarely" categories. These findings suggest AI tools are a routine component of respondents' academic activities and professional preparation. The pre-service teachers' use of AI reflects the growing prevalence of generative AI in higher education and teacher education programs. This finding is consistent with prior research indicating that pre-service teachers frequently use AI tools for learning, lesson planning, information retrieval, and content generation. Moreover, frequent exposure to AI technologies has been linked to increased awareness, acceptance, and openness to integrating AI in future teaching practices (Bae et al., 2024; Cetin & Celen, 2025).

Overall, the respondents were primarily female pre-service teachers from different teacher education programs and with varying levels of AI-related training. Most of them also reported using AI tools regularly. These findings suggest that AI has become part of their academic and professional preparation. As previous studies have shown, both AI-related training and frequent use of AI tools play an important role in developing AI literacy and competencies among pre-service teachers (Han, 2025; Runge et al., 2025). Therefore, this group provides a suitable context for examining AI literacy among future educators.

AI Literacy Level and Overall Behavioral Intention

Table 2: Overall Behavioral Intention, Domain-Specific and Overall AI Literacy Levels of Pre-Service Teachers

Domain	N	Mean	Std. Dev.	Interpretation
Affective Domain	226	3.88	0.68	High
Behavioral Domain	226	3.88	0.64	High
Cognitive Domain	226	3.83	0.65	High
Ethical Domain	226	4.23	0.74	Very High
Overall Behavioral Intention	226	3.17	0.47	Moderate
Overall AI Literacy Level	226	3.96	0.47	High

Note: Scores were interpreted as follows: 4.21-5.00 = Very High; 3.41-4.20 = High; 2.61-3.40 = Moderate; 1.81-2.60 = Low; and 1.00-1.80 = Very Low

Table 2 presents the AI literacy levels of pre-service teachers across the affective, behavioral, cognitive, and ethical domains, together with their overall behavioral intention and overall AI literacy level.

The findings show that the respondents attained a high overall AI literacy level (M = 3.96, SD = 0.47). Because AI literacy was measured through self-report, this indicates that the USTP pre-service teachers in this sample generally perceive themselves as having a good understanding of AI concepts, favorable attitudes toward AI technologies, and awareness of the importance of using AI responsibly in educational settings; it does not by itself demonstrate actual competency or classroom-ready pedagogical skill, which would require performance-based assessment. The results suggest that respondents feel reasonably prepared to engage with AI technologies in their academic work. This finding is consistent with previous studies showing that pre-service teachers generally report high levels of AI literacy and acknowledge the growing importance of AI in education (Cetin & Celen, 2025; Pingmuang et al., 2026).

Among the four domains, the ethical domain obtained the highest rating (M = 4.23, SD = 0.74), corresponding to a very high level. This indicates that the respondents demonstrate strong awareness of ethical concerns associated with AI, including privacy, fairness, transparency, accountability, and responsible use. The result suggests that future teachers recognize the importance of applying AI ethically in educational contexts. Similar findings have been reported by Han (2025) and Hsu (2026), who highlighted ethical awareness as a key component of AI literacy among educators. As AI becomes increasingly integrated into education, ethical competence remains critical for its responsible implementation in teaching and learning.

The affective domain (M = 3.88, SD = 0.68), behavioral domain (M = 3.88, SD = 0.64), and cognitive domain (M = 3.83, SD = 0.65) were all rated high. These findings indicate that the respondents generally hold positive attitudes toward AI, report willingness to engage with AI technologies, and report a solid self-perceived understanding of basic AI concepts and applications. The results suggest that these pre-service teachers are becoming increasingly aware of the potential benefits of AI and its role in education. This supports earlier research showing that future educators are developing stronger AI-related knowledge and are becoming more receptive to the use of AI in educational environments (Ayanwale et al., 2024; Runge et al., 2025).

In contrast, the respondents' overall behavioral intention was rated moderate (M = 3.17, SD = 0.47). Although the respondents reported high AI literacy across all domains, their intention to actively use AI in future teaching was comparatively lower. This suggests that self-reported AI knowledge and awareness does not necessarily translate into a strong commitment to use AI in practice, nor should it be assumed to reflect actual classroom-ready competency. Other factors, such as confidence, institutional support, access to resources, and perceived usefulness, may influence behavioral intention. Similar observations were reported by Runge et al. (2025), who

found that AI adoption among pre-service teachers is influenced not only by AI knowledge but also by pedagogical preparedness and ease of use.

Viewed through the ABCE (Affective–Behavioral–Cognitive–Ethical) Framework, the findings affirm that AI literacy is a multidimensional construct. While the USTP pre-service teachers in this study reported strong self-perceived competencies across all four domains, the moderate level of behavioral intention suggests that additional opportunities for authentic practice and hands-on experiences may be necessary to translate self-reported AI literacy into actual technology adoption. This highlights the need for teacher education programs such as USTP to provide meaningful AI-integrated learning experiences that help bridge the gap between self-perceived understanding of AI and demonstrated ability to apply it effectively in future classroom settings.

AI Literacy Level and Academic Program

Table 3 presents the descriptive statistics of AI literacy levels across the seven course specializations. Among the groups, BTVTEd–FGT obtained the highest mean score (M = 3.32, SD = 0.38), followed by BSEd–Science (M = 3.25, SD = 0.46) and BSEd–Mathematics (M = 3.24, SD = 0.32). In contrast, BTLEd–IA recorded the lowest mean score (M = 3.06, SD = 0.50).

Table 3: Distribution of pre-service teachers' AI literacy level scores according to course

Scale	Course	n	Mean	Std. Dev.
AI Literacy Level	BSEd-Science	61	3.25	0.46
	BSEd-Mathematics	29	3.24	0.32
	BTLEd-HE	77	3.08	0.48
	BTLEd-IA	16	3.06	0.50
	BTVTEd-CHS	8	3.16	0.30
	BTVTEd-FSM	23	3.10	0.61
	BTVTEd-FGT	12	3.32	0.38

Overall, the mean scores ranged from 3.06 to 3.32, indicating only slight differences in AI literacy levels among the course specializations. The relatively close mean values suggest that, within this USTP sample, pre-service teachers across the different programs reported comparable levels of AI literacy. Additionally, the standard deviations indicate moderate variability within each group, with BTVTEd–FSM showing the greatest variation (SD = 0.61) and BTVTEd–CHS showing the least variation (SD = 0.30). These findings imply that AI literacy is generally consistent among pre-service teachers regardless of their academic specialization.

Table 4: Results of analysis of variance according to the course of pre-service teachers' scores of AI Literacy Level

Scale	Source of Variance	Sum of Squares	df	Mean square	F	p
AI Literacy	Between Groups	1.782	6	0.297	1.375	0.226
Level	Within Groups	47.298	219	0.216		

A one-way analysis of variance (ANOVA) was conducted to examine whether AI Literacy Level differed according to course specialization. Levene's test confirmed that the assumption of homogeneity of variances was satisfied, $F(6, 219) = 0.70$, $p = 0.651$. The ANOVA (Table 4) revealed that the effect of course specialization on AI Literacy Level was not statistically significant, $F(6, 219) = 1.38$, $p = 0.226$, $\eta^2 = 0.036$. Although slight differences in mean AI Literacy Level were observed across courses, these differences were insufficient to conclude that AI literacy varied significantly among pre-service teachers from different specializations.

The findings suggest that AI literacy is relatively similar across course specializations. This may indicate that exposure to AI technologies is no longer confined to specific academic disciplines but is becoming widespread across teacher education programs. Recent studies have reported similar findings, showing that AI literacy among pre-service teachers is increasingly influenced by individual access to AI tools, technology-related experiences, and AI training rather than by academic specialization alone. For example, Cetin and Celen (2025) found that AI literacy among pre-service teachers was generally high and was more strongly associated with technology-related experiences and AI use than with field of study.

Likewise, Runge et al. (2025) reported that participation in AI-related courses and AI-related pedagogical knowledge were important predictors of AI acceptance and use among pre-service teachers, regardless of specialization.

These findings imply that AI literacy development may depend more on access to AI learning opportunities and practical engagement with AI technologies than on disciplinary background alone (Piaget, 1970; Vygotsky, 1978), consistent with the first expectation derived from constructivist theory: that categorical group membership, absent information on the quality of engagement it entails, would be a weak predictor of literacy. This null result also stands in contrast to Balasa's (2025) finding of significant discipline-based differences in a general Philippine pre-service teacher sample, suggesting that the relationship between academic background and AI literacy may itself depend on the specific population and teacher education context studied.

AI Literacy Level and Participants' Prior AI-related Trainings

Table 5 presents the distribution of AI literacy level scores according to the respondents' prior AI-related training or coursework. Respondents with no prior AI-related training obtained the highest mean score (M = 3.30, SD = 0.43), followed by those with moderate training (M = 3.15, SD = 0.49) and basic training (M = 3.14, SD = 0.39). Respondents with extensive training recorded the lowest mean score (M = 2.77, SD = 1.31).

Table 5: Distribution of pre-service teachers' AI literacy level scores according to their prior AI-related trainings

Scale	Prior AI-Related Training	n	Mean	Std. Dev.
AI Literacy Level	None	40	3.30	0.43
	Basic	95	3.14	0.39
	Moderate	87	3.15	0.49
	Extensive	4	2.77	1.31
	Total	**226**	**3.16**	**0.47**

Overall, the respondents obtained a moderate AI literacy level (M = 3.16, SD = 0.47). While slight differences in mean scores were observed across training categories, the scores were generally comparable. The relatively larger standard deviation among respondents with extensive training suggests greater variation in AI literacy levels within this group. These findings indicate that AI literacy levels were similar regardless of prior AI-related training or coursework.

A one-way analysis of variance (ANOVA) was conducted to examine differences in AI literacy levels based on prior AI-related training or coursework. Results of Levene's test indicated that the assumption of homogeneity of variances was satisfied, $F(3, 222) = 9.55$, $p = 0.051$. Results (Table 6) showed that differences in AI literacy level across training groups were not statistically significant, $F(3, 222) = 2.26$, $p = .082$, $\eta^2 = .03$. The findings suggest that prior AI-related training or coursework did not significantly influence the AI literacy levels of the pre-service teachers in this sample.

Table 6: Results of analysis of variance according to the prior AI-related trainings of pre-service teachers' scores of AI Literacy Level

Scale	Source of Variance	Sum of Squares	df	Mean square	F	p
AI Literacy Level	Between Groups	1.456	6	0.485	2.26	0.082
	Within Groups	47.624	222	0.215		

The findings showed that pre-service teachers had similar levels of AI literacy regardless of their prior AI-related training or coursework. Although respondents with no prior AI training obtained slightly higher mean scores than those with basic or moderate training, the differences were not statistically significant. This suggests that AI literacy may be developed through various learning experiences beyond formal training, such as self-directed learning, online resources, and regular use of AI technologies. Constructivism posits that learners build understanding through authentic experiences, reflection, and interaction with their environment. Consequently, pre-service teachers may develop AI literacy not only through formal AI coursework but also through continuous engagement with AI tools in academic and everyday contexts. Similar findings were reported by Cetin and Celen (2025), who found that AI literacy among pre-service teachers was closely associated with their use of AI in academic activities. Likewise, Ayanwale et al. (2024) emphasized that AI literacy develops through diverse experiences with AI technologies rather than formal instruction alone. However, previous studies have shown that well-designed AI-related courses can enhance AI competencies, knowledge, and pedagogical application (Han, 2025; Runge et al., 2025). Therefore, the nonsignificant differences observed in this study may reflect variations in the content and quality of AI training experiences among respondents. Overall, the findings suggest that both formal training and continuous engagement with AI technologies contribute to the development of AI literacy among pre-service teachers.

AI Literacy Level and Participants' Frequency of Using AI Tools

Table 7: Distribution of pre-service teachers' AI literacy level scores according to their frequency of using AI tools

Scale	Frequency of Using AI Tools	n	Mean	Std. Dev.
AI Literacy Level	Sometimes	58	3.09	0.35
	Often	118	3.17	0.39
	Very Often	50	3.25	0.70
	Total	**226**	**3.16**	**0.47**

Table 7 presents the AI literacy levels of pre-service teachers according to their frequency of using AI tools. Respondents who very often used AI tools obtained the highest mean score (M = 3.25, SD = 0.70), followed by those who often used AI tools (M = 3.17, SD = 0.39) and those who sometimes used AI tools (M = 3.09, SD = 0.35). The overall mean AI literacy score was 3.16 (SD = 0.47).

The results show a slight increase in AI literacy as the frequency of AI tool use increases. However, the differences in mean scores were relatively small, suggesting that pre-service teachers generally demonstrated similar levels of AI literacy regardless of how often they used AI tools. Overall, the findings indicate a moderate level of AI literacy among the respondents.

Table 8: Results of analysis of variance according to the prior frequency of using AI tools of pre-service teachers' scores of AI Literacy Level

Scale	Source of Variance	Sum of Squares	df	Mean square	F	p
AI Literacy Level	Between Groups	1.456	3	0.485	2.26	0.082
	Within Groups	47.624	222	0.215		

A one-way analysis of variance (ANOVA) was conducted to examine differences in AI literacy levels by the frequency of AI tool use. Levene's test indicated that the assumption of homogeneity of variances was satisfied $F(2, 223) = 5.08$, $p = 0.070$. Results (Table 8) revealed no significant differences in AI literacy levels among respondents who sometimes, often, or very often used AI tools, $F(2, 223) = 1.58$, $p = .208$, $\eta^2 = .014$. These findings indicate that the frequency of AI tool use did not significantly influence the AI literacy level of the pre-service teachers.

The results showed no significant difference in AI literacy levels based on the frequency of AI tool use, $F(3, 222) = 2.26$, $p = .082$. Although respondents who used AI tools more frequently tended to report slightly higher AI literacy scores, the differences were not statistically significant. This suggests that frequent use of AI tools alone may not be sufficient to develop AI literacy. AI literacy requires not only exposure to AI technologies but also an understanding of AI concepts, the critical evaluation of AI outputs, and the appropriate and ethical use of AI.

From a constructivist perspective, the finding supports the view that meaningful learning occurs through active engagement, reflection, and knowledge construction rather than through repeated exposure alone (Piaget, 1970; Vygotsky, 1978). Constructivist theory posits that learners develop deeper understanding when they actively interact with learning experiences, connect new information to prior knowledge, and reflect on those experiences. In the context of AI literacy, merely using AI tools frequently may not be sufficient unless pre-service teachers are also engaged in authentic tasks that encourage critical thinking, problem-solving, and reflection on the educational implications of AI. Therefore, AI literacy is likely strengthened by the quality of learning experiences rather than the frequency of technology use alone.

Similar findings were reported by Cetin and Celen (2025) and Ayanwale et al. (2024), who emphasized that AI literacy is influenced by a combination of knowledge, skills, and experiences rather than mere use of AI tools. Previous studies further suggest that structured AI-related instruction and training play a more important role in enhancing AI literacy and competencies among pre-service teachers (Han, 2025; Runge et al., 2025). Therefore, teacher education programs should provide meaningful learning experiences that help students develop deeper AI knowledge and application skills beyond routine AI tool usage.

Correlation between AI Literacy Level and Overall Behavioral Intention

A Pearson product–moment correlation was conducted to examine the relationship between AI literacy level and overall behavioral intention among pre-service teachers. Results revealed a very strong positive correlation between the two variables, $r(224) = .84$, $p < .001$. This finding indicates that higher AI literacy levels were associated with stronger behavioral intentions to use artificial intelligence technologies.

The findings revealed a strong positive relationship between AI literacy and behavioral intention among the pre-service teachers in this USTP sample. Respondents with higher AI literacy levels were more likely to report stronger intentions to use AI technologies in their academic and future teaching practices. This suggests that greater knowledge and understanding of AI may enhance confidence and willingness to adopt AI in educational settings. These findings are consistent with previous studies showing that AI literacy positively influences AI acceptance and use among pre-service teachers (Runge et al., 2025; Cetin & Celen, 2025). Furthermore, Ayanwale et al. (2024) reported that AI knowledge contributes to various AI-related competencies, including problem-solving and technology use. Overall, the results highlight the importance of strengthening AI literacy in teacher education programs such as USTP's to promote future teachers' readiness and willingness to integrate AI into classroom instruction. This pattern is consistent with the second expectation derived from constructivist theory: that the affective, behavioral, cognitive, and ethical dimensions of literacy would be closely tied to learners' willingness to act on that understanding.

Conclusion and Recommendation

Guided by Constructivist Learning Theory and the ABCE Framework, the findings indicate that the pre-service teachers surveyed at USTP reported a moderate overall level of AI literacy and behavioral intention, alongside high affective, behavioral, and cognitive literacy and very high self-perceived ethical literacy. This suggests that respondents perceive themselves as holding positive attitudes toward AI, understanding its basic concepts, and recognizing its ethical implications.

The study further revealed that course specialization, prior AI-related training, and frequency of AI tool use did not significantly influence AI literacy levels. These findings support the constructivist view that AI literacy is developed through active knowledge construction, authentic experiences, reflection, and engagement with technology rather than through demographic characteristics or exposure alone.

Moreover, the very strong positive relationship between AI literacy and behavioral intention indicates that, within this sample, higher self-reported AI literacy is associated with a greater willingness to use AI in future teaching practice. Consistent with the ABCE Framework, this finding highlights the interconnected nature of affective, behavioral, cognitive, and ethical dimensions in shaping AI adoption among the USTP pre-service teachers studied here.

Overall, the results point to a need for teacher education programs such as USTP's to provide meaningful, practice-oriented, and reflective AI learning experiences that could strengthen self-reported AI literacy and support the responsible integration of AI in teaching and learning, though whether such experiences also build demonstrated pedagogical competency remains a question for future research rather than a claim established by this study.

Thus, based on the findings, teacher education institutions such as USTP and similarly situated technical-vocational teacher education programs may consider enhancing the integration of artificial intelligence concepts and applications into the curriculum by providing structured, authentic learning experiences that develop not only self-reported AI knowledge but also demonstrated practical and pedagogical competencies. Professional development activities focusing on responsible and ethical AI use should likewise be strengthened. Given the strong correlational relationship between AI literacy and behavioral intention observed in this sample, interventions to improve AI literacy may plausibly increase pre-service teachers' readiness to integrate AI into their future teaching practice, though this remains to be confirmed beyond the specific programs studied here.

Multi-institutional studies that sample pre-service teachers from public and private higher education institutions across different regions of the Philippines, including institutions without a technical-vocational component, would help establish whether the AI literacy and behavioral intention patterns observed here generalize beyond a single-institution context. To address the self-report and social desirability concerns, future studies could pair AILQ scores with objective or performance-based measures of AI literacy, such as rubric-assessed AI-integrated lesson plans or think-aloud tasks, and could include a validated social desirability scale as a covariate to estimate and statistically account for its influence, particularly on the ethical domain. Longitudinal or panel designs that follow the same cohort of pre-service teachers from program entry through practice teaching would allow researchers to examine how AI literacy and behavioral intention develop over time and would provide a stronger basis for causal inference than the present cross-sectional design. Future studies should also use stratified or quota sampling to secure adequate and more evenly distributed cell sizes across course specializations and training-exposure categories, so that comparisons involving small

subgroups, such as pre-service teachers with extensive AI-related training, are adequately powered.

Limitations

Several limitations should be considered when interpreting these findings. First, the study was conducted at a single state university, the University of Science and Technology of Southern Philippines (USTP), involving pre-service teachers from a specific set of general secondary and technical-vocational teacher education programs; the discussion of findings in this study is accordingly focused on this USTP sample, and the findings may not generalize to pre-service teachers in other institutions, regions, or countries, particularly those with different resource conditions, institutional AI policies, or curricular structures. Second, AI literacy and behavioral intention were measured through the AILQ, a self-report instrument; as noted in the Methodology, self-report measures are inherently susceptible to social desirability bias, and respondents may have rated their AI knowledge, attitudes, and especially their ethical awareness more favorably than their actual competence or behavior would warrant, since responsible and ethical AI use is a socially sanctioned response in an academic setting, a concern reinforced by the finding that the ethical domain received the highest ratings among the four ABCE dimensions. No independent or performance-based measure was collected to corroborate these self-reported scores. Third, group sizes across the comparison variables were uneven: course specialization groups ranged from n = 8 (BTVTEd–CHS) to n = 77 (BTLEd–HE), and prior-training groups ranged from n = 4 (extensive training) to n = 95 (basic training). Such imbalance reduces the statistical power available to detect true differences in the smaller groups.

References

Ayanwale, M. A., Adelana, O. P., Molefi, R. R., Adeeko, O., & Ishola, A. M. (2024). Examining artificial intelligence literacy among pre-service teachers for future classrooms. *Computers and education open*, *6*, 100179.

Bae, H., Hur, J., Park, J., Choi, G. W., & Moon, J. (2024). Pre-Service Teachers' Dual Perspectives on Generative AI: Benefits, Challenges, and Integration into their Teaching and Learning. *Online Learning*, *28*(3), 131-156.

Balasa, K. A. (2025). Interplay of AI literacy, readiness-confidence, and acceptance among pre-service teachers in Philippine higher education: A gender, discipline, and

connectivity perspective. *EthAIca: Journal of Ethics, AI and Critical Analysis*, *4*, 429. https://doi.org/10.56294/ai2025429

Cetin, O., & Celen, G. (2025). Investigation of Pre-Service Teachers' Artificial Intelligence Literacy and Views on the Use of Artificial Intelligence in Education. *Journal of Education in Science, Environment and Health*, *11*(4), 285-304.

Chen, X., Xie, H., Zou, D., & Hwang, G. J. (2020). Application and theory gaps during the rise of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, *1*, Article 100002. https://doi.org/10.1016/j.caeai.2020.100002

Chiu, T. K. (2025). AI literacy and competency: Definitions, frameworks, development and future research directions. *Interactive Learning Environments*, *33*(5), 3225–3229. https://doi.org/10.1080/10494820.2025.2514372

Dayagbil, F. T., Boholano, H. B., & Sumalinog, G. G. (2025). Are they in or out? Exploring pre-service teachers' knowledge, perceptions, and experiences regarding artificial intelligence (AI) in teaching and learning. *Frontiers in Education*, *10*, Article 1665205. https://doi.org/10.3389/feduc.2025.1665205

Dilek, M., Baran, E., & Aleman, E. (2025). AI literacy in teacher education: Empowering educators through critical co-discovery. *Journal of Teacher Education*, *76*(3), 294–311. https://doi.org/10.1177/00224871251325083

Dilling, F., & Herrmann, M. (2024). Using large language models to support pre-service teachers’ mathematical reasoning: An exploratory study on ChatGPT as an instrument for creating mathematical proofs in geometry. *Frontiers in Artificial Intelligence*, *7*, Article 1460337. https://doi.org/10.3389/frai.2024.1460337

Du, H., Sun, Y., Jiang, H., Islam, A. Y., & Gu, X. (2024). Exploring the effects of AI literacy in teacher learning: An empirical study. *Humanities and Social Sciences Communications*, *11*. https://doi.org/10.1057/s41599-024-03101-6

Han, X. (2025). Improving pre-service teachers’ AI competencies: A quasi experimental study. *Frontiers in Psychology*, *16*, 1642465.

Hsu, H.-P. (2026). Artificial Intelligence Literacy and Competency in Pre-Service Teacher Education. *Encyclopedia*, *6*(4), 76. https://doi.org/10.3390/encyclopedia6040076

Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of artificial intelligence in education. *Computers and Education: Artificial Intelligence, 1,* Article 100001. https://doi.org/10.1016/j.caeai.2020.100001

Lamanauskas, V. (2025). Pre-service preschool and primary school teachers' attitudes on artificial intelligence: Readiness to use and potential challenges. In V. Lamanauskas (Ed.), *Science and technology education: Expectations and experiences. Proceedings of the 6th International Baltic Symposium on Science and Technology Education (BalticSTE2025)* (pp. 133–145). Scientia Socialis Press. https://doi.org/10.33225/BalticSTE/2025.133

Laru, J., Celik, I., Jokela, I., & Mäkitalo, K. (2025). The antecedents of pre-service teachers' AI literacy: Perceptions about own AI-driven applications, attitude towards AI and knowledge in machine learning. *European Journal of Teacher Education, 48*(5), 964–986. https://doi.org/10.1080/02619768.2025.2535623

Laupichler, M. C., Aster, A., Schirch, J., & Raupach, T. (2022). Artificial intelligence literacy in higher and adult education: A scoping literature review. *Computers and Education: Artificial Intelligence, 3,* Article 100101. https://doi.org/10.1016/j.caeai.2022.100101

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1–16). Association for Computing Machinery. https://doi.org/10.1145/3313831.3376727

Lumanlan, J. S., Ayson, M. R. I., Bautista, M. J. V., Dizon, J. C., & Ylarde, C. M. L. (2025). AI literacy among pre-service teachers: Inputs towards a relevant teacher education curriculum. *International Journal of Multidisciplinary Educational Research and Innovation, 3*(1), 242–253.

Maslovskaya, O., Struminskaya, B., & Durrant, G. (2022). The future of online data collection in social surveys: challenges, developments and applications. *Journal of the Royal Statistical Society Series A: Statistics in Society*, *185*(3), 768-772.

Miao, F., & Cukurova, M. (2024). *AI competency framework for teachers.* UNESCO. https://doi.org/10.54675/ZJTE2084

Mikeladze, T., Meijer, P. C., & Verhoeff, R. P. (2024). A comprehensive exploration of artificial intelligence competence frameworks for educators: A critical review. *European Journal of Education, 59*(3), e12663. https://doi.org/10.1111/ejed.12663

Mogadime, D., Moran, R., Moore, G., Rizvi, M., Gratacós, G., & Schlein, C. (2024, February). Women in teacher education: gendered stories of teaching, learning, and teacher education. In *Frontiers in Education* (Vol. 9, p. 1381108). Frontiers Media SA.

Ng, D. T. K., Wu, W., Leung, J. K. L., Chiu, T. K. F., & Chu, S. K.-W. (2024). Design and validation of the AI literacy questionnaire: The affective, behavioural, cognitive and ethical approach. *British Journal of Educational Technology*, *55*(3), 1082–1104.

Piaget, J. (1970). *Science of education and the psychology of the child*. Orion Press.

Pingmuang, P., Koraneekij, P., & Khlaisang, J. (2026). Development and Validation of an AI Literacy Scale for Pre-Service Teachers in Thailand. *Electronic Journal of e-Learning*, *24*(1), 01-18.

Runge, I., Hebibi, F., & Lazarides, R. (2025). Acceptance of pre-service teachers towards artificial intelligence (AI): The role of AI-related teacher training courses and AI-TPACK within the technology acceptance model. *Education Sciences*, *15*(2), 167.

Shi, L. (2025). Assessing teachers' generative artificial intelligence competencies: Instrument development and validation. *Education and Information Technologies, 30*. https://doi.org/10.1007/s10639-025-13684-5

UNESCO. (2023). *Gender equality in and through the teaching profession*. United Nations Educational, Scientific and Cultural Organization. https://www.unesco.org/en/articles/gender-equality-and-through-teaching-profession

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.

Zhao, H., & Zhang, X. (2017). The influence of field teaching practice on pre-service teachers' professional identity: A mixed methods study. *Frontiers in psychology*, *8*, 1264.

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Navigating the Lived Experiences of Special Education Teachers on the Use of Low-Technology Assistive Tools in Reading Instruction

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ABSTRACT

This study examined the lived experiences of special education teachers who used low-tech assistive technology to teach reading to learners with reading difficulties. Guided by Kolb's Experiential Learning Theory, the research employed a qualitative phenomenological design involving ten (10) public elementary school special education teachers from five schools in the division. Data were gathered through semi-structured interviews and focus group discussions and subjected to thematic analysis. The findings revealed that low-tech assistive tools, such as reading cards, portfolios, and reading kits, promoted learners' engagement, personalized instruction, and accessibility in resource-constrained settings. Teachers highlighted that these tools strengthened teacher–learner interaction, supported individualized and mastery-based learning, and encouraged active participation. A living cycle of practice emerged from the teachers' experiences, marked by creativity, engagement, reflection, and adaptation. This cycle shows how they sustained literacy instruction even when materials wore out or proved fragile. The study adds insights to the field by revealing how teachers keep their motivation alive through varied approaches, balance the tension between affordability and durability, and embody resilience in their everyday work. Rooted in the realities of the Gingoog City Division, the research offers a perspective that is both local and nationally relevant, bridging the ideals of policy with the realities of grassroots classrooms. It calls for embedding the design of adaptive low-tech assistive tools into teacher training and inclusive education quality assurance, in line with Republic Act 10533 (Enhanced Basic Education Act) and Republic Act 11650 (Inclusive Education Law). Finally, it strongly urges school administrators to provide sustained resource support, ensuring that inclusive education remains equitable, responsive, and truly accessible to diverse learners.

Keywords: Special education teachers, Low-technology assistive tools, Students with reading difficulties, Teacher experiences

Introduction

Assistive technology has become an essential part of inclusive teaching and learning in today's educational setting. It is widely recognized as helping students with disabilities overcome learning difficulties, gain independence, and achieve academic success. According to the World Health Organization (2024), access to appropriate assistive technologies is more than just a support mechanism; it is an issue of educational equity, ensuring that students with disabilities can fully engage in classes alongside their peers. The global push for inclusive education emphasizes the need to equip schools with assistive technologies that not only improve practical skills but also foster learners' sense of belonging and confidence.

Assistive technology is commonly classified into two broad categories: low-tech and high-tech. Low-technology assistive tools are simple, inexpensive, and non-digital supports such as flashcards, reading cards, portfolios, visual aids, and communication boards. High-technology assistive tools encompass advanced electronic or software-based systems like screen readers, AAC devices, and speech-to-text programs. This distinction underscores the accessibility of low-cost solutions and the transformative potential of technology-driven innovations in inclusive education (Putri, 2025).

In the Philippines, the Department of Education (DepEd) continues to promote assistive technology through Republic Act 10533 (Enhanced Basic Education Act) and Republic Act 11650 (Inclusive Education Law). Yet many public schools still face challenges in implementing high-technology tools because of limited funding, unstable electricity, and insufficient training (Chukwuemeka, 2019). As a result, teachers often turn to low-technology assistive tools that are simple, inexpensive, and non-digital materials such as flashcards, reading cards, portfolios, and visual aids. For many special education teachers, low-technology assistive tools continue to be the most practical option in supporting students with reading difficulties.

In this study, reading cards, portfolios, and reading kits are classified as low-technology assistive tools because they help students overcome challenges in reading and literacy tasks. Although these materials are commonly used as instructional aids, they become assistive tools because teachers intentionally employ them to address specific learner needs. Their value lies in providing visual and hands-on support, breaking down complex literacy tasks into manageable steps, and making information more accessible to diverse learners (Putri, 2025).

This study explores how special education teachers in the Gingoog City Division use these low-technology assistive tools in reading instruction. It seeks to understand their lived

experiences, the strategies they employ, and the challenges they face. More importantly, it highlights how creativity and resilience allow teachers to sustain inclusive literacy practices even in resource-constrained classrooms.

Statement of the Problem

This study aimed to explore the lived experiences of special education teachers in using low-technology assistive tools for reading instruction. Specifically, this study seeks to answer the following questions:

1) How do special education teachers describe their experiences in designing, adapting, and implementing low-tech assistive tools in reading instruction?

2) What pedagogical strategies do teachers employ when integrating low-technology assistive tools, and how do they perceive these strategies as influencing learners' engagement and progress in reading?

3) What challenges do teachers encounter in sustaining the use of low-technology assistive tools, and what forms of institutional or systemic support are needed to strengthen inclusive literacy instruction?

Framework of the Study

This framework illustrates how special education teachers in the Gingoog City Division implement low-technology assistive tools in reading instruction. The process is best understood as a cycle of practice and reflection, where teachers continuously design, adapt, and refine their approaches to meet learners' needs. The cycle begins with teacher creativity, where low-technology assistive tools such as flashcards, portfolios, and reading kits are designed or adapted to meet the diverse needs of learners. This stage reflects the concrete experience in Kolb's model, where teachers actively create tools that respond to classroom realities. Once introduced, these tools foster learner engagement, encouraging active participation, enjoyment, and confidence in reading activities. This corresponds to reflective observation, as teachers witness how learners respond and begin to notice patterns of success and challenge. Teachers then reflect on the effectiveness of the tools. They consider durability, accessibility, and workload, interpreting how these factors influence both learner outcomes and their own teaching practice. This stage aligns with abstract conceptualization, where teachers make sense of experiences and draw insights. Finally, teachers adapt and refine their strategies, modifying materials, improvising with available resources, or creating new supports. This is the active experimentation phase, where teachers test adjustments in the classroom, beginning the cycle anew. Through this cyclical process, low-tech tools are not static aids but dynamic instruments of inclusive practice. They embody resilience, practicality, and creativity, allowing teachers to

sustain literacy instruction even in resource-constrained settings.

Literature Review / Background Information

Low-technology assistive tools have long been part of literacy instruction. Reading cards help learners practice phonics and vocabulary (Lee, 2020), portfolios allow teachers to track progress and tailor interventions (Gonzales, 2022), and reading kits combine tactile and visual elements to strengthen comprehension (Ramirez, 2021).

These tools align closely with Kolb's Experiential Learning Theory, which emphasizes learning through cycles of experience, reflection, conceptualization, and experimentation (Sandoval, 2022). Teachers who use these materials experience their own learning cycle, designing tools, observing learner responses, reflecting on outcomes, and refining strategies (Salvacion, 2025).

However, challenges persist. Nordström (2019) found that repeated implementation without adequate support can lead to teacher fatigue and burnout. These problems underscore the dual reality of low-technology assistive tools. While they are accessible and useful, their usefulness depends on how teachers adapt them to classroom conditions and balance them with other professional responsibilities.

In Gingoog City, limited access to digital devices and internet connectivity compels teachers to improvise with low-technology assistive tools. Despite these constraints, their creativity and persistence demonstrate how inclusive education flourishes through adaptability and human connection.

Campado (2023) affirmed that incorporating assistive technology in literacy instruction has opportunities and challenges. The need for adaptable resources to encourage inclusion in integrated educational settings (Largo, 2025) and literacy difficulties highlight systemic issues in reading education (Kilag, 2024). It was also found that teachers have positive attitudes toward assistive technology; their practices remained grounded in low-technology assistive tools due to insufficient resources and inconsistent preparedness (Retiro, 2025). In like manner, the Education Commission (2025) reported that many public schools continue to face infrastructural challenges that hinder the effective use of digital tools, leaving low-technology assistive tools as the most practical option.

This study fills a gap in local research by documenting how SPED teachers in Gingoog City navigate these realities, adapt low-technology assistive tools, and sustain reading instruction for learners with reading difficulties.

Methodology

Research Design

The study employed a qualitative phenomenological design guided by Kolb's Experiential Learning Theory to explore the lived experiences of special education teachers in Gingoog City. The focus was not on directly measuring learner progress through standardized interventions, but rather on documenting how teachers themselves perceived the impact of their strategies. By centering teachers' voices, the design highlights the realities of implementing low-tech assistive tools in resource-constrained classrooms. These tools, such as flashcards, portfolios, and reading kits, were examined not only as instructional aids but also as adaptive responses to the challenges of inclusive education. The phenomenological approach allowed the study to capture teachers' reflections, improvisations, and adaptations, situating their experiences within the broader discourse on assistive technology. In this way, the research design clarifies what counts as assistive technology in the local context and illustrates how teachers creatively transform low-tech resources into meaningful supports for literacy instruction. The design emphasizes that reading improvement, while acknowledged as an outcome, is understood through the lens of teachers' lived experiences rather than through quantitative measurement.

Participants

Ten public elementary school teachers assigned to Special Education (SPED) classes in the Gingoog City Division took part in the study. They were purposively selected because of their hands-on experience with low-tech assistive tools and their formal academic preparation in special education. This ensured that the voices represented were those of teachers directly engaged in adapting and applying these tools in real classroom contexts. Recruitment was carried out in close coordination with school heads and division officials, which helped establish trust and support for the study. Participation was not predetermined by number; instead, interviews continued until data saturation was reached. By the tenth participant, recurring themes such as accessibility of materials, learner engagement, and the added workload of preparation appeared consistently across accounts. This point of saturation signaled that the dataset was rich enough to capture the shared realities and diverse perspectives of SPED teachers in the division.

Research Setting

The study was conducted in the Department of Education (DepEd) Gingoog City Division, located in Region X, Northern Mindanao. The division oversees 113 public schools, serving a diverse population of students and providing both inclusive and special education services.

Within this setting, classrooms reflect the realities of resource-constrained environments where teachers strive to meet the varied needs of students with disabilities. Five schools participated in the study: Don Restituto Baol Central School, Don Manuel Lugod Central School, Lunao Central School, Odiongan Central School, and Sta. Rita Elementary School. These schools represent the division's commitment to inclusive education, each with dedicated SPED programs that integrate students with diverse needs into the broader school community.

Data Collection

Data were gathered through a combination of semi-structured interviews, focus group discussions (FGDs), and observation notes. Individual interviews lasted 45–60 minutes, while FGDs ran for about 90 minutes, allowing teachers to reflect collectively on their shared experiences. Sessions were scheduled during Learning Action Cell (LAC) meetings, a familiar professional setting that encouraged open dialogue and collegial exchange. All sessions were audio-recorded with informed consent, then transcribed verbatim to preserve accuracy. When participants expressed themselves in local languages, transcripts were carefully translated into English, ensuring that meaning and nuance were retained. Observation notes complemented the verbal data, capturing non-verbal cues, classroom context, and the practical use of assistive tools. To strengthen credibility, the study employed triangulation, weaving together insights from interviews, FGDs, and observations. The researcher personally facilitated the sessions through in-person communication platforms, coordinating schedules based on teacher availability and adhering strictly to school guidelines. This approach ensured that data collection was both methodologically rigorous and respectful of participants' professional commitments.

Data Analysis

The study employed a thematic analysis approach to make sense of the rich qualitative data. Transcripts from interviews and focus group discussions, along with observation notes, were carefully read and re-read to identify recurring patterns. Initial codes were generated inductively, allowing themes to emerge directly from teachers' narratives rather than being imposed by the researcher. Coding was conducted manually, with attention to both explicit statements and underlying meanings. Themes such as accessibility, student engagement, and workload were refined through constant comparison across participants. This iterative process ensured that the analysis remained grounded in the lived experiences of SPED teachers.

To uphold trustworthiness, the following strategies were integrated into the analysis: Member Checking- the preliminary themes were shared with participants to validate interpretations and

ensure that their voices were accurately represented; Peer Debriefing-colleagues in special education were consulted to review coding decisions and thematic structures, providing external perspectives that minimized researcher bias; Audit Trail-detailed notes documented each stage of the analysis, from coding to theme development, allowing transparency in how conclusions were reached; Triangulation-data from interviews, FGDs, and observations were cross-examined, ensuring that themes were supported by multiple sources of evidence.

Ethical Considerations

This study adhered to the highest ethical standards to ensure the dignity, rights, and well-being of participants. Prior to data collection, informed consent was obtained from all teachers, with clear explanations of the study's purpose, procedures, and their right to withdraw at any time without consequence. Confidentiality was strictly maintained: participants' names and schools were anonymized in transcripts and reports, and all recordings and notes were securely stored. Only the researcher had access to raw data. Respect for participants was central to the process. Sessions were scheduled at times convenient for teachers, conducted in professional settings, and carried out with sensitivity to their workload and responsibilities. The researcher ensured that discussions remained non-intrusive, focusing on professional experiences rather than personal matters. Approval and coordination were sought from school heads and division officials, ensuring compliance with institutional guidelines. Ethical safeguards also included transparency in reporting, accurate representation of teacher voices, and avoidance of any harm or undue pressure.

This study was conducted in accordance with ethical guidelines that ensured privacy and respect for all participants. They were properly informed of the research's purpose and provided their consent to participate in the study conducted with complete confidentiality and anonymity. Their identities were protected by utilizing codes like "R1," "R2," and so on in representing their responses. All information provided by respondents was treated with the utmost confidentiality and used solely for academic purposes. Furthermore, the researcher made sure that all interviews were handled respectfully, with consideration for the personal and professional experiences revealed by the respondents. The responses were transcribed by the researcher with honesty and integrity, ensuring that the respondents' perspectives were properly represented.

Findings of the Study

The voices of the ten special education teachers in Gingoog City reveal a story of creativity, resilience, and challenge. Their experiences with low-technology assistive tools in reading

instruction unfolded into four interconnected themes: Accessibility and Convenience, Engagement and Motivation, Customization and Individualized Instruction, and Sustainability and Workload.

Accessibility and Convenience

Teachers consistently described low-technology assistive tools as practical and indispensable. Flashcards, portfolios, and reading kits were valued because they were affordable, easy to prepare, and usable without electricity or specialized training. One teacher explained, *"Low-tech tools are accessible and affordable… effective for mastery" (R8).* Yet, this convenience came with fragility. Materials wore out quickly, and learners sometimes lost interest when tools became repetitive. Teachers found themselves constantly replacing or redesigning resources. This dual reality accessible but unsustainable shaped their everyday practice.

Customization and Individualized Instruction

Teachers highlighted the importance of adapting tools to individual learner needs. They used one-on-one scaffolding, peer tutoring, and personalized portfolios to monitor progress and tailor instruction. Play-based strategies helped make repetitive practice more engaging. These practices reflected Kolb's experiential learning cycle: teachers experimented with tools, observed learner responses, reflected on outcomes, and refined strategies. One teacher noted, *"Direct instruction or one-on-one approach… helpful for my learners" (R6).* This adaptability turned low-tech tools into flexible instruments of inclusion.

Engagement and Motivation

The teachers observed that simple tools could spark joy and confidence in learners. Activities like word bingo, matching games, and phonics flashcards transformed reading sessions into interactive experiences. One teacher shared, "*My student's excitement in matching words showed me simple tools can make learning engaging" (R1).* Learners volunteered to participate, chose materials themselves, and displayed persistence in reading tasks. Teachers emphasized that these affective gains motivation, enjoyment, and confidence were as important as cognitive skills, because they sustained learners' willingness to keep trying.

Sustainability and Workload

Despite their value, teachers acknowledged the heavy burden of sustaining low-tech tools.

Materials were fragile, preparation was time-consuming, and many teachers spent personal money to maintain resources. One participant admitted, "*Low-tech tools do not suit pupils' taste… materials wear out" (R5).* This theme highlights the tension between accessibility and sustainability. Teachers' dedication kept literacy instruction alive, but the lack of systemic support placed strain on their time, energy, and finances.

Table 1: Theme Summary table

Research Question	Major Theme	Subtheme	Representative Quote	Interpretation
How do teachers describe their experiences?	Accessibility and Convenience	Practicality, affordability	"Low-tech tools are accessible and affordable… effective for mastery." (R8)	Teachers value low-tech tools because they are easy to obtain and sustain instruction despite limited resources.
What strategies are used?	Customization and Individualized Instruction	One-on-one scaffolding, peer support	"Direct instruction or one-on-one approach… helpful for my learners." (R6)	Teachers adapt tools to individual needs, reflecting experiential learning cycles.
What outcomes are perceived?	Engagement and Motivation	Enjoyment, confidence	"My student's excitement in matching words showed me simple tools can make learning engaging." (R1)	Teachers perceive affective gains (confidence, motivation) alongside cognitive skills.
What challenges exist?	Sustainability and Workload	Durability, fatigue	"Low-tech tools do not suit pupils' taste… materials wear out." (R5)	Teachers face tension between accessibility and sustainability, balancing creativity with workload.

Insights and Best Practices

Across all themes, teachers demonstrated resilience. They improvised with available materials, personalized instruction, and sustained learner engagement despite resource constraints. Their insights show that low-tech tools are not secondary substitutes but lifelines for inclusive literacy instruction in classrooms where high-tech solutions are unavailable.

The findings reveal that low-technology assistive tools are practical, adaptable, and effective in fostering both cognitive skills and emotional growth. Yet, their fragility and the added workload they create highlight the need for stronger administrative and policy support. Kolb's Experiential Learning Theory is visible throughout: teachers experience the realities of

low-tech tools, reflect on learner responses, conceptualize new strategies, and experiment with adaptations, sustaining both their own growth and their learners' progress.

Taken together, the voices of the ten SPED teachers weave a story of resourcefulness and perseverance. They showed that low-tech assistive tools are not mere stop-gap measures but essential lifelines in classrooms where high-tech solutions remain out of reach. Teachers valued these tools for their accessibility and adaptability, yet they also carried the burden of sustaining them amidst fragile materials, limited funds, and heavy workloads.

The findings answer the study's questions by revealing how teachers describe their experiences as both empowering and exhausting, how they employ creative and individualized strategies to meet diverse learner needs, how they perceive outcomes in terms of confidence, joy, and persistence as much as cognitive gains, and how they confront the challenges of sustainability with resilience.

Through Kolb's Experiential Learning Theory, these experiences come alive as cycles of trying, reflecting, adjusting, and innovating, a process that not only nurtures learners' literacy but also fuels teachers' own professional growth. In this way, the study underscores that inclusive education in Gingoog City is sustained not by technology alone, but by the commitment, creativity, and humanity of its teachers.

Discussion

This section interprets the findings of the study in relation to the research questions, Kolb's Experiential Learning Theory, and existing literature.

1. How do special education teachers describe their experiences using low-technology assistive tools?

Teachers consistently described low-technology assistive tools as accessible and convenient, echoing Lee (2020) and Gonzales (2022), who emphasized their practicality in literacy instruction. The fragility of materials, however, reflects Nordström's (2019) concern about sustainability and teacher fatigue. In the Gingoog City Division, this dual reality, tools that are both indispensable and fragile highlights the resilience of teachers who continue to innovate despite systemic limitations.

2. What pedagogical strategies do teachers employ?

Customization and individualized instruction emerged as central strategies. Teachers adapted flashcards for phonics, portfolios for progress tracking, and play-based activities for engagement. These practices mirror Kolb's cycle: teachers experimented with tools, observed

learner responses, conceptualized new strategies, and refined their approaches. Salvacion (2025) similarly noted that experiential learning thrives when teachers adapt tools to diverse learner needs. The findings affirm that low-tech tools are not static aids but flexible instruments shaped by teacher creativity.

3. What outcomes do teachers perceive?
Teachers reported both cognitive outcomes (decoding, phonics, comprehension) and affective outcomes (confidence, motivation, enjoyment). These perceptions align with Ramirez (2021), who emphasized the multimodal benefits of reading kits, and with Putri (2025), who highlighted the emotional dimension of literacy support. The affective gains are particularly significant: learners' excitement and persistence suggest that low-tech tools foster not only skill development but also the self-belief necessary for sustained literacy growth.

4. What challenges do teachers encounter?
Sustainability and workload were the most pressing challenges. Materials wore out quickly, preparation was time-consuming, and teachers often invested personal resources. This reflects Nordström's (2019) findings on teacher fatigue and resonates with Retiro (2025), who noted that positive attitudes toward assistive technology are often undermined by systemic gaps in support. The findings underscore the need for stronger administrative backing to ensure that inclusive education does not rely solely on teacher sacrifice.

5. What insights and best practices emerge?
Despite these challenges, teachers demonstrated resilience and adaptability. They improvised with available materials, personalized instruction, and sustained learner engagement. Their practices show that low-tech tools remain lifelines for inclusive literacy instruction in resource-constrained settings. This extends Kolb's theory by situating experiential learning in contexts where high-tech solutions are unavailable, reframing low-tech tools as primary instruments of inclusion rather than secondary substitutes.

Taken together, the answers to the research questions reveal a cycle of practice that is both deeply human and profoundly instructive. Teachers in Gingoog City described low-technology assistive tools as accessible lifelines, employed creative strategies to personalize instruction, and witnessed both cognitive and emotional growth in their learners. At the same time, they faced the fragility of materials and the weight of sustaining these practices with limited support.

These experiences mirror Kolb's experiential learning cycle: teachers create, learners engage, teachers reflect, and strategies are refined. What emerges is not just a set of classroom practices, but a living model of resilience and adaptation in inclusive education. The findings affirm that

low-tech tools, though simple, carry transformative power when placed in the hands of committed teachers.

By situating these insights within the broader literature, the study bridges national policy ideals with grassroots realities. It shows that inclusive education is sustained not by technology alone, but by the creativity, reflection, and persistence of teachers who make learning possible in resource-constrained settings.

Strengthening Theoretical Contribution

This study contributes to theory by demonstrating how Kolb's Experiential Learning Theory operates in inclusive education contexts where resources are limited. Teachers' use of low-technology tools reflect the cyclical process of concrete experience, reflective observation, abstract conceptualization, and active experimentation. Unlike studies that apply Kolb in general classroom settings, this research shows how experiential learning is uniquely visible in resource-constrained environments, where teachers must continually adapt tools to sustain literacy instruction. The findings also extend discussions of assistive technology frameworks by situating low-technology tools not as secondary or outdated, but as primary instruments of inclusion in contexts where high-tech solutions are unsustainable. This reframing highlights the novel contribution of the study: it bridges national inclusive education strategies with grassroots realities, showing how theory and practice converge in the everyday resilience of teachers.

Generalizability and Applicability

Although this study is situated in the specific context of Gingoog City, its insights have broader relevance. Many public schools in developing nations face similar challenges of limited funding, fragile materials, and heavy teacher workload. The strategies documented here, such as improvisation, play-based learning, and individualized scaffolding, can inform inclusive practices in other resource-constrained settings. At the same time, generalizability should be understood as transferability of insights rather than universal application. The findings are most applicable to contexts where high-tech tools are unsustainable, but they also offer lessons for blended approaches that combine low-tech and high-tech supports. By highlighting both the strengths and limitations of low-tech tools, this study provides a framework that other divisions and countries can adapt to their own realities.

Implications for Higher Education and Teacher Education Programs

The findings of this study carry important implications for higher education, particularly in the preparation of future teachers. Teacher education programs must go beyond theoretical discussions of assistive technology and provide hands-on training in the creative use of low-technology tools. By embedding modules on resource improvisation, inclusive pedagogy, and reflective practice, higher education institutions can better prepare teachers to navigate resource-constrained classrooms. Moreover, partnerships between universities and local school divisions can ensure that training is context-responsive, aligning national inclusive education policies with the realities faced by teachers in public schools. This study underscores the need for higher education to cultivate not only technical competence but also resilience, adaptability, and creativity qualities that teachers in Gingoog City demonstrated as they sustained literacy instruction despite limited resources.

Implications for Policy

The findings of this study also carry significant implications for inclusive education policy at both the national and local levels. While the Department of Education has emphasized the integration of assistive technologies, the lived experiences of teachers in Gingoog City reveal that low-technology assistive tools remain the backbone of literacy instruction in resource-constrained classrooms. Policies must therefore recognize that inclusive education is not only about digital innovation but also about sustaining the practical, low-cost tools that teachers rely on daily. First, there is a need for systematic resource allocation. Teachers reported investing personal time and money to maintain fragile materials, which highlights a gap in institutional support. Policy frameworks should ensure that schools receive regular supplies of durable low-tech resources, alongside training on creative adaptation. Second, inclusive education policies should embed teacher mentoring and workload management. The sustainability of low-tech tools depends not only on materials but also on the teachers who prepare and customize them. Providing structured mentoring, collaborative planning, and administrative support can reduce teacher fatigue and strengthen program implementation. Finally, policies must adopt a balanced approach to assistive technology. While high-tech tools are valuable, their effectiveness is limited without infrastructure and training. By formally recognizing the role of low-technology tools, policies can bridge the gap between national strategies and grassroots realities, ensuring that inclusive education remains both equitable and context-responsive.

CONCLUSIONS

This study has shown that low-technology assistive tools remain indispensable in literacy instruction, particularly in resource-constrained classrooms. Teachers in Gingoog City

demonstrated resilience and creativity as they adapted reading cards, portfolios, and reading kits to meet diverse students' needs. Their experiences highlight both the strengths of these tools- accessibility, engagement, and adaptability and the challenges of sustainability, including durability issues and added workload. Despite these limitations, teachers reported that low-tech assistive tools fostered both cognitive outcomes (decoding, phonics, vocabulary, comprehension) and affective outcomes (motivation, confidence, enjoyment, persistence). This dual impact underscores why such tools remain valuable: they not only build literacy skills but also nurture students' confidence and willingness to participate. The findings also reveal a tension between accessibility and sustainability. While low-tech assistive tools are affordable and readily available, their fragility and repetitive use can reduce effectiveness over time. Teachers often shoulder the burden of customizing and replenishing materials, which points to the need for stronger administrative and policy support. Kolb's Experiential Learning Theory was visible across all themes. Teachers engaged in cycles of experience, reflection, conceptualization, and experimentation, continually refining their strategies to respond to learner needs. This cyclical process sustained both teacher growth and learner progress, showing that inclusive education thrives when teachers are empowered to adapt.

RECOMMENDATIONS

Considering the study's findings on the use of low-technology assistive tools in teaching reading to students with reading difficulties, the following recommendations are proposed to enhance instructional effectiveness, sustainability, and inclusivity in special education settings:

Professional Development:
Embed training on adaptive design and creative use of low-technology assistive tools in teacher development programs. This could be integrated into a division-led training or workshop, in-service training (INSET) and/or division learning action plans. This will help teachers sustain learner engagement while reducing fatigue.

Administrative Support:
School leaders should allocate resources for replenishing and upgrading low-tech assistive tools. Mentoring and collaborative planning can also ease the workload of teachers who customize tools.

Policy Integration:
Incorporate low-tech assistive tools into inclusive education quality assurance frameworks, aligning with Republic Act 10533 (Enhanced Basic Education Act) and Republic Act 11650 (Inclusive Education Law). This ensures that grassroots practices are recognized and supported

at the national level.

Balanced Resource Planning:
Address the tension between accessibility and sustainability by combining low-tech assistive tools with selective high-tech supports where feasible. This balance can reduce teacher workload while maintaining affordability.

Future Research:
Further studies should explore student perspectives directly, complementing teacher accounts, and investigate long-term outcomes of low-tech assistive tool use in literacy development.

Ultimately, inclusive education is not defined by the sophistication of technology but by the creativity and persistence of teachers who make learning possible. In Gingoog City, low-technology assistive tools became more than classroom aids, they became symbols of equity, resilience, and hope.

References

Campado, R. J., Toquero, C. M. D., & Ulanday, D. M. (2023). Integration of assistive technology in teaching learners with special educational needs and disabilities in the Philippines. International Journal of Professional Development, Learners and Learning, 5(1), ep2308. https://doi.org/10.30935/ijpdll/13062

Chukwuemeka, E. J., & Samaila, D. (2019). Teachers' Perception and Factors Limiting the use of High-Tech Assistive Technology in Special Education Schools in North-West Nigeria. Contemporary Educational Technology, 11(1), 99–109. https://doi.org/10.30935/cet.646841

Education Commission 2 [EDCOM-2]. (2025). Philippine education report: Findings and recommendations. EDCOM Secretariat. https://edcom2.gov.ph

Gonzales, M. A., Reyes, D. R., & Salvador, P. R. (2022). The role of portfolios in literacy development for struggling readers. Journal of Special Education Strategies, 12(3), 45–60.

Kilag, J. T., Salac, J. R., Bula, E. A., & De Castro, R. (2024). Investigating factors impacting literacy skills in Philippine elementary schools. International Multidisciplinary Journal of Research for Innovation, Sustainability, and Excellence, 1(5), 1–15.

Largo, R. C., Pabatao, R. E., Villaber, J. M., & Tero, J. P. (2025). Assessing the role of adaptive materials in inclusive classrooms at Colon Integrated School. International Journal of Educational Studies, 8(2), 85–96. https://doi.org/10.34293/education.v8i2.321

Lee, J. K., & Parker, M. L. (2020). Developing Literacy Skills Using Visual Learning Tools. Education and Reading Research Journal, 15(4), 112-125.

Nordström, T., Nilsson, S., Gustafson, S., & Svensson, I. (2019). Assistive technology applications for students with reading difficulties: Special education teachers' experiences and perceptions. Disability and Rehabilitation: Assistive Technology, 14(8), 798–808.

Putri, M. H. (2025). The Low-to High-Tech Assistive Technology for the Learning Process of Students with Special Needs in Inclusive Classrooms: A Literature Review. Ideguru: Jurnal Karya Ilmiah Guru, 10(3), 1988-1996.

Ramirez, C. P., & Fernandez, L. D. (2021). Utilizing reading kits to support learners with reading difficulties. Philippine Journal of Educational Technology, 7(1), 22–35.

Retiro, J. P., Jumao-As, D. L., Gonzales, F. M., & Pepito, R. J. (2025). Enhancing literacy of learners with disabilities through digital assistive technologies. International Journal of Inclusive Education and Technology, 12(1), 88–103.

Salvacion, R., Satojito, J., Adviser, E., & Martir, E. (2025). International Journal of Science and Management Studies (IJSMS) Teachers' Innovative Strategies and Engagement: Their Influence to Learners' Performance. https://doi.org/10.51386/25815946/ijsms-v8i5p113

Sandoval, M. T. (2022). The Evidence-Informed Learning Cycle of Experiential Learning in the Core Subjects and its Relationship to Academic Performance of Grade 10 Students in Manila Ecclesiastical Province School Association (MaPSA), NCR (pp. 35–50). Education Review.

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Psychological Readiness for Learning in the AI Era: Academic Risk-Taking, Self-Directed Learning, and Academic Buoyancy Among First-Year University Students

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ABSTRACT

This study aimed to investigate the relationships among academic risk-taking, self-directed learning, and academic buoyancy. Using a sample of 1,368 first-year undergraduate students at NTU in the 2025 academic year, hierarchical multiple regression analysis was conducted to examine the effects of academic risk-taking and self-directed learning on academic buoyancy. The results indicated that students with higher levels of academic risk-taking and self-directed learning showed greater academic buoyancy. Moreover, the interaction between academic risk-taking and self-directed learning was statistically significant, suggesting that self-directed learning moderates the relationship between academic risk-taking and academic buoyancy. The findings highlight that while both academic risk-taking and self-directed learning are essential for fostering academic buoyancy, students still struggle with the practical skill of self-management despite recognizing the importance of independent learning, revealing an intention–action gap. The findings suggest that universities should foster a culture emphasizing informational feedback and practical support to better prepare adaptive learners for an uncertain future.

Keywords: Academic Risk-taking, Self-directed Learning, Academic Buoyancy, Student Success, Higher Education

Introduction

The contemporary world has transitioned from the SPOD (Steady, Predictable, Ordinary, and Definite) era to the VUCA (Volatility, Uncertainty, Complexity, and Ambiguity) era. This shift is driven by rapid advances in artificial intelligence (AI), continuous technological innovation,

and globalization. In such an environment, professional competence can quickly be replaced by emerging technologies or shifting societal demands.

In this context, higher education institutions should reconsider a fundamental question: What should universities teach? When future skills are hard to anticipate, education's central mission is to cultivate students' capacity to navigate the unknown. This includes encouraging them to embrace challenges, tolerate uncertainty, maintain psychological flexibility, continuously adapt their learning strategies, and develop the ability to learn how to learn. In doing so, students are better equipped to view challenges as opportunities for learning and growth rather than as threats of failure.

To effectively cultivate these essential competencies, universities must ensure that their learning environments provide an appropriate level of challenge, which is crucial for student growth and development. However, several important questions remain: Are students willing to choose challenging learning tasks? When confronted with academic setbacks, can they adjust their learning strategies, recover from failure, and persist in their learning? Furthermore, does self-directed learning (SDL) help students transform these challenges into opportunities for growth?

As a research-intensive university, National Taiwan University (NTU) presents first-year students with demanding academic requirements, challenges in exploring academic and career interests, and opportunities for interdisciplinary learning. Although this research does not directly measure AI use or digital literacy, it focuses on the underlying psychological learning readiness that equips students to navigate this highly uncertain educational landscape. Specifically, the current investigation examines the relationships among academic risk-taking (ART), self-directed learning (SDL), and academic buoyancy (AB). By analyzing how students adapt to these academic challenges, the findings aim to provide empirical evidence to inform curriculum design, learning support initiatives, and talent development policies.

Accordingly, the present study addresses three research hypotheses.

Hypothesis 1. Students with higher levels of academic risk-taking will report higher levels of academic buoyancy.

Hypothesis 2. Students with higher levels of self-directed learning will report higher levels of academic buoyancy.

Hypothesis 3. Self-directed learning positively moderates the relationship between academic risk-taking and academic buoyancy.

Literature Review / Background Information

Why Academic Buoyancy Matters

In the AI era, students are expected not only to acquire new knowledge and skills continuously but also to tackle complex problems that often have no single correct answer. They also face increasing competitive pressure. These challenges represent the everyday academic pressures and setbacks that students repeatedly encounter throughout their university studies. Adaptive learners can thrive under conditions of uncertainty (Laukkonen et al., 2019). Martin and Marsh (2008) conceptualized this capacity as academic buoyancy. AB is students' ability to navigate everyday academic setbacks, such as poor grades, competing deadlines, examination pressure, and difficult coursework (Martin & Marsh, 2008; Zhao & Yu, 2018).

A growing body of research shows that AB is an important determinant of academic success, positively predicting students' enjoyment of school life, classroom participation, self-esteem, academic achievement, learning engagement, and learning motivation (Martin & Marsh, 2006; Aydın & Michou, 2020; Absellatif, 2022; Bostwick et al., 2022). AB also plays an important role in promoting students' well-being (Kargar Behbahani et al., 2024) and reducing test-taking anxiety (Nurjamin et al., 2023). Therefore, students with higher levels of AB are more likely to remain actively engaged in learning, persevere in the face of academic challenges, and ultimately achieve their learning goals.

Academic Risk-Taking as an Antecedent of Academic Buoyancy

Clifford (1988) defined ART as students' willingness to choose more challenging learning tasks that involve a higher possibility of failure but offer greater learning value. ART has been regarded as an important psychological characteristic that facilitates learning. Students willing to take on more challenging tasks tend to invest more effort and, over time, are more likely to develop stronger self-efficacy (Clifford & Chou, 1991). Clifford (1991) also demonstrated that when students were encouraged to engage in challenging learning activities, learn from their mistakes, persist in the face of setbacks, and revise their approaches, they gradually developed greater tolerance for failure. These characteristics and learning processes closely resemble the defining features of AB proposed by Martin and Marsh (2008). Therefore, students with higher levels of ART may be more likely to develop stronger AB.

Despite these theoretical connections, no empirical evidence examines this relationship. Furthermore, more importantly, it remains unclear under what conditions students' willingness to embrace academic challenges translates into a greater capacity to cope with everyday academic setbacks. Accordingly, the present study investigates whether SDL moderates this relationship and clarifies the conditions under which ART is associated with higher levels of AB.

Self-Directed Learning as a Moderator Between Academic Risk-Taking and Academic Buoyancy

Knowles (1975) defined SDL as "a process in which individuals take the initiative, with or without the help of others, in diagnosing their learning needs, formulating learning goals, identifying human and material resources for learning, choosing and implementing appropriate learning strategies, and evaluating learning outcomes" (p. 18). Self-directed learners can actively employ these skills throughout their learning process, including goal setting, resource identification, strategy selection and implementation, and learning evaluation. Without self-directed ability, students may find it difficult to transform challenging experiences into the capacity to recover from everyday academic difficulties and sustain engagement. In this regard, ART entails a willingness to embrace challenges, whereas SDL enables students to respond effectively through continuous planning, monitoring, and adaptation.

Taken together, ART reflects students' willingness to enter learning situations characterized by challenge and the possibility of failure, whereas SDL reflects their ability to proactively plan, implement, monitor, and regulate their learning after encountering such challenges. It is therefore reasonable to propose that SDL may not only directly enhance students' AB but also strengthen the positive relationship between ART and AB.

Methodology

Participants and Procedure

The participants in this study were first-year undergraduate students enrolled at NTU in the 2025 academic year. An invitation to complete an online learning experience survey was distributed via email with a link to the questionnaire. Participation was voluntary, and participants were required to read the research information and provide electronic informed consent before accessing the questionnaire. Each participant could submit the questionnaire only once. Respondents who completed the questionnaire were eligible to enter a prize draw.

The survey was administered from September to October 2025. A total of 3,952 questionnaires were distributed, and 1,440 responses were received, yielding a response rate of 36.4%. Respondents were excluded if all 12 ART items were rated 4 or above, or if they showed invariant responding across all 12 items with ratings of 3 or below. Based on these criteria, 72 cases were excluded from the analysis. The final analytic sample consisted of 1,368 valid responses, representing an effective response rate of 34.6%.

Measures

The questionnaire consisted of three measures, including (1) academic risk-taking, (2) self-directed learning, and (3) academic buoyancy. All constructs were measured using a six-point Likert scale ranging from 1 ("strongly disagree") to 6 ("strongly agree").

Academic risk-taking was measured using the 12-item School Failure Tolerance (SFT) scale (Clifford, 1988), as adopted by Li et al. (2023). The original scale consisted of both positively and negatively worded items. In the present study, the eight positively worded items were retained because the reverse-worded items showed comparatively weak measurement performance in the preliminary measurement evaluation. The eight retained items were therefore used to construct the ART score ($\alpha = .80$).

Self-directed learning was measured using the Self-directed Learning Scale (Lounsbury et al., 2009). This unidimensional scale consists of 10 positively worded items ($\alpha = .86$).

Academic buoyancy was measured using the Academic Buoyancy Scale (Martin & Marsh, 2008). The scale is unidimensional and consists of four positively worded items ($\alpha = .86$).

Confirmatory factor analysis (CFA) was conducted to examine the measurement structure of ART, SDL, and AB by comparing a hypothesized three-factor model with a one-factor model. Descriptive statistics and Pearson's correlation analysis were conducted for all variables. Hierarchical multiple regression analysis was then performed to examine the effects of ART and SDL on AB, with SDL specified as the moderator. The interaction term between ART and SDL was included to test the moderating effect of SDL. All analyses were conducted using R version 4.5.3.

Findings

Descriptive Statistics and Measurement Evaluation

Academic Risk-Taking. As shown in Table 1, the mean score on the eight positively worded ART items was 34.38 out of 48, indicating a moderately high level of ART among first-year NTU students. This finding is consistent with previous research suggesting that university students generally demonstrate a considerable degree of willingness to take academic risks (Tan et al., 2017). Clifford (1991) also found that students tend to prefer a near-moderate level of academic risk. In general, students hold positive attitudes toward challenging learning tasks and are willing to engage actively when the level of difficulty is perceived as manageable.

The two highest-rated items were "If I get a low grade in a difficult task, I study my errors and rework the problems I get wrong" and "School work that really makes me think is fun." These findings suggest that most students tend to reflect on and learn from academic setbacks and appreciate intellectually challenging coursework.

In contrast, the two lowest-rated items were "I would rather make mistakes on a difficult task than get a perfect score on an easy but boring task" and "I would rather study a difficult module (course) than an easy one." However, these items also exhibited relatively large standard deviations (SDs) of 1.23 and 1.05, respectively. While some students strongly preferred challenging learning opportunities, others appeared to place greater emphasis on achieving favorable academic outcomes.

Table 1: Means And Standard Deviations of Academic Risk-Taking.

Academic Risk-Taking	Mean	*SD*
1. I like to try difficult assignments even if I get some wrong.	4.17	*1.05*
2. School work that really makes me think is fun.	4.72	*1.01*
3. I would rather study a difficult module (course) than an easy one.	3.80	*1.05*
4. It is fun to try to answer questions that are difficult or challenging.	4.39	*1.01*
5. I would rather make mistakes on a difficult task than get a perfect score on an easy but boring task.	3.58	*1.23*
6. When I make mistakes in a difficult task, I just keep trying and trying.	4.50	*.83*
7. If I get a low grade in a difficult task, I study my errors and rework the problems I get wrong.	4.74	*.82*
8. If I get a low score in difficult school work, I usually make up my mind to buckle down and study hard.	4.58	*1.02*
Total Score	34.38	*5.19*

Self-Directed Learning. As shown in Table 2, the mean total score for SDL was 45.97 out of 60, indicating a moderately high level of SDL among NTU first-year students. This finding is consistent with previous research involving university students, which similarly reported relatively high levels of SDL (Aşkın Tekkol & Demirel, 2018). Taken together, the findings suggest that most students perceived themselves as able to assume personal responsibility for their learning, preferred to take charge of the learning process, and could plan, implement, and evaluate their own learning. They also tended to be goal-oriented and able to learn independently or with limited external guidance.

The three highest-rated items were "I view self-directed learning based on my own initiative as important for success in school and in my future career," "I like to be in charge of what I learn and when I learn it," and "If there is something I don't understand in a class, I will find a way to learn it on my own." These findings indicate that most students recognized the importance of SDL, valued autonomy over their learning content and schedule, and were willing to take the initiative to resolve learning difficulties encountered in class.

The four lowest-rated items were “I am better at learning things on my own than most students,” “If there is something I need to learn, I find a way to do so right away,” “I am good at finding answers on my own for things that are not explained in class,” and “I am good at finding the right resources to help me do well in school.” These results suggest that although students valued and actively engaged in SDL, they were relatively less confident in their ability to learn independently, respond promptly to learning needs, and identify effective learning strategies and resources.

Table 2: Means And Standard Deviations of Self-Directed Learning.

Self-Directed Learning	Mean	*SD*
1. I regularly learn things on my own outside of class.	4.59	*.95*
2. I am good at finding answers on my own for things that are not explained in class.	4.44	*1.01*
3. If there is something I don't understand in a class, I will find a way to learn it on my own.	4.81	*.85*
4. I am good at finding the right resources to help me do well in school.	4.44	*1.04*
5. I view self-directed learning based on my own initiative as important for success in school and in my future career.	5.12	*.86*
6. I set my own goals for what I will learn.	4.58	*1.03*

7. I like to be in charge of what I learn and when I learn it.	5.01	*.97*
8. If there is something I need to learn, I find a way to do so right away.	4.24	*1.03*
9. I am better at learning things on my own than most students.	4.15	*1.23*
10. I am motivated to learn on my own instead of passively relying on other people.	4.59	*1.10*
Total Score	45.97	*6.68*

Academic Buoyancy. As shown in Table 3, the mean total score for AB was 15.38 out of 24, indicating a moderately high level of AB among students. This finding suggests that most participants perceived themselves as having a reasonable capacity to cope with everyday academic setbacks and challenges.

The highest-rated item was "I don't let study stress get on top of me," indicating that most students believed they could manage academic stress without becoming overwhelmed. In contrast, the lowest-rated item was "I don't let a bad mark affect my confidence," suggesting that receiving poor grades continued to undermine students' self-confidence. In addition, the standard deviation for each item exceeded 1.00, indicating considerable individual differences in students' perceived AB across all items.

Table 3: Means and Standard Deviations of Academic Buoyancy.

Academic Buoyancy	Mean	*SD*
1. I don't let study stress get on top of me.	4.17	*1.23*
2. I'm good at dealing with setbacks (e.g., bad mark, negative feedback on my work.)	3.83	*1.22*
3. I think I'm good at dealing with schoolwork pressures.	3.90	*1.21*
4. I don't let a bad mark affect my confidence.	3.48	*1.34*
Total Score	15.38	*4.21*

As shown in Table 4, all three study variables—ART, SDL, and AB—exhibited slight negative skewness, with skewness coefficients of −.20, −.12, and −.23, respectively. These values indicate that most participants scored relatively high, with only a few scoring at the lower end of the scales.

The kurtosis coefficient for ART was .21, indicating a slightly more peaked distribution than a normal distribution. In contrast, SDL and AB had kurtosis coefficients of −.16 and −.07, respectively, indicating slightly flatter distributions. Nevertheless, the skewness and kurtosis values for all three variables were close to zero, suggesting that their distributions approximated normality.

Table 4: Descriptive Statistics Results of the Study Variables.

	Mean	*SD*	Skew	Kurtosis	Max	Min
Academic Risk-Taking	34.48	*5.19*	-.20	.21	48	14
Self-Directed Learning	45.97	*6.68*	-.12	-.16	60	20
Academic Buoyancy	15.38	*4.21*	-.23	-.07	24	4

A three-factor CFA was conducted to examine the distinctiveness of ART, SDL, and AB (see Table 5). The hypothesized model showed generally acceptable fit, $\chi^2(206) = 2434.09$, CFI = .969, TLI = .965, RMSEA = .089, 90% CI [.086, .092], and SRMR = .068. Latent correlations among ART, SDL, and AB ranged from .468 to .633, supporting their empirical distinctiveness (see Table 6). In contrast, a one-factor model showed substantially poorer fit, $\chi^2(209) = 8507.55$, CFI = .885, TLI = .873, RMSEA = .170, 90% CI [.017, .017], and SRMR = .120. These findings supported the proposed three-factor measurement structure.

Table 5: Confirmatory Factor Analysis of the Measurement Model.

Model	χ^2	df	CFI	TLI	RMSEA [90% CI]	SRMR
Three-factor model	2434.09	206	.969	.965	.089 [.086, .092]	.068
One-factor model	8507.55	209	.885	.873	.170 [.017, .017]	.120

Table 6: Latent Correlations Among the Study Constructs for Assessing Discriminant Validity

	Academic Risk-Taking	Self-Directed Learning	Academic Buoyancy
Academic Risk-Taking	1		
Self-Directed Learning	0.633***	1	
Academic Buoyancy	0.491***	0.468***	1

Note. *p<.05, **p<.01, ***p<.001

Correlation Analysis

As shown in Table 7, Pearson's product-moment correlation analysis was conducted to examine the relationships among the study variables. ART was moderately and positively correlated with AB (r = .42, $p < .001$), and SDL was also moderately and positively correlated with AB (r = .40, $p < .001$). These findings were consistent with the study hypothesis.

In addition, ART was moderately and positively correlated with SDL (r = .53, $p < .001$). Hierarchical multiple regression analysis was subsequently conducted to examine whether ART and SDL jointly predicted AB and whether SDL moderated the relationship between ART and AB.

Table 7: Bivariate Correlations of the Study Variables.

	Academic Risk-Taking	Self-Directed Learning	Academic Buoyancy
Academic Risk-Taking	1		
Self-Directed Learning	.53***	1	
Academic Buoyancy	.42***	.40***	1

Note. *p<.05, **p<.01, ***p<.001

Hierarchical Multiple Regression Analysis

Regression assumptions were examined prior to hypothesis testing. Visual inspection of the standardized residuals plotted against the standardized predicted values revealed no substantial nonlinear or funnel-shaped pattern, suggesting that the assumptions of linearity and homoscedasticity were reasonably satisfied. The histogram and normal P–P plot of the standardized residuals indicated that the residuals were approximately normally distributed. The Durbin–Watson statistic was 1.976, indicating no substantial autocorrelation of residuals. Multicollinearity was not a concern, with variance inflation factors (VIFs) ranging from 1.004 to 1.401 and tolerance values ranging from .714 to .996. Although a small number of observations had standardized or studentized residuals exceeding ±3, the maximum Cook's distance was .066, well below the conventional threshold of 1, indicating that no individual observation exerted undue influence on the regression estimates. Overall, the diagnostic results indicated no substantial violations of the regression assumptions. With no substantial violations of the regression assumptions identified, hierarchical multiple regression analysis was then conducted to examine whether SDL moderated the relationship between ART and AB.

In Step 1, ART and SDL were entered as predictors. As shown in Table 8, the regression model was statistically significant, F (2, 1365) = 191.53, $p < .001$, explaining 21.8% of the variance

in AB (Adjusted R^2 = .218). Both ART (β = .290, p < .001) and SDL (β = .245, p < .001) had significant positive effects on AB.

Table 8: Hierarchical Multiple Regression Analysis Predicting Academic Buoyancy from Academic Risk-Taking, Self-Directed Learning, and their Interaction.

Variables	Model 1: Academic risk-taking, Self-directed learning				Model 2: Academic risk-taking, Self-directed learning, Academic risk-taking × Self-directed learning			
	β	SE	t	95% CI	β	SE	t	95% CI
Academic risk-taking	.290	.023	10.252***	[.190, .280]	.288	.023	10.227***	[.189, .279]
Self-directed learning	.245	.018	8.661***	[.119, .189]	.249	.018	8.807***	[.122, .192]
Academic risk-taking × Self-directed learning					.057	.003	2.362*	[.001, .011]
Adjusted R^2	.218				.221			
F	191.53***				129.98***			
$\triangle R^2$	-				.003			
△F	-				5.577*			

Note. *p<.05, **p<.01, ***p<.001

These results supported Hypothesis 1, indicating that students with higher levels of ART also tended to demonstrate greater AB. This finding is consistent with previous research showing that students with a growth mindset and higher emotional intelligence tend to exhibit greater AB (Liu, 2025). Individuals with a growth mindset are more likely to view mistakes as opportunities for learning, accept the possibility of failure, and engage in challenging academic tasks. When students demonstrate interest in challenging tasks and invest greater effort in them, they may be more likely to persist and successfully overcome academic difficulties (Clifford & Chou, 1991).

Hypothesis 2 was also supported, as students with higher levels of SDL tended to report greater AB. Martin and Marsh (2006) suggested that helping students develop self-regulatory skills may strengthen their capacity to persist when facing academic challenges. These skills overlap considerably with the competencies required for SDL. Students with these competencies may

therefore respond more constructively to everyday academic setbacks and maintain engagement despite difficulties.

In Step 2, the interaction term between ART and SDL was added to the model. The interaction effect was statistically significant (β = .057, $p < .05$). The proportion of explained variance increased from .218 to .221, representing a significant improvement in model fit ($\Delta R^2 = .003$, $p < .05$). Although the increase in explained variance was statistically significant, its magnitude was small.

To further examine the nature of the moderating effect, a simple slope analysis was conducted at three levels of SDL: one standard deviation below the mean, the mean, and one standard deviation above the mean. As shown in Table 9, ART had a significant positive effect on AB at all three levels of SDL, with simple slopes of .19, .23, and .27, respectively. These results indicate that the positive association between ART and AB strengthened as SDL levels increased (see Figure 1).

Table 9: Simple Slope Analysis of the Relationship Between Academic Risk-Taking and Academic Buoyancy at Different Levels of Self-Directed Learning.

Level of Self-Directed Learning	SDL Value	Simple Slope	SE	t
Low (−1 SD)	39.29	.19	.03	6.78***
Mean	45.97	.23	.02	10.23***
High (+1 SD)	52.65	.27	.03	9.72***

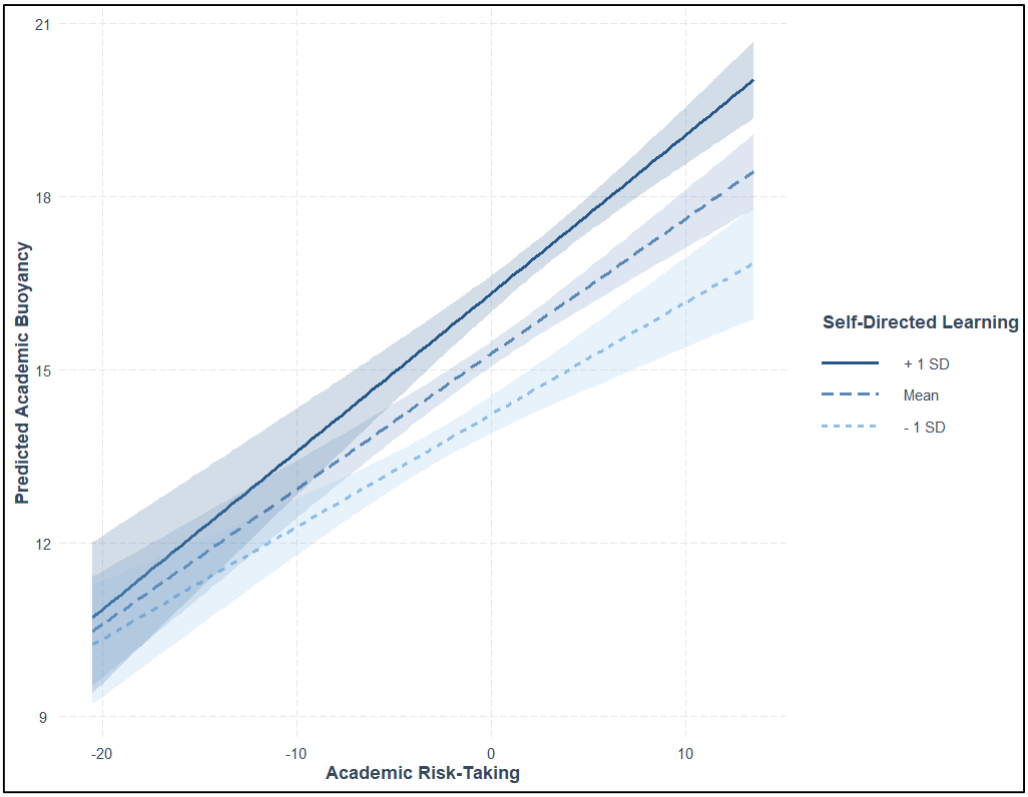


Figure 1: Interaction Between Academic Risk-Taking and Self-Directed Learning in Predicting Academic Buoyancy.

These findings indicate that SDL significantly moderated the relationship between ART and AB, thereby supporting Hypothesis 3. Specifically, the positive association between ART and AB strengthened as students' SDL levels increased.

To further identify the region where the moderating effect was statistically significant, the Johnson–Neyman technique was used. As shown in Figure 2, the positive effect of ART on AB became statistically significant ($p < .05$) when the raw SDL score exceeded 25.46 (corresponding to a mean-centered score greater than −20.51). Because the minimum observed SDL score in the sample was 20 and the first quartile was already 41 (see Table 10), nearly all participants (99.85%, n = 1,366) fell within the region of significance.

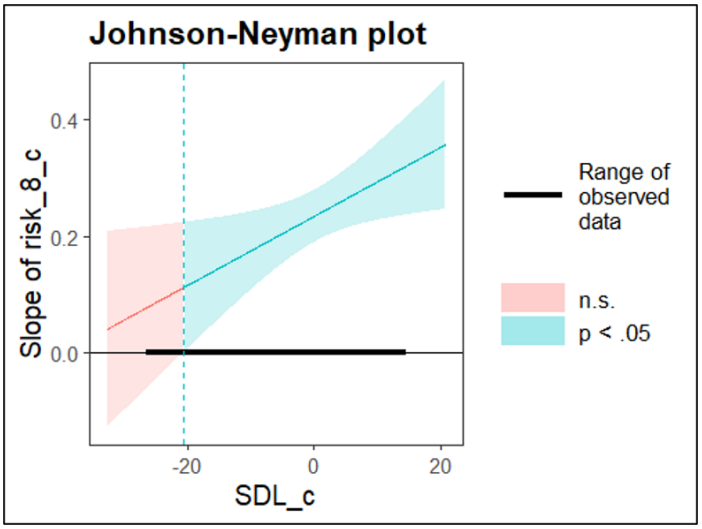


Figure 2: Johnson-Neyman Analysis of the Conditional Effect of Academic Risk-Taking on Academic Buoyancy across Levels of Self-Directed Learning.

Table 10: Descriptive Statistics for Raw and Mean-Centered Self-Directed Learning Scores.

Statistic	SDL_total (Raw Score)	SDL_c (Mean-Centered)
Minimum	20	-25.97
First Quartile (Q1)	41	-4.97
Median	46	.03
Mean	45.97	.00
Third Quartile (Q3)	50	4.03
Maximum	60	14.03

In other words, when students possess both a willingness to embrace academic challenges and the ability to independently adjust their learning processes, their experiences of taking on challenges may be more likely to be transformed into psychological and behavioral resources for coping with everyday academic setbacks. SDL may therefore help students reflect on challenging experiences, modify ineffective strategies, mobilize appropriate resources, and sustain their efforts when difficulties arise. In this sense, ART may contribute more strongly to AB when it is accompanied by the capacity to manage and adapt one's own learning.

Discussion

The Psychological "Readiness Gap": Cognitive Ambition vs. Emotional Vulnerability

The findings reveal that, while NTU first-year undergraduate students perceive themselves to have a moderately high level of AB, their performance in this area is slightly lower than their ART and SDL scores when total scores are standardized. This difference might exist because SDL is a set of competencies that can be practiced through learning activities, while AB is a deeper psychological mechanism that requires more time and experience to develop.

Furthermore, although both ART and AB are psychological mechanisms, they operate at different stages. ART is a proactive “approach” motivation where students actively seek challenges. In contrast, AB is a reactive mechanism required only after a setback occurs. Within the buoyancy scale, the item "I don’t let a bad mark affect my confidence" received the lowest mean score. This suggests that while NTU first-year undergraduate students are cognitively ready to embrace difficulty, they remain emotionally vulnerable to its consequences, particularly regarding the impact on grades. This reinforces the idea that the willingness to choose a challenge (risk-taking) does not automatically give students the psychological strength to recover from the failure that follows (buoyancy).

Self-Directed Learning as a Moderator: Supporting the Translation of Challenge into Adaptation

A significant, albeit small, finding of this study is that SDL positively moderates the relationship between ART and AB. Students’ willingness to take academic risks is somewhat more strongly associated with academic buoyancy when they can better manage their own learning. Although the interaction explained only a small additional proportion of variance ($\Delta R^2 = .003$), the pattern suggests that SDL may modestly strengthen this positive relationship.

One possible interpretation is that SDL functions as a “strategic toolkit.” While ART reflects a willingness to engage with challenge and uncertainty, SDL provides capacities such as goal setting, resource identification, and strategy adjustment that may help students respond more adaptively to setbacks. However, given the small moderation effect, SDL should be viewed as providing a modest additional advantage rather than as a necessary condition for ART to contribute to academic buoyancy.

The Paradox of Self-Directed Learning: High Value Recognition vs. Execution Gaps

The results reveal a paradox in students' psychological learning readiness within this AI-driven educational context. Students reported their highest scores in valuing the importance of SDL for their future success and preferring to be in charge of their learning. However, they felt much less confident in actually doing it, especially in "finding the right resources" and "taking action

right away." This "intention-action gap" shows that although students know they need to be independent, they still struggle with the practical skill of self-management. In the contemporary VUCA environment driven by the rapid growth of AI, students' primary challenge is often not a lack of information but a "choice dilemma" caused by an information explosion. When faced with an overwhelming array of tools and resources, identifying the most effective path forward becomes difficult, leading to hesitation despite a proactive mindset. Consequently, institutional support must move beyond simply motivating students toward independence. Universities should provide “navigational support” through courses or workshops. For instance, they could integrate scaffolded learning activities into first-year or inquiry-based courses. These activities allow instructors to guide students in developing SDL skills such as resource evaluation, time management, and effective use of AI tools. Providing opportunities for students to bridge the gap between their intention to take initiative and their ability to translate that intention into action is essential. This can help transform autonomy into the resilience needed to overcome academic setbacks

Cultivating a Growth Mindset and "Fail-Forward" Culture through Risk-Taking

Finally, this study confirms that ART is an important predictor of AB. The highest-rated items, "If I get a low grade in a difficult task, I study my errors and rework the problems I get wrong," and "School work that really makes me think is fun," indicate that many NTU first-year undergraduate students already have a growth mindset. They view mistakes as chances to learn and are willing to put in the effort to overcome challenges. According to Clifford (1991), giving students optimally challenging tasks and informational feedback helps them learn from their mistakes and develop failure tolerance. Universities can actively encourage academic risk-taking by adopting pass/fail grading for exploratory courses and incorporating reflection reports into assessments. Rewarding students for reflecting on academic mistakes and adjusting their learning strategies can reframe low grades as constructive information for improvement. Combined with flexible course withdrawal policies, these approaches can create a safe academic environment that mitigates grade anxiety and helps students build long-term academic buoyancy.

Conclusion

This study highlights that while ART and SDL are both essential for fostering AB among first-year students, their interaction is the key to true resilience. The identified "readiness gap," characterized by high academic ambition coupled with emotional vulnerability to grades, demonstrates that the willingness to take risks does not inherently provide the psychological resilience to recover from setbacks. SDL acts as a moderator that bridges this gap, providing

students with the strategic toolkit needed to transform academic challenges into growth opportunities.

To build institutional readiness that fosters psychological learning readiness amid AI-driven uncertainty, universities must move beyond encouraging students to be "ambitious" or "independent." Instead, institutions should focus on cultivating a "fail-forward" culture that emphasizes informational feedback and practical navigational support. By strengthening students' practical SDL skills and helping them decouple self-worth from grades, higher education can better prepare adaptive learners to navigate an uncertain future.

While this study provides meaningful insights from a research-intensive university, its single-institution, cross-sectional, and self-reported design limits the generalizability of the findings and may introduce common method bias. Because ART, SDL, and AB were all assessed through self-report at a single time point, shared response tendencies may have inflated or otherwise influenced the observed correlations and regression estimates. Although the three-factor CFA demonstrated substantially better fit than the one-factor model, common method variance cannot be fully ruled out. Future research should therefore examine these relationships across more diverse educational settings and employ longitudinal designs, multiple data sources, and behavioral or institutional indicators to strengthen causal inference and reduce reliance on a single measurement method.

Moreover, the regression models did not include demographic or academic background variables as controls. Accordingly, the observed relationships among ART, SDL, and AB should be interpreted without assuming that potential background differences have been fully accounted for. Future research could incorporate theoretically relevant covariates, such as gender, field of study, admission pathway, socioeconomic background, and prior academic achievement, to examine whether the present findings remain consistent. It would also be valuable to investigate whether these relationships differ across student subgroups. Lastly, although the study is conceptualized within the AI era, we did not empirically measure students' technology-mediated learning behaviors or digital competencies. Incorporating objective behavioral data or specific AI-related variables in future studies will yield a more comprehensive assessment of student learning readiness for AI-driven learning environments.

References

Abdellatif, M. S. (2022). Academic buoyancy of university students and its relationship to academic average in light of some demographic variables. *Cypriot Journal of Educational Sciences, 17*(7), 2361–2370. https://doi.org/10.18844/cjes.v17i7.7599

Aşkin Tekkol, İ., & Demirel, M. (2018). An investigation of self-directed learning skills of undergraduate students. *Frontiers in Psychology, 9*, Article 2324. https://doi.org/10.3389/fpsyg.2018.02324

Aydın, G., & Michou, A. (2020). Self-determined motivation and academic buoyancy as predictors of achievement in normative settings. *British Journal of Educational Psychology, 90*(4), 964–980. https://doi.org/10.1111/bjep.12338

Bostwick, K. C. P., Martin, A. J., Collie, R. J., Burns, E. C., Hare, N., Cox, S., Flesken, A., & McCarthy, I. (2022). Academic buoyancy in high school: A cross-lagged multilevel modeling approach exploring reciprocal effects with perceived school support, motivation, and engagement. *Journal of Educational Psychology, 114*(8), 1931–1949. https://doi.org/10.1037/edu0000753

Clifford, M. M. (1988). Failure tolerance and academic risk-taking in ten- to twelve-year-old students. *British Journal of Educational Psychology, 58*(1), 15 – 27. https://doi.org/10.1111/j.2044-8279.1988.tb00875.x

Clifford, M. M. (1991). Risk taking: Theoretical, empirical, and educational considerations. *Educational Psychologist, 26*(3-4), 263–297. https://doi.org/10.1080/00461520.1991.9653135

Clifford, M. M., & Chou, F. C. (1991). Effects of payoff and task context on academic risk taking. *Journal of Educational Psychology, 83*(4), 499–507. https://doi.org/10.1037/0022-0663.83.4.499

Kargar Behbahani, H., Namaziandost, E., & YarAhmadi, M. (2024). Dynamic assessment as the linchpin of academic buoyancy, reflective thinking, and academic resilience for intermediate Iranian EFL learners: A phenomenological study. *International Journal of Language Testing, 14*(2), 133–150. https://doi.org/10.22034/ijlt.2024.449951.1334

Knowles, M. S. (1975). *Self-directed learning: A guide for learners and teachers*. Association Press.

Laukkonen, R. E., Biddell, H., & Gallagher, R. (2019, August 27). Preparing humanity for change and artificial intelligence. https://doi.org/10.31234/osf.io/g5qwc

Li, G. Y., Fwu, B. J., Yang, T. R., & Chen, Y. K. (2023). To approach or to avoid: The quadripolar model of achievement motivation revisited in a Confucian-heritage context. *Frontiers in Psychology, 13*, 1046775. https://doi.org/10.3389/fpsyg.2022.1046775

Liu, R. (2025). Psychological resources for academic buoyancy: The roles of growth mindset and emotional intelligence in Chinese university students. *Frontiers in Psychology, 16*, 1580929. https://doi.org/10.3389/fpsyg.2025.1580929

Lounsbury, J. W., Levy, J. J., Park, S. H., Gibson, L. W., & Smith, R. (2009). An investigation of the construct validity of the personality trait of self-directed learning. *Learning and Individual Differences, 19*(4), 411–418. https://doi.org/10.1016/j.lindif.2009.03.001

Martin, A. J., & Marsh, H. W. (2006). Academic resilience and its psychological and educational correlates: A construct validity approach. *Psychology in the Schools, 43*(3), 267–281. https://doi.org/10.1002/pits.20149

Martin, A. J., & Marsh, H. W. (2008). Academic buoyancy: Towards an understanding of students' everyday academic resilience. *Journal of School Psychology, 46*(1), 53–83. https://doi.org/10.1016/j.jsp.2007.01.002

Nurjamin, A., Salazar-Espinoza, D. E., Saenko, N., & Bina, E. (2023). Learner-oriented assessment matters: testing the effects of academic buoyancy, reflective thinking, and learner enjoyment in self-assessment and test-taking anxiety management of the EFL learners. *Language Testing in Asia, 13*, 30. https://doi.org/10.1186/s40468-023-00247-z

Tan, E. W., Lim, S. W. H., & Manalo, E. (2017). Global-local processing impacts academic risk taking. *Quarterly Journal of Experimental Psychology, 70*(12), 2434–2444. https://doi.org/10.1080/17470218.2016.1240815

Zhao, F., & Yu, G. (2018). Everyday academic resilience: Active adaption to everyday academic pressures. *Advances in Psychological Science, 26*(6), 1054–1062. https://doi.org/10.3724/SP.J.1042.2018.01054

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Exploring Opportunities and Challenges in Collaborating with Parents to Support Children with Special Educational Needs: Reflections From Pre-Service Teachers in Thailand

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ABSTRACT

Parent–teacher collaboration is an important component of supporting children with special educational needs (SEN), yet limited attention has been given to how pre-service special education teachers develop collaborative competence through authentic engagement with families, particularly in non-Western contexts. This study explored the opportunities and challenges experienced by pre-service special education teachers in collaborating with parents of children with SEN in Thailand and examined their perceived preparedness for such collaboration. An exploratory qualitative design was employed with 15 pre-service teachers enrolled in a Bachelor of Education programme in Special Education at a university in Bangkok, Thailand. Data were generated through a focus group discussion and analysed using thematic analysis. Three themes emerged. First, parents served as important sources of contextual knowledge, enabling participants to understand children beyond classroom observations. Second, collaboration required the negotiation of practical and relational constraints, including limited and episodic communication, differences between professional and parental knowledge, and socio-economic barriers. Third, participants' preparedness for parent collaboration was still developing and was associated with the need for sustained engagement with families and greater professional and interdisciplinary support. The findings suggest that parent engagement is not merely a means of obtaining information about children but also an important context for pre-service teachers' professional learning. Teacher education programmes should therefore position parent collaboration as an explicit professional competence and provide structured opportunities for authentic family engagement, guided reflection, mentoring, and interdisciplinary support.

Keywords: Parent–Teacher Collaboration, Special Educational Needs, Pre-Service Teachers, Special Education, Teacher Education

Introduction

Inclusive education has become an increasingly important principle in supporting children with Special Educational Needs (SEN) across both mainstream and special education settings. Within this perspective, supporting children with SEN requires more than appropriate classroom instruction; it also depends on meaningful collaboration among teachers, families, and other professionals involved in children's learning and development. Parents are particularly important partners because their knowledge of their children's learning, behaviour, development, and everyday experiences can complement teachers' professional and pedagogical knowledge. Effective parent–teacher collaboration can therefore contribute not only to students' academic learning but also to their emotional and social development, confidence, and overall well-being (George & Kanupka, 2019). In special education, such collaboration is especially important because the educational needs of children with SEN are often closely connected to their developmental, familial, social, and cultural contexts.

Despite its recognised importance, effective collaboration with parents cannot be assumed to develop automatically as part of becoming a teacher. Working with families requires competencies that extend beyond instructional knowledge, including communication, mutual understanding, negotiation of different perspectives, and the ability to respond sensitively to diverse socio-cultural circumstances. These demands may be particularly challenging for pre-service teachers, who are still developing their professional knowledge and identities while having relatively limited experience of engaging with parents in authentic educational settings. Previous research suggests that opportunities for pre-service teachers to develop the knowledge, skills, and confidence required to work with parents, particularly parents of children with SEN, remain limited (Gyimah & Amoako, 2016). Differences in parental involvement, socio-cultural backgrounds, and communication practices may further complicate the translation of university-based preparation into effective collaboration in practice (McBride Pinheiro et al., 2022). This creates a tension within teacher education: pre-service teachers may be expected to collaborate professionally with families during field experiences and future practice, while opportunities to develop such competence through authentic engagement remain insufficient.

Existing research provides substantial evidence regarding the importance of family involvement and parent–teacher collaboration in supporting children with SEN. However, three interrelated gaps remain. First, there is a population gap. Much of the existing literature has focused on in-service teachers, parental roles, or student outcomes, while comparatively limited attention has been given to pre-service teachers and how they experience collaboration with parents during their professional preparation (Jones & Peterson-Ahmad, 2017; McDevitt

& Mello, 2021; Vorapanya & Pachanavon, 2025). This distinction is important because pre-service teachers occupy a transitional professional position: they are expected to apply knowledge acquired through teacher education but may not yet possess the experience, authority, or confidence of practising teachers. Examining their perspectives can therefore provide insight into how collaborative competence begins to develop during teacher preparation.

Second, there is a contextual gap. Much of the literature informing understandings of parent–teacher collaboration has emerged from Western educational contexts. Consequently, there remains limited understanding of how collaboration is experienced within non-Western settings such as Thailand. Parent–teacher relationships do not occur independently of their socio-cultural environments; cultural norms, communication patterns, social relationships, and expectations concerning parental involvement may influence how teachers and families understand and negotiate their respective roles (Murray et al., 2013; Woolfolk, 2018). Findings generated primarily from Western settings may therefore not fully explain the experiences of pre-service teachers working with families of children with SEN in Thailand. Context-specific investigation is needed to understand how these relationships are experienced within the social, cultural, and educational conditions of Thai teacher preparation.

Third, there is a practice gap concerning how collaborative competence is developed through teacher education. Although collaboration with parents is widely recognised as an important aspect of supporting children with SEN, collaborative competence may be implicitly expected rather than systematically developed through structured and authentic experiences. Existing research provides insufficient understanding of how pre-service teachers themselves experience opportunities and difficulties when engaging with parents, how they negotiate the relationship between professional knowledge and parents' experiential knowledge of their children, and how adequately they perceive their teacher education preparation to support such engagement. The issue, therefore, is not simply whether parent–teacher collaboration is important, but how pre-service teachers learn to enact such collaboration in practice and what conditions enable or constrain that learning.

Taken together, these population, contextual, and practice gaps indicate the need to examine parent–teacher collaboration from the perspectives of pre-service teachers within the Thai special education context. Such investigation can contribute to understanding collaboration not merely as a professional expectation but also as an important dimension of professional learning during teacher preparation. Accordingly, this study aimed to explore the opportunities and challenges experienced by pre-service teachers in collaborating with parents to support children with SEN in Thailand and to examine how they perceived their preparedness for such

collaboration. The study addressed the following research questions: 1) What opportunities do pre-service teachers perceive in collaborating with parents to support children with SEN? 2) What challenges do they encounter in this collaboration? and 3) How do they reflect on their experiences and preparedness in engaging with parents?

By addressing these questions, the study seeks to contribute empirical evidence concerning a comparatively underexplored group—pre-service special education teachers—and to extend understanding of parent–teacher collaboration within the Thai educational context. More importantly, examining pre-service teachers' experiences may provide insights into how teacher education programmes can move beyond treating collaboration as an implicit professional expectation towards developing it as an explicit competence through structured, experiential, and context-sensitive preparation. Such understanding may inform the design of teacher education experiences that better prepare future special education teachers to establish meaningful partnerships with families and provide responsive support for children with SEN.

Literature Review

1. Understanding Special Education Through the Lens of Teacher Education

Special education has increasingly been reconceptualised within the broader framework of inclusive education, reflecting a shift in how the needs of learners with SEN are understood. Historically, the medical model tended to locate learning difficulties or disabilities primarily within the individual learner. In contrast, perspectives informed by the social model of disability draw greater attention to the interaction between learners and the structural, pedagogical, and contextual barriers that may restrict their participation in education (Bolat, 2019; Sutton et al., 2020). From this perspective, supporting learners with SEN requires more than identifying individual difficulties or providing specialised interventions; it also involves creating responsive and flexible learning environments that accommodate learner diversity and promote meaningful participation (Deniz & İlik, 2021). Although misconceptions about SEN continue to influence how future teachers may understand learner needs (Jones & Peterson-Ahmad, 2017), the broader conceptual shift towards inclusion has important implications for how the professional role of teachers is understood.

As understandings of special education have broadened, the professional responsibilities of teachers have similarly expanded. Teachers are no longer positioned solely as providers of instruction but are increasingly expected to adapt teaching to diverse learner needs, create inclusive learning environments, and work collaboratively with other individuals involved in supporting learners with SEN (Gunpinar & Mackin, 2020; Phiukhao et al., 2025). In this sense,

effective special education practice requires both pedagogical competence and collaborative competence. The latter is particularly important because understanding and responding to the needs of children with SEN may require knowledge that extends beyond what teachers can observe within the classroom. Collaboration with parents and other professionals can provide access to learners' developmental, familial, social, and contextual experiences and can support more responsive educational decision-making. Consequently, collaboration should not be regarded as an additional or peripheral responsibility of teachers; rather, it represents an important dimension of contemporary professional practice in special and inclusive education. This expanded understanding of teacher professionalism has significant implications for teacher education. Preparing pre-service teachers for special and inclusive education requires the integration of theoretical knowledge, practical experience, and opportunities for reflection on professional practice (Woolfolk, 2018). However, existing research suggests that teacher education programmes may continue to place greater emphasis on instructional and pedagogical knowledge than on the relational and collaborative dimensions of teaching (Sutton et al., 2020). Competencies associated with working with families and other stakeholders may therefore be implicitly expected of pre-service teachers without being explicitly and systematically developed through their professional preparation (Eggen & Kauchak, 2016). This raises an important distinction between knowing about inclusive and special education and being able to enact inclusive practice in authentic professional contexts. Conceptual knowledge of SEN alone may not adequately prepare future teachers to communicate with families, negotiate different perspectives, participate in shared decision-making, or respond to the complex circumstances surrounding individual learners.

A central tension therefore exists between the professional expectations associated with contemporary special education and the opportunities provided within teacher education to develop the competencies required to meet those expectations. Pre-service teachers may be expected to support diverse learners and collaborate with their families during field experiences and subsequent professional practice, yet they frequently report limited confidence in translating theoretical knowledge into real-world contexts, particularly when engaging with parents of children with SEN (Woolfolk, 2018). Opportunities for authentic interaction with learners and their families may also remain limited during professional preparation (Eggen & Kauchak, 2016). The issue is therefore not simply whether pre-service teachers possess knowledge about SEN, but whether teacher education enables them to transform such knowledge into relational, collaborative, and context-responsive professional practice. This theory–practice tension is particularly important because the opportunities available for developing collaborative competence are likely to be shaped by educational structures, institutional arrangements, and socio-cultural contexts. Examining how these issues are situated within specific teacher education systems is therefore necessary, particularly in

contexts such as Thailand where the preparation of pre-service teachers for special and inclusive education continues to encounter practical and structural challenges.

2. Special Education in the Thai Teacher Education Context

Building on the broader shift towards inclusive and collaborative professional practice discussed above, the Thai teacher education context presents a complex setting in which educational aspirations, conceptual understandings, and professional practice do not always align. Although special and inclusive education has gained increasing recognition as part of efforts to promote educational equity, translating these principles into the preparation of future teachers remains challenging. One concern relates to conceptual understanding. Special education may still be understood narrowly in relation to visible physical disabilities, while less visible conditions, including intellectual disabilities and learning difficulties, may receive insufficient recognition (Erdem, 2020). Confusion between special education and remedial teaching has also been identified, with the two sometimes treated as interchangeable despite their different purposes and approaches. Such conceptual ambiguity is important because how pre-service teachers understand SEN may influence not only how they identify and respond to learners' needs but also how they interpret their professional responsibilities and communicate those needs to parents and other professionals (Bolat, 2019). The challenge is therefore not simply one of acquiring terminology or theoretical knowledge, but of developing conceptual understanding that can inform appropriate and inclusive professional practice.

A second tension concerns the relationship between theoretical preparation and opportunities for authentic professional experience. Coursework related to special or inclusive education may provide pre-service teachers with foundational knowledge about learner diversity, educational needs, and instructional approaches, yet opportunities to apply this knowledge in authentic contexts can remain limited (Greenbank, 2023). Early field experiences involving learners with SEN may not always be sufficiently available before formal practicum, while competencies such as differentiated instruction, classroom adaptation, and collaboration with parents may not be systematically integrated into professional preparation (Gyimah & Amoako, 2016). This creates a distinction between knowing about special education and being able to enact inclusive practice. Theoretical understanding is necessary, but it may be insufficient when pre-service teachers are required to respond to individual learners, interpret complex educational circumstances, communicate with families, and make context-sensitive professional decisions. Consequently, the quality of teacher preparation depends not only on what pre-service teachers learn about SEN but also on the opportunities through which they can connect such knowledge with authentic professional practice.

This theory–practice tension is particularly evident in relation to pre-service teachers' preparedness for working with learners with SEN and their families. Although pre-service teachers may demonstrate positive attitudes towards supporting diverse learners, they can experience uncertainty when applying university-based knowledge in actual educational settings (Sutton et al., 2020). Rather than interpreting such uncertainty solely as an individual lack of confidence, it is important to consider the opportunities available within teacher education for developing professional competence through experience. In particular, limited interaction with parents of children with SEN prior to and during practicum may restrict opportunities to practise communication, understand family perspectives, negotiate different forms of knowledge, and participate in collaborative decision-making (Erdem, 2020). From this perspective, preparedness is not simply a personal attribute that pre-service teachers either possess or lack; it is also shaped by the quality and continuity of the professional learning experiences made available to them. Collaborative competence therefore needs opportunities for practice, reflection, and engagement with the individuals who participate in supporting children with SEN.

Taken together, these conceptual, structural, and experiential tensions point to a broader gap between the expectations of contemporary special education and the professional preparation available to pre-service teachers. The central issue is not simply whether special education content is included within teacher education curricula, but whether pre-service teachers are provided with sufficiently authentic opportunities to transform conceptual knowledge into inclusive, relational, and collaborative professional practice. This issue is particularly significant in relation to parent–teacher collaboration. Although future teachers may be expected to work with families as part of supporting children with SEN, collaborative competence may remain implicitly expected rather than explicitly developed through structured professional experiences. Understanding what meaningful collaboration with parents involves, what opportunities it offers for pre-service teachers' professional learning, and what factors constrain its development therefore becomes an important next step in examining the preparation of future special education teachers in Thailand.

3. Parent–Teacher Collaboration in Supporting Children with Special Educational Needs

Parent–teacher collaboration is widely recognised as an important component of educational support for children with SEN. Parents possess knowledge of their children's developmental histories, behaviour, daily experiences, family circumstances, and needs outside school that may not be readily accessible through classroom observation alone. Teachers, in turn, contribute professional and pedagogical knowledge concerning learning, instruction,

assessment, and educational support. Bringing these different forms of knowledge together can contribute to a more comprehensive understanding of the child and support educational responses that are sensitive to individual needs and circumstances (George & Kanupka, 2019; McBride Pinheiro et al., 2022). However, parental involvement and parent–teacher collaboration should not necessarily be treated as equivalent. Parental involvement may include attending school meetings, receiving information, or supporting learning activities at home, whereas meaningful collaboration implies a more reciprocal relationship in which teachers and parents exchange knowledge, negotiate perspectives, and contribute to decisions concerning the educational support of the child.

From this perspective, meaningful parent–teacher collaboration extends beyond the transmission of information between school and home. It can be understood through several interconnected dimensions, including communication, trust, mutual respect, recognition of parental knowledge, and shared decision-making. Communication provides opportunities for teachers and parents to exchange information about children's learning, development, and behaviour, but communication alone does not necessarily constitute partnership. Sustained collaboration also requires teachers and parents to recognise the legitimacy of each other's knowledge and perspectives and to establish relationships in which concerns can be discussed openly and respectfully (Murray et al., 2013; Accardo et al., 2020). Trust and mutual respect are therefore important relational conditions for collaboration, while shared participation in educational decision-making moves the relationship beyond one-way communication towards partnership. In this sense, collaboration can be viewed as a reciprocal professional relationship rather than simply a mechanism through which schools communicate information to families.
A particularly important dimension of such collaboration concerns the relationship between teachers' professional knowledge and parents' experiential knowledge. Teachers may draw on theoretical, pedagogical, and professional understandings developed through teacher education and classroom experience, whereas parents possess situated knowledge developed through their continuing experience of living with and supporting their children. These forms of knowledge are different, but they need not be regarded as competing sources of authority. Instead, their integration can support a more contextualised understanding of children's needs and the forms of educational support that may be appropriate (McDevitt & Mello, 2021; Pansé-Barone et al., 2024). This is particularly significant in special education, where information concerning a child's development, behaviour at home, previous interventions, medical or specialist support, and family circumstances may influence educational planning. Meaningful collaboration therefore requires more than obtaining information from parents; it involves recognising parents as legitimate contributors to the process of understanding and supporting their children. For pre-service teachers, learning to negotiate these different forms of knowledge may represent an important dimension of professional learning.

Despite the value placed on partnership, however, a distinction may exist between collaboration as an educational principle and collaboration as it is enacted in practice. Parent–teacher relationships are shaped by institutional arrangements, communication opportunities, socio-cultural expectations, and the socioeconomic circumstances of families. Differences in expectations regarding teachers' and parents' responsibilities may influence communication and participation, while cultural norms can affect how families interact with educational professionals (Murray et al., 2013; Woolfolk, 2018). Socioeconomic circumstances may further influence parents' ability to attend school meetings, access professional or specialist services, and participate consistently in school-based activities (McBride Pinheiro et al., 2022). Consequently, limited parental participation should not automatically be interpreted as a lack of interest or commitment. Similarly, the existence of parent–teacher contact does not necessarily indicate that reciprocal collaboration has been achieved. Interaction may remain episodic or primarily informational when opportunities for sustained dialogue, mutual knowledge sharing, and shared decision-making are limited. Understanding collaboration therefore requires attention not only to whether interaction occurs but also to the quality, reciprocity, continuity, and context of that interaction.

These challenges have particular implications for the preparation of pre-service teachers. If meaningful collaboration depends on communication, trust, mutual respect, recognition of different forms of knowledge, and participation in decision-making, such competence is unlikely to develop through theoretical coursework alone. Pre-service teachers need opportunities to engage with families in authentic educational contexts, reflect on those experiences, negotiate perspectives different from their own, and learn how family circumstances influence the educational support available to children with SEN (Gyimah & Amoako, 2016; Jones & Peterson-Ahmad, 2017). Yet opportunities for sustained engagement with parents may remain limited during teacher preparation, creating a tension between the collaborative responsibilities expected of future teachers and the experiences through which those responsibilities can be learned. Existing literature therefore establishes the importance of parent–teacher collaboration, but provides less understanding of how pre-service special education teachers experience such collaboration as part of their professional preparation, particularly within the Thai educational context. Examining the opportunities they perceive, the challenges they encounter, and their reflections on preparedness can consequently provide insight into how collaborative competence is developed—and where teacher education may need to provide more explicit, structured, and context-sensitive support.

Methodology

Research Design

This study employed an exploratory qualitative research design informed by an interpretivist perspective to examine how pre-service special education teachers understood and reflected on their experiences of collaborating with parents to support children with SEN. An exploratory qualitative approach was considered appropriate because the study sought to understand participants' perceptions, experiences, and interpretations rather than to measure the prevalence of particular views or generalise the findings to a wider population. From an interpretivist perspective, participants' understandings of parent–teacher collaboration were viewed as situated within the educational, professional, and socio-cultural contexts in which their experiences occurred. Accordingly, the study aimed to generate contextually situated insights into the opportunities and challenges associated with parent–teacher collaboration and into how pre-service teachers perceived their preparedness for such professional engagement.

Participants and Sampling

The participants were 15 pre-service teachers enrolled in a Bachelor of Education programme in Special Education at a university in Bangkok, Thailand. Purposive sampling was used to recruit participants whose educational and field-based experiences were relevant to the phenomenon under investigation. All participants had undertaken field-based teacher training and had some experience of engaging with parents in educational contexts involving children with SEN. Participation in the study was voluntary.

The selection of participants was intended to provide perspectives from pre-service special education teachers who could reflect on parent–teacher interaction as part of their developing professional experience rather than to achieve statistical representation of the wider population of pre-service teachers. Their position as pre-service teachers was particularly relevant to the study because they were in the process of translating university-based knowledge about SEN into professional practice while simultaneously developing their understanding of how to engage with children, families, and other educational stakeholders.

Research Instrument

Data were generated using eight open-ended questions developed in alignment with the three research questions. The questions were designed to encourage participants to describe and reflect on their experiences rather than to provide predetermined or restricted responses. They addressed three principal areas: (1) opportunities perceived through collaboration with parents in supporting children with SEN; (2) challenges encountered when engaging with parents; and (3) participants' reflections on their experiences and preparedness for parent–teacher

collaboration. The open-ended format enabled participants to elaborate on their experiences, perspectives, and concerns in their own words while providing a common structure for the focus group discussion. The questions therefore served as prompts for exploring participants' experiences and reflections in relation to the objectives of the study.

Data Collection

Data were collected through a single focus group discussion involving all 15 participants. A focus group was selected as an exploratory method because it enabled participants to share experiences, express different perspectives, and reflect collectively on issues concerning collaboration with parents of children with SEN. The discussion was guided by the eight open-ended questions and lasted approximately 60 minutes.

The focus group discussion was conducted entirely in Thai, enabling participants to describe and reflect on their experiences in the language in which they could most naturally communicate their perspectives. With participants' consent, the discussion was audio-recorded and subsequently transcribed verbatim in Thai. The verbatim transcript preserved participants' original linguistic expressions and constituted the primary textual dataset for analysis. No translation into English was undertaken during data collection or transcription.

Given that the study involved a single focus group, the data were treated as an exploratory account of participants' perspectives rather than as an exhaustive or comprehensive representation of the experiences of pre-service special education teachers. The study did not use thematic saturation as a criterion for terminating data collection. Instead, the single focus group constituted the planned qualitative data source through which the exploratory research questions were investigated.

Data Analysis

The focus group data were analysed using thematic analysis (Clarke & Braun, 2017). The entire analytical process was conducted in Thai using the original Thai-language verbatim transcript. Analysis began with repeated reading of the transcript to develop familiarity with the participants' accounts. Meaningful segments of data relevant to the research questions were identified and assigned initial codes in Thai. Related codes were subsequently compared and organised into broader categories. Through an iterative process of comparison, review, and refinement, recurring patterns across the dataset were identified and developed into themes and subthemes representing the principal opportunities, challenges, and reflections on preparedness expressed by the participants.

The analysis sought to move beyond isolated statements towards identifying relationships and patterns across participants' accounts. Particular attention was given to how participants described their interactions with parents, the forms of knowledge and information exchanged through those interactions, the practical and contextual conditions that enabled or constrained collaboration, and their perceptions of their own professional preparedness. Coding decisions were revisited after a two-week interval to examine their consistency and to refine the developing analytical structure. This process functioned as a reflexive re-examination of the coding and interpretation rather than as a statistical assessment of intra-coder reliability.

Codes, categories, themes, subthemes, and interpretations were all initially developed in Thai. Conducting the analysis in the same language as the original data enabled the analytical process to remain closely grounded in participants' linguistic expressions and intended meanings and avoided introducing English translation as an intermediate stage in theme development.

Trustworthiness

Several strategies were employed to enhance the trustworthiness of the qualitative analysis. Credibility was supported through systematic and repeated engagement with the original Thai-language verbatim transcript and through the development of codes, categories, and themes grounded in participants' accounts. In addition, peer debriefing was conducted with three university lecturers in special education and was integrated into the analytical process.

The three peer debriefers critically reviewed the analysis at multiple levels, including the initial codes, the organisation of codes into categories, the development of themes and subthemes, and the interpretations derived from the data. They provided feedback concerning the coherence of the coding structure, relationships among categories and themes, and the extent to which the interpretations were supported by participants' original accounts. The researcher subsequently revisited and revised the codes, categories, themes, subthemes, and interpretations in response to their feedback. The entire peer-debriefing process was conducted in Thai, enabling the reviewers to evaluate the analysis in relation to the original Thai-language data rather than translated English versions.

Dependability was further supported through the systematic progression from initial codes to categories, themes, and subthemes and through the re-examination of coding decisions after a two-week interval. Confirmability was strengthened through peer scrutiny of the analytical process and subsequent revision of the analysis in response to critical feedback. Transferability was addressed by providing contextual information concerning the participants and the teacher education setting so that readers could judge the potential relevance of the findings to other educational contexts. Member checking was not conducted because of time constraints. This

is acknowledged as a methodological limitation, and the findings should therefore be understood as the researcher's interpretation of participants' accounts rather than as interpretations subsequently validated by the participants themselves.

Translation and Reporting

Translation from Thai into English was undertaken only after the thematic analysis and peer-debriefing process had been completed and when the findings were prepared for presentation in the English-language manuscript. Selected participant quotations and relevant descriptions of the findings were translated into English with attention to preserving the intended meanings of the original Thai expressions while ensuring clarity and readability for an international audience.

Thus, English translation functioned as part of the reporting process rather than as an intermediate stage in data collection, transcription, coding, categorisation, thematic development, or peer review. The analytical findings reported in this article were therefore developed and critically reviewed on the basis of the participants' original Thai-language accounts before being represented in English.

Ethical Considerations

Ethical principles were observed throughout the research process. Ethical approval was obtained prior to data collection. Participants were informed about the purpose of the study, the nature of their involvement, the focus group procedures, and the intended use of the research data. Informed consent, including consent for audio recording of the focus group discussion, was obtained before data collection. Participation was voluntary, and participants were informed of their right to withdraw from the study.

Confidentiality and anonymity were maintained throughout data management, analysis, and reporting. Identifying information was not disclosed when presenting participants' accounts or quotations. These procedures were intended to protect participants' privacy and autonomy while providing an appropriate environment in which they could discuss their experiences and perspectives concerning collaboration with parents of children with SEN.

Results

Theme 1: Parents as Sources of Contextual Knowledge

The first theme reflected participants' recognition that parents provided forms of knowledge about children with SEN that extended beyond what pre-service teachers could observe within the classroom. Through interactions with parents, participants gained insights into children's

family circumstances, home environments, developmental and medical histories, and access to professional support. These accounts indicated that parent engagement broadened participants' understanding of the child beyond school-based observations.

1.1 Understanding Children Beyond the Classroom

Participants described interactions with parents as providing greater insight into the family and socio-economic circumstances surrounding individual children. Such information helped participants understand that children's behaviours and learning experiences at school were connected to circumstances outside the classroom.

For example, one participant explained:

"When I talked with the parents, I understood more about the student's family situation, especially their financial condition."

Participants also recognised parental educational backgrounds as relevant to understanding how families supported their children. As another participant reflected:

"Parents' educational background helped me understand why they support their child in a certain way."

The home environment was similarly identified as an important source of contextual understanding. One participant observed that:

"Students' behaviours are closely related to how they are raised at home."

Taken together, these accounts indicated that engagement with parents enabled participants to interpret children's behaviours and learning needs in relation to their wider family circumstances rather than relying exclusively on what they observed at school.

1.2 Accessing Developmental and Professional Support Information

Parents were also described as important sources of information concerning children's developmental and medical histories, including diagnoses, treatment, and access to specialist services. This information was not always readily available to pre-service teachers through their classroom experiences.

One participant explained:

"Parents told me about the student's diagnosis and the treatment they have been receiving from a specialist doctor."

Similarly, another participant stated:

"Without talking to parents, I would not have known about the student's medical condition in detail."

However, participants' accounts also revealed differences in children's access to continuing professional support. These differences were particularly evident in relation to families' financial circumstances. One participant reported:

"Some parents said they could not take their child to see a specialist regularly because of financial limitations."

Another participant similarly noted that:

"Some students have not received continuous treatment, even though they need it."

These accounts suggested that communication with parents not only provided information about individual children's developmental and medical circumstances but also made visible the socio-economic conditions influencing families' access to professional support.

Theme 2: Negotiating Collaboration Under Practical and Relational Constraints

Although participants recognised the value of parent engagement, their accounts also revealed constraints on how collaboration occurred in practice. These constraints concerned both opportunities for sustained communication and the negotiation of different forms of knowledge held by pre-service teachers and parents.

2.1 Limited and Episodic Parent–Teacher Communication

Participants generally described their opportunities to communicate with parents as limited and irregular. Contact tended to occur when parents came to school rather than through sustained communication throughout the participants' field-based experiences.

As one participant explained:

"Most of the time, I only met parents when they came to school, so the communication was quite limited."

Another participant similarly reflected:

"There were not many chances to talk with parents outside school hours."

Participants' accounts further indicated that opportunities for parent engagement were affected by families' socio-economic circumstances. Employment responsibilities and transportation difficulties could affect children's attendance and, consequently, opportunities for interaction between families and schools.

One participant noted:

"Some students were absent because their parents had to work far away and could not bring them to school."

Another participant explained:

"Transportation costs can be a problem for some families, so students cannot attend school regularly."

These experiences showed that limited parent–teacher communication was not simply a matter of individual willingness to communicate. Participants encountered practical circumstances surrounding family employment, transportation, and school attendance that shaped opportunities for sustained engagement.

2.2 Negotiating Professional and Parental Knowledge

A second challenge concerned differences between the forms of knowledge that pre-service teachers brought from their university preparation and the knowledge parents had developed through everyday experience with their children. Participants recognised that their theoretical understanding of special education did not necessarily provide the same insights as parents' sustained experience of their children in daily life.

One participant articulated this distinction clearly:

"I learned theories about special education, but parents understand their child's behaviour from daily experience."

Rather than describing one form of knowledge as inherently more valuable than the other, participants' accounts revealed the practical challenge of bringing these different forms of knowledge together when considering appropriate support for children.

As another participant explained:

"It can be difficult to combine our theoretical knowledge with parents' practical experience when planning how to support the student."

The challenge described by participants therefore involved more than acquiring information from parents. Their accounts reflected the need to negotiate between university-based theoretical knowledge and parents' experiential understanding of their own children when considering how support might be planned in practice.

Theme 3: Developing Preparedness for Parent Collaboration

The third theme concerned participants' perceptions of their preparedness for working collaboratively with parents. Their accounts indicated that this aspect of professional competence was still developing. Participants identified two conditions that they considered particularly important for strengthening their preparedness: sustained relational engagement with parents and access to professional and interdisciplinary support.

3.1 Need for Sustained and Relational Engagement

Participants expressed a desire for parent engagement to become more regular and structured rather than being limited to occasional encounters. Regular meetings were perceived as providing opportunities to follow children's progress and to adjust support collaboratively over time.

One participant suggested:

"I think we should have regular meetings with parents, at least once a month, to follow up on the student's progress."

Another participant similarly explained:

"Meeting parents regularly would help us plan together and adjust how we support the student."

Participants also expressed a preference for face-to-face communication. Such interaction was perceived as facilitating clearer mutual understanding and making discussion about support easier.

As one participant stated:

"I prefer talking with parents face-to-face because we can understand each other more clearly."

Another participant added:

"When we communicate in person, it is easier to discuss and agree on how to support the student."

These accounts indicated that participants did not view preparedness for parent collaboration solely in terms of possessing knowledge about SEN. They also associated preparedness with opportunities to communicate with parents regularly and to develop relational experience through direct interaction.

3.2 Need for Professional and Interdisciplinary Support

Participants further described professional support as important to their developing preparedness, particularly when working with children whose needs required knowledge beyond their own emerging expertise. They expressed a need for opportunities to consult specialists and receive guidance from university supervisors.

One participant explained:

"I would like more opportunities to consult with specialists, such as doctors, to better understand each student's condition."

Another participant emphasised the role of university supervision:

"Guidance from supervisors would help me know how to support students more effectively in specific cases."

These accounts suggested that participants understood parent collaboration as occurring within a broader network of professional support. Their developing preparedness was therefore associated not only with increased opportunities to engage with parents but also with access to specialist knowledge and guidance when responding to the individual circumstances of children with SEN.

Discussion

This study explored how pre-service special education teachers in Thailand experienced and understood collaboration with parents in supporting children with SEN. Taken together, the findings suggest that parent–teacher collaboration served not only as a means of exchanging information about children but also as an important context for pre-service teachers' professional learning. Through engagement with parents, participants encountered forms of

contextual and experiential knowledge that complemented their university-based understanding of special education. At the same time, their experiences revealed that meaningful collaboration was not automatically achieved through contact with parents; rather, it was shaped by the continuity of communication, the negotiation of different forms of knowledge, socio-economic circumstances, and access to professional support. These findings suggest that collaborative competence should be understood as a dimension of professional learning that requires deliberate development within teacher education.

The first theme demonstrated that parents provided pre-service teachers with knowledge about children that extended beyond what could be observed within the classroom. Participants gained insights into family circumstances, home environments, parental educational backgrounds, developmental and medical histories, and access to professional services. This finding is consistent with literature emphasising that effective support for learners with SEN requires attention to the broader socio-cultural and familial contexts in which learning and development occur (Jones & Peterson-Ahmad, 2017; Vorapanya & Pachanavon, 2025). However, the present findings extend this argument by highlighting the significance of such contextual knowledge for the professional learning of pre-service teachers. Participants' accounts suggest that understanding a child with SEN cannot be developed solely through formal coursework or classroom observation; interaction with parents provides access to dimensions of the child's life that may otherwise remain invisible within school settings. In this sense, parent engagement is not merely an opportunity to apply previously learned special-education knowledge but is itself a site of professional learning through which pre-service teachers develop a more contextualised understanding of the children they support. This reinforces the importance of experiential learning opportunities within teacher preparation programmes (Eggen & Kauchak, 2016; Sutton et al., 2020).

This interpretation also strengthens the position of parents as contributors to educational knowledge rather than as passive recipients of professional advice. Previous research has recognised parents as important participants in educational planning and support for children with SEN (Gyimah & Amoako, 2016; Pansé-Barone et al., 2024). The present study adds to this perspective by illustrating how parental knowledge contributes specifically to the learning of future special education teachers. Parents possessed knowledge derived from sustained experience with their children across home, medical, and community contexts, whereas pre-service teachers brought theoretical and pedagogical knowledge developed through university preparation. The significance of collaboration therefore lies not simply in transferring information from parents to teachers but in bringing different forms of knowledge into relation with one another. From this perspective, effective collaboration requires recognition that

professional knowledge and parental experiential knowledge may be different but potentially complementary sources for understanding and supporting a child with SEN.

The second theme further revealed that integrating these different forms of knowledge was not necessarily straightforward. Participants described difficulties in reconciling theoretical knowledge acquired through special education coursework with parents' practical and lived understanding of their children. This finding supports the view that collaboration involves more than information exchange; it requires the negotiation of perspectives and recognition of different forms of expertise (Ibrahim, 2020). Importantly, the findings should not be interpreted as suggesting that either professional knowledge or parental knowledge is inherently superior. Rather, they indicate that pre-service teachers need opportunities to learn how to listen to, interpret, and integrate parental perspectives with professional knowledge when considering support for children. This represents an important dimension of collaborative competence because meaningful partnership depends not only on communication but also on mutual recognition of the knowledge that different participants contribute to decisions concerning the child.

At the same time, participants' experiences suggest that opportunities to develop such reciprocal relationships were constrained by the episodic nature of parent contact. Communication commonly occurred when parents visited the school, while opportunities for sustained interaction were limited. Previous research has similarly emphasised that meaningful parent–teacher collaboration depends on continuing interaction rather than occasional contact (Murray et al., 2013). Viewed in relation to the present findings, this distinction is important because contact with parents should not automatically be equated with collaboration. Episodic exchanges may provide useful information, but sustained collaboration requires opportunities for continuing communication, mutual understanding, and joint consideration of how children can be supported. The experiences reported in this study therefore appeared to be closer in some instances to episodic information exchange than to a fully developed reciprocal partnership. For pre-service teachers in particular, limited continuity of parent interaction may reduce opportunities to practise the relational and communicative dimensions of professional collaboration during their preparation.

The findings also demonstrate that the quality and continuity of collaboration cannot be understood solely as matters of individual willingness or communication skill. Participants identified financial constraints, parental employment commitments, transportation difficulties, and unequal access to specialist services as conditions affecting children's school participation and opportunities for parent–teacher interaction. These findings are consistent with research indicating that educational participation in inclusive settings is closely connected to wider

social and economic inequalities (Gyimah & Amoako, 2016). A significant implication is that limited parental participation should not automatically be interpreted as a lack of parental interest or commitment. Families may value collaboration while simultaneously encountering structural barriers that constrain their capacity to participate in school-based activities or maintain regular contact with teachers. Parent–teacher collaboration should therefore be understood as context-dependent: expectations for family participation need to take account of the social and economic circumstances within which families are situated.

The third theme concerned participants' developing preparedness for collaboration with parents. Their desire for more regular and structured opportunities to meet families indicates a continuing gap between recognising the importance of collaboration and having sufficient opportunities to practise it. Although theoretical preparation can introduce principles of special education and family engagement, collaborative competence involves relational and situated forms of professional learning that are difficult to develop through coursework alone. The findings therefore reinforce the need for teacher education programmes to create structured opportunities through which pre-service teachers can engage with families, reflect on these interactions, and learn how to respond to different parental perspectives and circumstances. Such opportunities may help bridge the distinction between knowing about collaboration and being able to enact collaborative practice in authentic educational contexts (Eggen & Kauchak, 2016; Sutton et al., 2020).

Participants' preference for face-to-face interaction provides an additional insight into the relational dimension of collaboration. They perceived in-person communication as facilitating clearer understanding and making it easier to discuss and agree on ways of supporting children. This finding should not be interpreted as evidence that face-to-face communication is inherently more effective than digital or other forms of communication, since communication modes were not systematically compared in this study. Rather, it indicates how these pre-service teachers perceived relational quality within their own experiences. For teacher education, the implication is therefore not to privilege one communication mode universally, but to prepare pre-service teachers to consider how different forms of communication may facilitate or constrain mutual understanding according to the circumstances and needs of individual families.

Preparedness also appeared to extend beyond the individual competence of the pre-service teacher. Participants expressed a need for guidance from university supervisors and opportunities to consult professionals, including medical specialists, when working with complex cases. This finding is consistent with literature emphasising the importance of collaboration across professional domains in supporting learners with SEN (Jones & Peterson-

Ahmad, 2017). Rather than interpreting the need for such support as evidence of individual deficiency, it may be more appropriate to understand these participants as developing professionals whose judgement is strengthened through access to mentoring and interdisciplinary expertise. Preparedness for parent collaboration should therefore not be conceptualised solely as an attribute possessed by an individual teacher; it is also developed through participation in networks of professional guidance, supervision, and interdisciplinary support.

It is also noteworthy that school leadership and school-level structures were not prominent in participants' accounts of parent collaboration. This absence should not be interpreted as evidence that institutional support was unavailable or unimportant, particularly because the study did not specifically investigate school leadership. Nevertheless, it raises a relevant question concerning the extent to which pre-service teachers perceive family collaboration as an individual professional responsibility rather than as a practice supported systematically by schools. Previous research has suggested that administrative support and institutional resources can influence collaboration among teachers, parents, and other professionals (Murray et al., 2013). In the Thai context, where the implementation of inclusive educational practices may vary across settings, future research should examine more directly how school structures and leadership practices enable or constrain opportunities for pre-service teachers to work collaboratively with families.

Overall, the findings make three interrelated contributions. Empirically, the study provides insight into the experiences of pre-service special education teachers, a group whose perspectives on parent collaboration warrant greater attention during the transition from university learning to professional practice. Contextually, the findings demonstrate that collaboration is shaped by relational, socio-economic, and structural conditions rather than by communication skills alone. Pedagogically, the findings suggest that collaboration with families should not be treated as an implicit expectation that pre-service teachers will naturally acquire during field experience. Instead, collaborative competence should be intentionally developed through structured opportunities for authentic family engagement, guided reflection, professional mentoring, and interdisciplinary support. Teacher education programmes may therefore need to position family collaboration as an explicit professional learning outcome that is taught, practised, supported, and reflected upon throughout pre-service preparation.

Conclusion

This study explored pre-service special education teachers' experiences of collaborating with parents to support children with SEN. The findings showed that parent engagement provided

contextual and experiential knowledge that extended pre-service teachers' understanding of children beyond university coursework and classroom observation. However, collaboration was constrained by limited communication, differences between professional and parental knowledge, and socio-economic circumstances affecting family participation.

A key conclusion is that parent engagement is not merely a means of obtaining information about children but also an important context for pre-service teachers' professional learning. Collaborative competence requires pre-service teachers to integrate their developing professional knowledge with parents' experiential understanding of their children while responding sensitively to individual family circumstances.

Teacher education programmes should therefore position parent collaboration as an explicit component of professional preparation rather than an implicit competence expected to develop naturally during field experience. Structured opportunities for authentic parent engagement, guided reflection, mentoring, and interdisciplinary support may help pre-service teachers bridge the gap between university preparation and the relational and collaborative demands of professional practice.

References

Accardo, A. L., Xin, J. F., & Shuff, M. (2020). Special education teacher preparation and family collaboration. *School Community Journal, 30*(2), 53–72.

Bolat, Y. (2019). A phenomenological investigation with prospective teachers of special education: If it was me! *International Journal of Educational Methodology, 5*(4), 607–622.

Clarke, V., & Braun, V. (2017). Thematic analysis. *The Journal of Positive Psychology, 12*(3), 297–298.

Deniz, S., & İlik, Ş. Ş. (2021). The professional competence of teachers in inclusive practice and their advice for prospective teachers. *Asian Journal of Contemporary Education, 5*(2), 57–74.

Eggen, P. D., & Kauchak, D. P. (2016). *Educational psychology: Windows on classrooms* (10th ed.). Pearson.

Erdem, H. Ş. (2020). Perspectives of volunteer pre-service teachers and parents on a summer program for children with autism spectrum disorders. *European Journal of Special Education Research, 6*(2), 1–22.

George, C. L., & Kanupka, J. W. (2019). Educating pre-service teachers on fathers' involvement in raising children with disabilities. *International Journal of Special Education, 34*(1), 51–67.

Greenbank, A. (2023). "Now I feel that the parents are partners and not enemies": Training preservice teachers to work in partnership with parents of students with disabilities. *School Community Journal, 33*(2), 97–114.

Gunpinar, Y., & Mackin, R. K. (2020). What teacher candidates have to say: Analyzing perceptions of program effectiveness across 14 universities. *AILACTE Journal, 17*, 23–48.

Gyimah, E. K., & Amoako, R. (2016). Pre-service teachers' perceptions on procedures to identify and assess children with special educational needs and disabilities. *Journal of Education and Practice, 7*(21), 110–118.

Ibrahim, A. (2020). Practicum students' views about field experience program for children with autism spectrum disorders. *International Journal of Education and Practice, 8*(3), 457–469.

Jones, B. A., & Peterson-Ahmad, M. B. (2017). Preparing new special education teachers to facilitate collaboration. *International Journal of Special Education, 32*(4), 697–707.

Karabulut, A. (2021). Investigation of special education teachers' concern levels regarding their children. *International Electronic Journal of Elementary Education, 13*(4), 535–548.

McBride Pinheiro, B., McDermott-Fasy, C., Imber, S., & LaCava, P. G. (2022). How one teacher preparation program addressed its students' needs during the "new normal." *Thresholds, 45*(1), 19–40.

McDevitt, S. E., & Mello, M. P. (2021). From crisis to opportunity: Family partnerships with special education preservice teachers. *School Community Journal, 31*(2), 325–346.

Murray, M. M., Handyside, L. M., Straka, L. A., & Arton-Titus, T. V. (2013). Parent empowerment: Connecting with preservice special education teachers. *School Community Journal, 23*(1), 145–168. https://files.eric.ed.gov/fulltext/EJ1005865.pdf

Pansé-Barone, C., George-Puskar, A., & Bensaid, B. J. (2024). Addressing students' beliefs to enhance family-professional collaboration. *Journal of Special Education Preparation, 4*(1), 48–56.

Phiukhao, P., Poovatnakul, V., Meekhun, K., & Wattananarong, A. (2025). The success factors of teachers' mainstreaming education management. *Journal of Academic for Public and Private Management, 7*(1), 29–40.

Sutton, K. K., Lewis, K. D., & Beauchat, K. A. (2020). The role of teacher preparation programs in fostering preservice teachers' ability to engage with families. *School Community Journal, 30*(2), 39–52.

Toncharoen, R., Trairatanasuwan, P., Trakulbangkla, P., Jongjairak, Y., Teerapuk, N., Sakunkoljak, Y., & Roonnajak, C. (2025). Teacher development through coaching and mentoring processes. *Journal of Education, Bansomdejchaopraya Rajabhat University, 19*(2), 97–112.

Vorapanya, S., & Pachanavon, A. (2025). The shifted perspectives from an era of change: Inclusive education in Thailand. *Valaya Alongkorn Review Journal, 15*(1), 239–254.

Woolfolk, A. (2018). *Educational psychology* (14th ed.). Pearson.

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Growth Mindset and Techno-Solutionist Thinking among Graduate Students: The Mediating Role of Trust in AI

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Abstract

The integration of artificial intelligence (AI) into graduate education raises questions about the psychological dispositions associated with preferences for technological solutions. This study examined whether trust in AI statistically accounts for part of the association between growth mindset and techno-solutionist thinking among 323 master's and doctoral students at a private higher education institution in the southern Philippines. A cross-sectional correlational survey used established and adapted measures of the three constructs. Composite reliability was high (Cronbach's α = .920–.976), although confirmatory factor analysis of the adapted Techno-Solutionist Thinking Scale indicated marginal support for its two-factor structure (CFI = .917; TLI = .899; RMSEA = .092). Growth mindset was positively correlated with trust in AI (r = .459) and techno-solutionist thinking (r = .536), while trust in AI was positively correlated with techno-solutionist thinking (r = .624). PROCESS Model 4 with 5,000 bootstrap resamples identified a significant indirect association through trust in AI (B = 0.234, 95% bootstrap CI [0.163, 0.307]); the direct association remained significant (B = 0.335, p < .001). The outcome model explained 46.9% of observed variance. Trust in AI was treated as an AI-specific construct, not a comprehensive measure of technology readiness or over trust. These findings support an initial empirical model in which adaptive learning beliefs coexist with stronger technology-centered solution preferences. The cross-sectional design does not establish a causal or developmental pathway. Graduate programs should pair openness to AI with critical literacy, ethical reflection, and consideration of non-technological alternatives.

Keywords: growth mindset; trust in AI; techno-solutionist thinking; graduate education; critical AI literacy

Introduction

Digital technologies increasingly influence how research problems are framed and how scholarly work is organized. Critical scholarship examines the values and priorities embedded in these changes, including the emphasis placed on innovation, efficiency, and data-driven

decision-making (Slaughter & Rhoades, 2004; Williamson, 2017; Selwyn, 2022). In graduate education, AI tools can support information retrieval, writing, analysis, and research planning. Their availability, however, does not establish their suitability for every educational, organizational, or social problem.

A growth mindset reflects the belief that abilities can be developed through effort, learning, and appropriate strategies (Dweck, 2006). It can support persistence and willingness to engage with unfamiliar approaches. Trust in AI concerns confidence in systems that may assist users under uncertainty. Both dispositions are relevant to graduate students, whose theses and dissertations require independent judgment about theoretical perspectives, methods, and proposed interventions. Openness to technology and confidence in its usefulness nevertheless differ from a considered judgment about whether technology addresses the causes of a problem.

Techno-solutionism refers to a preference for technological responses to problems that may also require social, organizational, ethical, or policy-based action. Morozov (2013) critiques the reduction of complex problems to narrowly technical challenges. Nagpal et al. (2025) provide an empirical operationalization of techno-solutionism through near-term and long-term orientations. Applying this construct to graduate research allows examination of technology-centered preferences without assuming that all technology use is uncritical or that positive attitudes necessarily produce inappropriate reliance.

This study builds on the authors' earlier investigation of growth mindset and AI-related readiness perceptions among postgraduate students (Labis et al., 2025). The present inquiry extends attention to techno-solutionist thinking. It asks whether stronger growth-oriented beliefs and trust in AI coexist with a stronger preference for technological solutions, and whether trust statistically accounts for part of the growth mindset–techno-solutionism association.

The Philippine graduate-school setting is relevant because research proposals must address locally situated problems whose causes may include resource constraints, institutional practices, relationships, or cultural conditions. A technological intervention may assist with a task without resolving those broader conditions. Graduate research formation is therefore an appropriate setting for examining how learning beliefs and AI confidence relate to problem-solving preferences. Institutional innovation pressures and adviser expectations are plausible contextual influences, but they were not measured in this study.

The contribution is an initial empirical model at the intersection of educational psychology, AI trust, and critical technology studies. The study does not establish that growth mindset develops into techno-solutionism or causes harmful research practices. Rather, it examines

whether adaptive learner dispositions are associated with technology-centered preferences and identifies implications for research methods training, supervision, and critical AI literacy.

Theoretical Framework

The study integrates growth mindset theory, scholarship on trust in automation, and critical technology perspectives. Dweck (2006) provides the motivational basis for understanding receptiveness to learning, while Lee and See (2004) explain trust as relevant to reliance on systems under uncertainty. Morozov (2013), Winner (1986), and Feenberg (1991, 2002) provide a critical basis for examining the assumptions embedded in technological choices.

Morozov's critique directs attention to whether technical problem definitions neglect structural or political dimensions. Winner's account of the politics of technology highlights how artifacts may embody arrangements of authority and power. Feenberg's critical theory explains how social values and interests become embedded in technical codes and argues for more democratic engagement with technological design. Applied to graduate education, these perspectives encourage scrutiny of whose problem is being addressed, which alternatives are considered, and which stakeholders may be affected. These applications inform interpretation; they are not empirically tested institutional effects in the present study.

Nagpal et al. (2025) complement these critiques by conceptualizing techno-solutionism as a measurable belief orientation. Their near-term and long-term dimensions provide the operational basis for the adapted outcome measure. The present study therefore combines an individual-level associational model with critical perspectives that guide questions about research judgment, rather than treating a statistical mediation result as proof of an institutional mechanism.

Related Literature and Conceptual Framework

Growth mindset and technology engagement

Growth mindset theory emphasizes beliefs about the malleability of ability and adaptive responses to challenge (Dweck, 2006; Yeager & Dweck, 2012). Claro et al. (2016) found an association between growth mindset and academic achievement in a large Chilean student sample, with particular relevance to socioeconomic disadvantage. This evidence concerns learning and achievement rather than AI trust, but it supports examining growth-oriented beliefs in unfamiliar learning contexts.

Chen and Yi (2024) found that people with growth mindsets were more inclined to anthropomorphize AI-enabled technologies; openness to experience and reduced perceived threat helped account for this pattern. Their findings concern consumers and AI perceptions, not the present graduate-student mediation model. They nevertheless suggest that mindset may be relevant to how people interpret and engage with AI. Earlier research in the authors'

graduate-school context also reported a positive association between growth mindset and trust in AI (Labis et al., 2025). These findings motivate, rather than establish, the proposed association in the present study.

Trust in AI and technology readiness

Trust in automation concerns expectations that a system can support goal achievement under conditions of uncertainty (Lee & See, 2004). Schaefer et al. (2016) identify factors associated with trust, and Kohn et al. (2021) review the range of measures used to assess it. Hoffman et al. (2018) emphasize evaluation of explanations and appropriate trust in explainable AI. Together, these perspectives support distinguishing perceived competence and reliability from actual reliance and objective system performance.

Technology readiness is broader than AI trust. Parasuraman's (2000) Technology Readiness Index comprises optimism, innovativeness, discomfort, and insecurity. The present study did not administer this index. Trust in AI is treated as the measured mediator and, only in a narrow conceptual sense, as a proxy for one readiness-related psychological orientation. It does not measure general digital competence, all dimensions of readiness, actual AI use, or trust calibration.

Trust is also distinct from overtrust. Overtrust entails confidence or reliance exceeding what system performance and task risk warrant. Because no external performance benchmark was included, high reported trust cannot demonstrate inappropriate reliance. A user may trust an AI tool while checking its outputs and rejecting its use when a task requires other forms of judgment or intervention.

Trust in AI and techno-solutionist thinking

Trust in AI concerns confidence in a system's capability and usefulness; techno-solutionist thinking concerns the broader preference for technological solutions. Nagpal et al. (2025) distinguish confidence in current technologies' capacity to address immediate problems from confidence that future technological progress can address broader societal challenges. The adapted scale situates these orientations within graduate research, particularly theses and dissertations.

Reasonable technological optimism recognizes a tool's potential when evidence and context support its use. A techno-solutionist orientation gives technology presumptive priority, potentially overlooking non-technological alternatives. Actual overreliance would require evidence from choices or behavior. The present measure assesses endorsement of technology-centered solutions rather than diagnoses deficient reasoning. Selwyn (2022) similarly encourages attention to AI's actual capacities, social contexts, and value-laden claims rather than speculative promises.

Conceptual gap and proposed model

The empirical gap concerns the joint associations among growth mindset, AI-specific trust, and techno-solutionist thinking in graduate students. The proposed model specifies growth mindset as X, trust in AI as M, and techno-solutionist thinking as Y. It retains both a direct X–Y association and an indirect association through M. Program type is examined only through supplementary mean comparisons and is not a moderator or proxy for institutional culture. Arrow direction represents the proposed statistical model, not demonstrated temporal ordering.

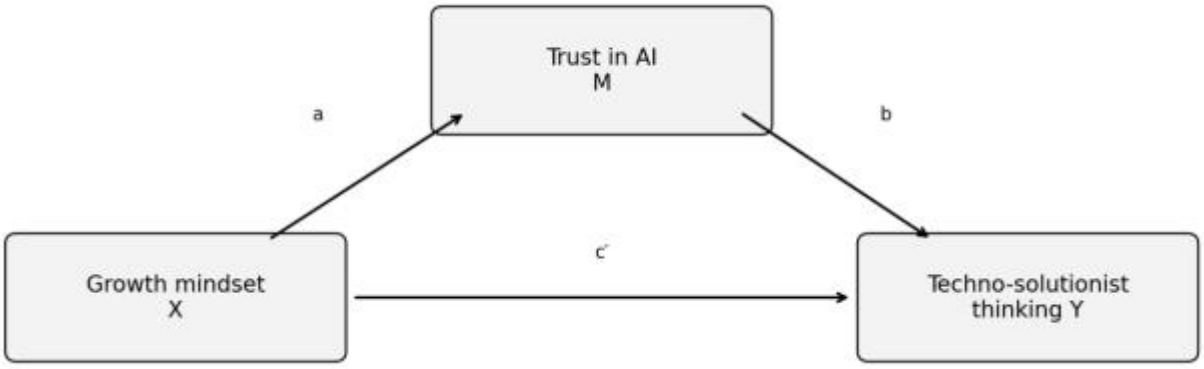


Figure 1. Proposed associational model. Growth mindset is X, trust in AI is M, and techno-solutionist thinking is Y. The a and b paths form the indirect association; c′ is the direct association. Arrows do not establish causality.

Study Objectives

The study aimed to describe the three constructs, estimate their associations, and examine whether trust in AI statistically accounts for part of the association between growth mindset and techno-solutionist thinking among graduate students. Supplementary analyses explored mean differences between master's and doctoral students. The proposed indirect association was evaluated through a bootstrap confidence interval.

Methodology

The study employed a quantitative cross-sectional correlational design. Descriptive statistics summarized the constructs, Pearson correlations described their bivariate associations, and PROCESS Model 4 estimated a statistical indirect association (Hayes, 2022). All variables were measured at one time point without experimental manipulation. Mediation is therefore interpreted associationally rather than causally.

Participants and sampling

The analytic sample comprised 323 graduate students from a private higher education institution in the southern Philippines: 225 master's students (69.7%) and 98 doctoral students (30.3%). The enrolled graduate population was 881, including 669 master's and 212 doctoral students. Recruitment used an online survey distributed with assistance from program coordinators and graduate school offices. Participation depended on voluntary response; the realized sample was therefore a nonprobability voluntary-response sample.

Respondents represented 36.7% of the enrolled population. This figure indicates sample coverage rather than a formal response rate because invitation exposure was not documented. Program-specific coverage was 33.6% for master's students and 46.2% for doctoral students. Participant description in the analysis was limited to program type. The sample cannot be assumed to represent the population's demographic or disciplinary distribution.

Measures

Growth mindset was assessed using the English version of the Growth Mindset Test attributed to Wisessathorn et al. (2022), administered without modification. The measure contains 37 items across three reported domains: Positive Attitude and Optimism (21 items), Confidence in Self-Development (10 items), and Recognizing the Value of Intellectual Growth (6 items). Item content concerns beliefs that ability can develop through effort and continued learning. Final-sample total-scale internal consistency was $\alpha = .976$. Final-sample domain reliability coefficients are not reported.

Trust in AI was assessed with the previously adapted 10-item measure used in the authors' earlier graduate-student research (Labis et al., 2025), drawing conceptually on Schaefer et al. (2016) and Hoffman et al. (2018). It addresses confidence in AI competence and reliability, understandability and transparency, and willingness to rely on AI-supported academic decisions. Representative content concerns confidence in decisions informed by an AI system's explanations. This description paraphrases item content rather than quotes an administered item. Total-scale reliability was $\alpha = .920$.

Techno-solutionist thinking was assessed using the 14-item Techno-Solutionist Thinking Scale (TSTS), adapted with permission from Nagpal et al. (2025). Near-Term Techno-solutionism (NTS) comprised 10 items concerning current technological solutions to immediate graduate-research problems; Long-Term Techno-solutionism (LTS) comprised four items concerning expectations that future technology will address broader educational or social problems. These descriptions summarize content rather than reproduce item wording. Adaptation followed Beaton et al. (2000), reformulating contexts for Philippine graduate education. All three measures used a four-point agreement scale, from 1 (strongly disagree) to 4 (strongly agree). The analysis used overall composite scores on this response metric.

TSTS adaptation and measurement evidence

Nine experts evaluated the 14 adapted items. I-CVI values ranged from .778 to 1.000, and S-CVI/Ave was .921. A pilot with 34 graduate students yielded α = .903 for NTS and α = .828 for LTS. In the full sample, total-scale reliability was α = .924. Pilot subscale estimates are distinct from final-sample composite reliability and do not establish structural stability.

A two-factor CFA using maximum likelihood estimation yielded $\chi^2(75) = 281.22$, $p < .001$; $\chi^2/df = 3.75$; CFI = .917; IFI = .917; TLI = .899; NFI = .891; GFI = .878; AGFI = .830; and RMSEA = .092, 90% CI [.081, .104]. These indices provide mixed evidence: CFI and IFI exceeded .90, but other indices and the elevated RMSEA indicate marginal fit. The two-factor structure remains provisional. High alpha cannot compensate for structural misfit, and aggregate fit indices do not identify specific items for deletion.

The mediation model used an overall TSTS composite despite the two-factor measurement model. Further validation should determine whether a higher-order or other total-score structure is warranted, or whether the two dimensions should be modeled separately. Item refinement requires examination of wording, standardized loadings, residuals, and factor overlap, followed by independent replication. An ordinal estimator would also be useful given the four-category responses.

Data collection and ethics

The composite questionnaire was administered online through a secure survey platform. Participants viewed an informed-consent statement before proceeding, and participation was voluntary. The institutional Research Ethics Board reviewed and approved the protocol before content validation and data collection.

Statistical analysis

Descriptive statistics, total-scale Cronbach's alpha estimates, Pearson correlations, and independent-samples comparisons by program type preceded mediation analysis. Welch's adjusted test was used for growth mindset because Levene's test indicated unequal variances. Program comparisons were exploratory and did not estimate interactions or moderated mediation.

PROCESS Model 4 used 5,000 bootstrap resamples. Growth mindset was X, trust in AI was M, and techno-solutionist thinking was Y. A 95% bootstrap confidence interval excluding zero indicated a statistically significant indirect association. Approximate standardized slopes were calculated by multiplying each unstandardized coefficient by the predictor SD and

dividing by the outcome SD. Because these conversions use rounded summary values, they are not newly estimated standardized PROCESS output.

The predictor correlation of r = .459 implies approximate tolerance = .789 and VIF = 1.27 in the two-predictor outcome model, suggesting little collinearity. These are calculations from the reported correlation rather than case-level diagnostics. Bootstrap inference accommodates a nonnormal sampling distribution of the indirect estimate but does not establish linearity, homoscedasticity, residual adequacy, independence, or absence of influential observations. These diagnostics and robust-inference sensitivity require case-level evaluation.

Results

Participant profile

Table 1. *Participant characteristics by program type*

Program	n	Sample %	Population n	Coverage %
Master's	225	69.7	669	33.6
Doctoral	98	30.3	212	46.2
Total	323	100.0	881	36.7

Note. Coverage = sample n ÷ population n. Coverage is not a verified response rate.

Master's students constituted the majority of respondents. Doctoral students represented 30.3% of the sample compared with 24.1% of the population, indicating higher participation relative to program size.

Descriptive statistics reliability and correlations

Table 2. *Means standard deviations reliability and Pearson correlations*

Variable	M	SD	α	1	2	3
1. Growth mindset	3.56	.408	.976	—		
2. Trust in AI	3.08	.512	.920	.459**	—	
3. Techno-solutionist thinking	3.34	.434	.924	.536**	.624**	—

Note. N = 323; ** p < .01. Alpha values refer to final-sample overall composites.

All three composites showed high internal consistency, although the growth mindset estimate merits examination for possible item redundancy. Growth mindset correlated positively with trust in AI and techno-solutionist thinking; trust was also positively correlated with techno-solutionist thinking. The mean TSTS score of 3.34 indicates endorsement of the adapted

statements. No validated normative or behavioral cutoff was established, so this score cannot identify a problematic level of reliance.

Supplementary program comparisons

Table 3. *Exploratory mean comparisons by program type*

Variable	Master's M (SD)	Doctoral M (SD)	t (df)	p	g
Growth mindset	3.53 (.43)	3.63 (.36)	2.14 (216.29)	.033	.24
Trust in AI	3.07 (.51)	3.10 (.52)	0.51 (321)	.610	.06
Techno-solutionist thinking	3.32 (.43)	3.41 (.44)	1.69 (321)	.092	.21

Note. Master's n = 225; doctoral n = 98. Growth mindset uses the reported Welch test. Absolute t and reported Hedges' g magnitudes are shown; p values are unadjusted.

Doctoral students reported slightly higher growth mindset scores, with a small, reported effect. Levene's $F = 4.07$, $p = .044$ supported the Welch comparison. The trust and techno-solutionist thinking comparisons did not reach $p < .05$. Non significance does not establish equivalence. The growth mindset difference is exploratory and would not meet a Bonferroni threshold of .0167 for three comparisons. These tests do not assess program differences in mediation paths.

Statistical mediation

Table 4. *Mediator model predicting trust in AI*

Predictor	B	β approx.	SE	t	95% CI
Constant	1.028	—	.223	4.617	[.590, 1.467]
Growth mindset	.576	.459	.062	9.267	[.454, .698]

Note. Both $p < .001$. $R^2 = .211$; $F(1, 321) = 85.87$, $p < .001$. B and CI are unstandardized; β is an approximate conversion.

Growth mindset was positively associated with trust in AI (path a, B = .576). The mediator model explained 21.1% of observed variance in trust.

Table 5. *Outcome model predicting techno-solutionist thinking*

Predictor	B	β approx.	SE	t	95% CI
Constant	.902	—	.160	5.634	[.587, 1.217]
Growth mindset c′	.335	.315	.049	6.880	[.239, .431]
Trust in AI b	.406	.479	.039	10.449	[.329, .482]

Note. All $p < .001$. $R = .685$; $R^2 = .469$; $F(2, 320) = 141.06$, $p < .001$.

Both growth mindset and trust retained positive associations with techno-solutionist thinking when modeled together. Trust had the larger standardized slope, although the difference between slopes was not formally tested. The model accounted for 46.9% of observed variance; this is an in-sample statistic rather than evidence of out-of-sample prediction or intervention effectiveness.

Table 6. *Direct indirect and total associations*

Association	B	SE	SE type	95% CI
Direct c′	.335	.049	OLS	[.239, .431]
Indirect a × b	.234	.037	Bootstrap	[.163, .307]
Total c	.569	.051	OLS	—

Note. The indirect CI uses 5,000 bootstrap resamples; the direct CI is the regression CI. The total-association CI is not reported.

The indirect association was significant (B = .234, 95% bootstrap CI [.163, .307]). The direct association remained significant, consistent with partial statistical mediation. Approximately 41.1% of the fitted total association (.234/.569) was represented by the indirect component. This ratio describes an associational decomposition, not a proportion of causal change transmitted through trust.

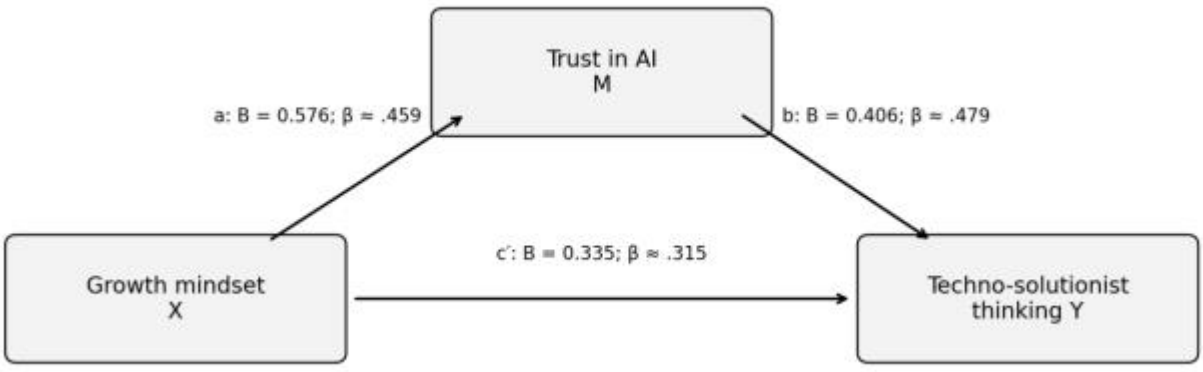


Figure 2. *Estimated cross-sectional model. All component slopes $p < .001$. Indirect B = .234, 95% bootstrap CI [.163, .307]; total B = .569. Standardized slopes are approximate conversions. Arrows do not establish temporal ordering.*

Discussion

The study provides initial empirical evidence that Growth Mindset, Trust in AI, and Techno-Solutionist Thinking are positively related in this graduate-student sample. The results

support the hypothesized statistical model: Growth Mindset was positively associated with Trust in AI, both Growth Mindset and Trust in AI were positively associated with Techno-Solutionist Thinking, and the bootstrapped indirect effect through Trust in AI was statistically significant. These findings should be read as a pattern of cross-sectional associations, not as evidence that one construct develops into another over time.

The positive Growth Mindset–Trust in AI association is consistent with the idea that students who view competence as improvable may approach unfamiliar tools as learnable rather than fixed barriers. This interpretation fits Dweck's (2006) emphasis on adaptive responses to challenge and emerging research showing links between growth-oriented beliefs and engagement with AI. However, the present design cannot determine whether Growth Mindset increases Trust in AI, whether trusting AI reinforces confidence in learning new technologies, or whether both are shaped by other factors such as prior AI experience, digital competence, or program culture.

Trust in AI had the larger standardized slope of Techno-Solutionist Thinking in the outcome model. This pattern is theoretically relevant because it separates confidence in an AI system from the broader judgment that technological solutions should be favored. Trust is not inherently problematic, and the present Trust in AI measure does not assess overtrust. A well-calibrated user can trust an AI tool while continuing to verify outputs, recognize limitations, and reject the tool when the task requires human, organizational, policy, or relational responses. The observed association therefore suggests that stronger AI confidence co-occurs with stronger technology-centered solution preferences, not that respondents necessarily rely on AI beyond its capabilities.

The mean TSTS score of 3.34 on a 4-point scale likewise requires careful interpretation. It indicates relatively strong endorsement of the adapted statements in this sample, but the TSTS has no validated cut point that defines 'problematic' techno-solutionism. The mean should therefore be treated as descriptive evidence of a relatively technology-favorable orientation rather than a diagnosis of uncritical dependence. The marginal CFA fit further strengthens the need for caution because measurement error or incomplete factor specification may affect the estimated relationships.

The significant indirect effect is consistent with the possibility that Trust in AI statistically accounts for part of the association between Growth Mindset and Techno-Solutionist Thinking. It does not demonstrate a developmental sequence. Longitudinal or experimental data would be needed to establish temporal ordering, and even longitudinal mediation would require strong assumptions about confounding. The continued direct association of Growth Mindset with Techno-Solutionist Thinking also indicates that Trust in AI does not exhaust the relationship between the constructs.

Critical technology perspectives help interpret these associations, but they should not be treated as measured institutional effects. Morozov (2013), Winner (1986), Feenberg (1991, 2002), and Slaughter and Rhoades (2004) provide theoretical reasons to consider how innovation cultures, academic incentives, and technical priorities may shape research choices. The present study, however, did not directly measure adviser expectations, institutional AI policy, academic capitalism, thesis-review norms, or program culture. Any reference to 'AI-rich institutional conditions' is therefore contextual interpretation rather than an empirically tested institutional mechanism.

The supplementary master's–doctoral comparisons describe group means rather than establish sensitivity of the mediation estimates. Doctoral students showed a small difference in Growth Mindset, whereas Trust in AI and Techno-Solutionist Thinking did not differ significantly by program. Because no subgroup mediation or interaction terms were estimated, these findings cannot be used to claim that program type moderates the mediation model. Future work with larger and more balanced program groups should test measurement invariance first and then formally evaluate moderated mediation if theory supports it.

Implications for Graduate Education

The findings support examining how graduate education can pair the benefits of a growth mindset with critical AI engagement. They do not show that growth mindset or trust is undesirable, nor establish the effectiveness of a particular intervention. For the higher education institution and comparable institutions, the following practices are proposed for piloting and evaluation.

Research methods and critical AI literacy

Research methods courses can integrate a short AI ethics and critical literacy module covering output verification, fabricated references, bias, privacy, methodological fit, and researcher accountability. Case exercises should require students to compare technological and non-technological responses to the same problem. Assessment should reward the quality of problem analysis and justification rather than novelty or the amount of AI used.

Proposal review and supervision

Thesis and dissertation proposals can include an explicit technology-justification statement. Students should explain the problem's causes, show why a proposed tool is suitable, compare at least one feasible non-technological alternative, and identify affected stakeholders. Panels can ask what would remain unresolved if the tool performed exactly as intended. A proposal rubric can include contextual fit, ethical justification, feasibility, alternative analysis, and human accountability.

Faculty development can use sample proposals to help mentors distinguish methodological suitability from convenience and technological enthusiasm. Supervisors can ask students to explain why an AI contribution was accepted or rejected, verify the supporting evidence, and demonstrate understanding of analysis decisions. These practices preserve experimentation while keeping scholarly judgment with the student.

Reflection and institutional AI governance

An AI-use reflection statement can document tools used, purposes, verification steps, rejected outputs, limits, and decisions retained by the researcher. Such statements should support honest reflection and should not be treated as proof of misconduct merely because AI was used. Institutional guidance can clarify permitted uses, disclosure expectations, handling of sensitive information, human verification, and routes for consultation.

Institutional research offices can evaluate these practices through consented feedback and consistent assessment of proposal justification before and after a pilot. Evaluation should examine source accuracy, consideration of alternatives, contextual reasoning, and unintended burdens. The adapted TSTS should not be used as an individual screening threshold or a substitute for reviewing actual research decisions.

Limitations and Future Research

Several limitations constrain interpretation. First, the study is cross-sectional. PROCESS Model 4 decomposes observed associations into direct and indirect components, but it cannot establish temporal ordering or causality. Longitudinal panel designs, cross-lagged approaches, and appropriately designed interventions are needed to examine temporal ordering, reciprocal relationships, and competing directional models among the three constructs.

Second, the sample came from one private higher education institution in the southern Philippines and was obtained through voluntary online participation. The sample represented 36.7% of the enrolled graduate population, but a formal response rate cannot be calculated from the retained records because invitation exposure was not documented. Generalization to public institutions, other Philippine regions, other countries, or disciplinary contexts should therefore be made cautiously. Multi-institution studies should use clearer sampling frames and report invitation, eligibility, and completion counts.

Third, participant description was limited to program type. Future studies should report relevant characteristics such as discipline, age group, gender, professional status, prior AI use, AI training, and research stage when ethically appropriate. These variables may help explain heterogeneity in trust and solution preferences.

Fourth, all focal variables were collected through the same self-report survey at one time point. Social desirability, acquiescence, consistency motives, and other common-method processes may affect observed correlations. The study did not include a marker variable, temporal separation, multiple informants, or behavioral measures, so common method bias cannot be ruled out. Future research should combine self-report with behavioral indicators such as verification behavior, tool-choice tasks, proposal content coding, or supervisor ratings.

Fifth, Trust in AI is a narrow AI-specific construct and should not be treated as a comprehensive measure of technological readiness. The study also did not directly assess overtrust or trust calibration. Future research should distinguish appropriate trust, distrust, overtrust, actual reliance, and verification behavior and should compare Trust in AI with established multidimensional readiness measures.

Sixth, although the TSTS demonstrated strong internal consistency and favorable aggregate content-validity evidence, the CFA showed mixed and only marginally acceptable fit. The adapted two-factor structure therefore remains provisional. Multi-institution validation should report standardized loadings, residuals, factor correlations, composite reliability, average variance extracted, HTMT or comparable discriminant-validity evidence, and measurement invariance across program types and institutions. Item revision should be guided by theory together with loading, residual, and modification-index evidence rather than by fit improvement alone.

Seventh, the very high total Growth Mindset reliability estimate ($\alpha = .976$) may reflect strong coherence but may also indicate redundant item content. Future psychometric work should examine item-total correlations, McDonald's omega, and whether a shorter form retains adequate construct coverage.

Eighth, institutional pressure and research culture were theoretically discussed but not directly measured. Future models should examine adviser influence, thesis-panel expectations, institutional AI policy, innovation climate, research incentives, and critical AI literacy as potential antecedents, moderators, or contextual covariates. Qualitative interviews and analysis of thesis proposals would be especially useful for understanding how graduate students justify technology-based solutions and how those justifications change during supervision.

Finally, because program type was not modeled as a moderator, the present master's–doctoral analysis should be regarded only as supplementary. Future studies with adequate subgroup sample sizes can test measurement invariance followed by moderated mediation or multigroup structural models.

Additional limitations concern the absence of final-sample subscale reliability reporting and case-level regression diagnostics. Future studies should document missing-data handling, inspect residual and influence patterns, and evaluate robust inference when indicated. Program-specific indirect associations require formal estimation; mean comparisons alone cannot establish their stability. Measurement invariance should precede comparisons of latent means or structural paths.

Conclusion

This study tested an initial cross-sectional model linking Growth Mindset, Trust in AI, and Techno-Solutionist Thinking among graduate students. Growth Mindset was positively associated with Trust in AI and with Techno-Solutionist Thinking, while Trust in AI was also positively associated with Techno-Solutionist Thinking. A significant bootstrapped indirect effect showed that Trust in AI statistically accounted for part of the Growth Mindset–Techno-Solutionist Thinking association. Because the data were collected at one time point, this pattern should not be interpreted as a developmental or causal pathway.

The main educational implication is not that Growth Mindset or trust in AI is undesirable. Rather, graduate education should pair openness to learning and technological experimentation with critical AI literacy, calibrated trust, ethical reflection, and explicit consideration of non-technological alternatives. Such an approach preserves the adaptive value of a Growth Mindset while strengthening students' capacity to judge when technology is genuinely appropriate for the problem they are trying to solve.

References

Beaton, D. E., Bombardier, C., Guillemin, F., & Ferraz, M. B. (2000). Guidelines for the process of cross-cultural adaptation of self-report measures. *Spine, 25*(24), 3186–3191. https://doi.org/10.1097/00007632-200012150-00014

Chen, Q. Q., & Yi, Y. (2024). Mindsets and mirrors: How growth mindsets shape anthropomorphism in AI-enabled technologies. *Psychology & Marketing, 41*(12), 3072–3090. https://doi.org/10.1002/mar.22108

Claro, S., Paunesku, D., & Dweck, C. S. (2016). Growth mindset tempers the effects of poverty on academic achievement. *Proceedings of the National Academy of Sciences, 113*(31), 8664–8668. https://doi.org/10.1073/pnas.1608207113

Dweck, C. S. (2006). *Mindset: The new psychology of success*. Random House.

Feenberg, A. (1991). *Critical theory of technology*. Oxford University Press.

Feenberg, A. (2002). *Transforming technology: A critical theory revisited*. Oxford University Press.

Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach (3rd ed.)*. The Guilford Press.

Hoffman, R. R., Mueller, S. T., Klein, G., & Litman, J. (2018). Metrics for explainable AI: Challenges and prospects [Preprint]. arXiv. https://doi.org/10.48550/arXiv.1812.04608

Kohn, S. C., de Visser, E. J., Wiese, E., Lee, Y.-C., & Shaw, T. H. (2021). Measurement of trust in automation: A narrative review and reference guide. *Frontiers in Psychology, 12*, Article 604977. https://doi.org/10.3389/fpsyg.2021.604977

Labis, F. A., Cunanan, G. M., & Opina, M. F. D. (2025). Growth mindset and the psychology of AI readiness among postgraduate students. *Annual SEAAIR Conference Proceedings, 5*, 412–422. South East Asian Association for Institutional Research. https://seaairweb.info/conference/2025Proceedings.pdf

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors, 46*(1), 50–80. https://doi.org/10.1518/hfes.46.1.50_30392

Morozov, E. (2013). *To save everything, click here: The folly of technological solutionism*. PublicAffairs.

Nagpal, M., De Cremer, D., & Van Hiel, A. (2025). Is technology uniquely placed to solve our problems? An examination into techno-solutionism, what it entails and what it predicts. *Business & Society, 64*(5), 933–967. https://doi.org/10.1177/00076503241271298

Parasuraman, A. (2000). Technology readiness index (TRI): A multiple-item scale to measure readiness to embrace new technologies. *Journal of Service Research, 2*(4), 307–320. https://doi.org/10.1177/109467050024001

Schaefer, K. E., Chen, J. Y. C., Szalma, J. L., & Hancock, P. A. (2016). A meta-analysis of factors influencing the development of trust in automation: Implications for understanding autonomy in future systems. *Human Factors, 58*(3), 377–400. https://doi.org/10.1177/0018720816634228

Selwyn, N. (2022). The future of AI and education: Some cautionary notes. *European Journal of Education, 57*(4), 620–631. https://doi.org/10.1111/ejed.12532

Slaughter, S., & Rhoades, G. (2004). *Academic capitalism and the new economy: Markets, state, and higher education*. Johns Hopkins University Press.

Williamson, B. (2017). *Big data in education: The digital future of learning, policy and practice*. SAGE.

Winner, L. (1986). *The whale and the reactor: A search for limits in an age of high technology*. University of Chicago Press.

Wisessathorn, M., Saetang, P., Paimpuech, R., & Sarobrass, C. (2022). The development of growth mindset test for coding teachers. *Journal of Education and Innovation, 24*(2), 232–247. https://so06.tci-thaijo.org/index.php/edujournal_nu/article/view/242173

Yeager, D. S., & Dweck, C. S. (2012). Mindsets that promote resilience: When students believe that personal characteristics can be developed. *Educational Psychologist, 47*(4), 302–314. https://doi.org/10.1080/00461520.2012.722805

Declaration of AI Assisted Writing

Perplexity AI and Grammarly assisted with writing and organization during preparation of the manuscript. ChatGPT assisted with editorial revision, formatting, and reference checks. The authors retain responsibility for the study's concept, design, data collection, analysis, interpretation, and final content.

P26059

Teacher Non-Verbal Communication and AI Use as Complementary Predictors of Perceived Course Learning Outcomes among Thai Pre-Service Teachers

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ABSTRACT

Teacher non-verbal communication (NVC) and AI use were examined at a Thai university in relation to students' perceived course learning outcomes in foreign language learning. An explanatory sequential mixed-methods design was employed. The quantitative phase included 72 undergraduate pre-service teachers who completed a 5-point Likert-type questionnaire assessing teacher NVC, AI use, and self-reported perceived course learning outcomes. Internal consistency was high for the three construct scores (Cronbach's α = .920, .906, and .932, respectively). Spearman's rho was used for bivariate associations because the three composite variables deviated from normality, while multiple linear regression was retained after diagnostic tests indicated that the regression residuals and other key model assumptions were acceptable. The quantitative findings were subsequently elaborated through semi-structured interviews with 12 purposively selected participants representing varied levels of perceived learning experience.

Perceived learning outcomes were positively associated with teacher NVC (r_s = .516, $p < .001$) and AI use (r_s = .561, $p < .001$), while teacher NVC and AI use were also positively associated (r_s = .363, p = .002). The multiple regression model was statistically significant, $F(2, 69) = 21.95$, $p < .001$, explaining 38.9% of the variance in perceived learning outcomes (R^2 = .389; adjusted R^2 = .371). Both teacher NVC (B = 0.387, β = .355, $p < .001$) and AI use (B = 0.406, β = .446, $p < .001$) made unique positive contributions to the model. These outcomes are self-reported course learning outcomes and should not be interpreted as objective language proficiency. Qualitative findings indicated that participants valued teacher NVC for confidence and emotional support, expressed concerns about the accuracy of AI-generated information, and generally viewed teachers and AI as complementary. Given the small, single-institution sample, the findings should be interpreted as context-specific rather than broadly generalizable.

Keywords: Teacher non-verbal communication; AI-assisted language learning; Course Learning Outcomes; Human–AI complementarity; Open-admission university

INTRODUCTION

Generative AI has emerged as a significant force in the field of modern foreign language acquisition, facilitating interactive grammatical feedback and simulated conversations. A substantial body of research has verified that AI improves learner engagement, motivation, and autonomy (Zhang et al., 2025; Zhu & Wang, 2025; Chniete et al., 2025). However, the teacher's indispensable function in utilizing nonverbal communication (NVC) remains affirmed in the face of these technological advancements. Studies in language education categorize nonverbal communication (NVC) into four facets: kinesics (gestures and facial expressions), proxemics (spatial distance), paralinguistics (vocal characteristics), and the communicative-cognitive viewpoint (Matthews, 2023). Instruction with pitch gestures has been demonstrated to enhance learners' capacity to distinguish tones at both the behavioral and neurological levels, particularly in languages with intricate tonal systems, such as Chinese (Baills et al., 2019; Gillette, 2017). This empirical evidence underscores the fact that non-verbal communication continues to fulfill a role that AI has not yet been able to fully replace in the acquisition of highly complex languages.

LITERATURE REVIEW

A related, but conceptually different, issue is learners' self-efficacy—their confidence in their own communicative competence. The perceived learning outcomes scale used in this study includes items concerning self-perceived confidence, but self-efficacy is not measured as a separate, independent construct with its own scale or hypothesis in this study; rather, it is one component of students' overall perceived learning outcomes. Therefore, future research needs to empirically explore whether the combined use of AI and teacher NVC fosters learner self-efficacy as a separate construct, using a specific self-efficacy measure.

Several gaps from the literature review have led to this study. First, the AI (high-tech) and teacher NVC (human touch) have still been examined separately without systematic integration. Second, overemphasis on objective achievement relative to perceived course learning outcomes is observed, although perception accounts for variance of up to 58.8% in long-term achievement (Ajam et al., 2023). Third, empirical evidence on the combined role of AI and teacher NVC in Thai open-admission university contexts is lacking. Fourth, the perception–reality gap between AI's perceived and actual effectiveness remains unconfirmed. This study aims to fill these gaps by examining the combined impact of teacher non-verbal communication and AI use on students' perceived course learning outcomes within the framework of Thai higher education to help develop a balanced, evidence-based

instructional model for the digital age. Descriptively, the broader experiences of students, including ethical concerns related to AI use, are also explored to provide further context for the quantitative findings but are not treated as hypothesized relationships in the main model.

Thus, the main objective of this study is to investigate the relationships between teacher NVC and AI use and between AI use and students' perceived course learning outcomes, while a secondary descriptive objective is to describe students' experiences and ethical concerns about AI use, which are reported separately from the hypothesis-testing findings. The study hypothesizes that (H1) NVC is positively related to CLOs. (H2) AI use is positively related to CLOs. (H3) NVC and AI use jointly and significantly predict CLOs.

THE PURPOSE OF THE RESEARCH

The purpose of this research is to study and analyze Teacher Non-Verbal Communication and AI Use as Complementary Predictors of Perceived Course Learning Outcomes Among Thai Pre-Service Teachers.

METHODOLOGY

The study employed an explanatory sequential mixed-methods design. The target population comprised 111 undergraduate pre-service teachers who attended the course and completed the final assessment. A minimum quantitative sample of 68 was estimated using G*Power, and 72 valid questionnaires were obtained (64.86% of the target population). Because participants were drawn from one course context at a single Thai open-admission university, the quantitative sample is relatively small and institution-specific; accordingly, the findings are interpreted within this context rather than as representative of pre-service teachers generally.

The questionnaire contained researcher-developed items informed by the study's conceptual framework and relevant prior literature. The framework specified two complementary predictors of perceived learning outcomes. Teacher non-verbal communication was conceptualized through kinesics, paralanguage, proxemics, and affective support, whereas AI usage and integration was conceptualized through cognitive scaffolding, personalization, immediate feedback, and human–AI synergy. Perceived learning outcomes were conceptualized in terms of perceived competence, engagement and motivation, satisfaction, and perceived value. All three main construct scores were assessed using 5-point Likert-type items. Ethical AI awareness was treated as supplementary descriptive information related to AI use and was not included as a component of the dependent variable. The present study reports internal-consistency evidence for the resulting construct scores; however, the

instrument was not established as a previously validated standardized scale, and a separate pre-study pilot or formal expert content-validation procedure was not conducted. This limitation is acknowledged when interpreting the measurement results. Following the quantitative analysis, 12 participants were purposively selected for semi-structured interviews using a maximum-variation strategy. Selection sought participants representing high, moderate, and low levels of perceived learning experience so that the qualitative phase could explain both convergent and contrasting quantitative patterns. Interviews continued until the analysis yielded sufficient thematic recurrence and no substantively new themes emerged. Quantitative data were analyzed using descriptive statistics, Spearman's rank-order correlations, and multiple regression; qualitative data were analyzed thematically and integrated with the quantitative findings. Before participation, students received information on the study purpose, voluntary participation, confidentiality, withdrawal without academic consequences, and the separation of research participation from course grading; informed consent was obtained.

RESULTS

Participant characteristics

4.1 Characteristics of Participants

The sample for the quantitative phase was made up of 72 undergraduate pre-service teachers who were studying on foreign language teacher education programs. This is presented in Table 1. Of the pre-service teachers, 50 (69.4%) identified as female, 14 (19.4%) identified as male and eight (11.1%) identified as gender-diverse or did not wish to disclose. Half of the participants (50.0%) were aged 20-22. They included students in all years of study within the English, Thai, Early Childhood Education, Elementary Education, Social Studies Education, Mathematics Education, Computer Education, Art Education, Physical Education, and Chinese teacher education programs.

Of the users, 40 (55.6%) used AI almost every day, 11 (15.3%) used AI 3-5 times a week, 15 (20.8%) used AI 1-2 times a week, and 6 (8.3%) used AI rarely or never. A total of 47 respondents (65.3%) reported that they had used AI to support language learning for over 6 months. Most of the study participants completed foreign language courses in face-to-face (50.0%) or blended learning format (43.1%), while 6.9% reported having most of their courses studied via online learning.

Table 1. Participant Characteristics (N = 72)

Characteristic	*n*	*%*
Gender		
Female	50	69.4
Male	14	19.4
Gender-diverse / Prefer not to disclose	8	11.1
Age		
Below 20 years	8	11.1
20–22 years	36	50.0
23–25 years	13	18.1
Above 25 years	15	20.8
Year of study		
Year 1	6	8.3
Year 2	19	26.4
Year 3	22	30.6
Year 4 or above	25	34.7
Frequency of AI use		
Almost every day	40	55.6
3–5 times per week	11	15.3
1–2 times per week	15	20.8
Rarely or never	6	8.3
AI experience for language learning		
More than 6 months	47	65.3
6 months or less	25	34.7
Course delivery mode		
Face-to-face	36	50.0
Blended learning	31	43.1
Primarily online	5	6.9

Reliability of research tools

Internal consistency of the three construct scores was assessed using Cronbach's alpha (Table 2). Teacher non-verbal communication (α = .920), AI use for language learning (α = .906), and perceived learning outcomes (α = .932) all showed high internal consistency. These coefficients provide evidence of score reliability in the present sample, but they do not by themselves establish construct validity. Because the items were researcher-developed rather than taken unchanged from a previously validated standardized instrument, the reliability findings should be interpreted together with the measurement-development limitation described in the Methodology section.

Table 2. Internal Consistency Reliability of the Study Measures

Construct	*Cronbach's α*	*Interpretation*
Teacher Non-Verbal Communication	.920	High internal consistency
AI Use for Language Learning	.906	High internal consistency
Perceived Learning Outcomes	.932	High internal consistency

As a supplementary, non-preregistered analysis, the eight items within each predictor construct were additionally examined according to the four sub-dimensions specified in the conceptual framework—

kinesics, paralanguage, proxemics, and affective support for teacher non-verbal communication, and cognitive scaffolding, personalization, immediate feedback, and human–AI synergy for AI usage and integration. Because the instrument was not developed or validated at the sub-dimension level, item-to-sub-dimension assignment was made post hoc on the basis of item content rather than a predetermined, equally weighted mapping; the four sub-dimensions therefore contain different numbers of items. Table 2b reports the resulting item groupings together with descriptive statistics and Cronbach's alpha for each sub-dimension.

Table 2b. Post Hoc Sub-Dimension Descriptive Statistics and Reliability for Teacher Non-Verbal Communication and AI Usage & Integration

Construct	***Sub-dimension***	***Items included (by content)***	***n***	***M (SD)***	***Cronbach's α***
Teacher Non-Verbal Communication	Kinesics	Items 1–4 (gestures, pitch gestures, eye contact, facial expression)	4	4.24 (0.65)	.832
	Paralanguage	Item 5 (tone, rhythm, loudness)	1	4.40 (0.74)	—
	Proxemics	Item 6 (physical distance)	1	4.10 (0.89)	—
	Affective Support	Items 7–8 (anxiety reduction, engagement)	2	4.26 (0.73)	.928
AI Usage & Integration	Personalization	Items 1, 5 (simulated conversation practice, cultural-context search)	2	3.60 (0.92)	.644
	Immediate Feedback	Items 2, 6 (grammar/writing correction, pronunciation practice)	2	3.68 (0.87)	.709
	Cognitive Scaffolding	Item 3 (AI as personal tutor)	1	3.72 (1.00)	—
	Human–AI Synergy	Items 4, 7, 8 (judgment-free practice space, motivation, awareness of AI limitations)	3	3.92 (0.76)	.791

Note. Item numbers indicate their order within each construct. Single-item sub-dimensions are reported descriptively (—), while the exploratory classifications do not affect the overall predictor scores or hypothesis testing. Harman's single-factor test showed that the first factor explained 39.8% of the variance, suggesting that common-method bias was not a dominant concern, although some potential bias may remain.

Descriptive Statistics

Table 3. Descriptive Statistics of the Study Variables (N = 72)

Variable	*Status*	*Mean*	*SD*
Teacher Non-Verbal Communication	Main predictor (overall score)	4.24	0.63
AI Usage & Integration	Main predictor (overall score)	3.75	0.77
Perceived Learning Outcomes	Dependent variable (overall score)	3.88	0.69
Ethical AI Awareness	Supplementary descriptive information	4.00	0.73

Table 3 presents descriptive statistics for the three main study constructs in accordance with the conceptual framework. Participants reported relatively high levels of teacher non-verbal communication (M = 4.24, SD = 0.63), AI usage and integration (M = 3.75, SD = 0.77), and perceived learning outcomes (M = 3.88, SD = 0.69). The inferential analyses use these overall construct scores. Ethical AI awareness (M = 4.00, SD = 0.73) is reported only as supplementary descriptive information related to AI use and is not included in the dependent-variable score or interpreted as a learning outcome. This presentation keeps the statistical model consistent with the conceptual framework: teacher non-verbal communication and AI usage and integration are the two predictors, and perceived learning outcomes is the dependent variable.

Relationships Among Teachers' Nonverbal Communication, AI Usage & Integration, and Perceived Learning Outcomes

Table 4. Spearman's Rank-Order Correlations Among the Study Variables (N = 72)

Variable	***1***	***2***	***3***
1. Teachers' Nonverbal Communication	—		
2. AI Usage & Integration	.363**	—	
3. Perceived Learning Outcomes	.516***	.561***	—

Note. Values are Spearman's rank-order correlation coefficients (r_s).p < .01**, p < .001***.

As shown in Table 4, perceived learning outcomes were positively associated with teacher NVC (r_s = .516, p < .001) and AI usage and integration (r_s = .561, p < .001). Teacher NVC and AI usage and integration were also positively associated (r_s = .363, p = .002). These coefficients indicate associations among self-reported construct scores and should not be interpreted as causal effects or as direct evidence of objectively measured language proficiency.

Prediction of Perceived Learning Outcomes

Table 5. Summary of the Multiple Regression Model Predicting Perceived Learning Outcomes

Model	R	R^2	Adjusted R^2	F	df	p
Regression Model	.624	.389	.371	21.95	(2, 69)	< .001

As shown in Table 5, the multiple linear regression model was statistically significant, $F(2, 69) = 21.95$, $p < .001$, with $R = .624$, $R^2 = .389$, and adjusted $R^2 = .371$. Thus, teacher NVC and AI usage and integration jointly accounted for 38.9% of the variance in self-reported perceived learning outcomes in this sample. Although the three composite variables were individually non-normal (teacher NVC: $W = .902$, $p < .001$; AI usage and integration: $W = .899$, $p < .001$; perceived learning outcomes: $W = .937$, $p = .001$), regression diagnostics supported the model assumptions: residuals were approximately normal (Shapiro–Wilk $W = .982$, $p = .384$), the Breusch–Pagan test did not indicate serious heteroscedasticity ($LM = 3.61$, $p = .165$), the Ramsey RESET test supported the linear functional form ($F = 0.13$, $p = .717$), the Durbin–Watson statistic was 1.76, VIF values were 1.04 for both predictors, and the maximum Cook's distance was .214. These diagnostics support use of the linear regression model for this sample, while the modest sample size warrants cautious interpretation.

Table 6. Multiple Regression Coefficients Predicting Perceived Learning Outcomes

Predictor	*B*	*SE*	*β*	*t*	*p*	*95% CI*
Constant	0.717	—	—	—	—	—
Teachers' Nonverbal Communication	0.387	0.105	.355	3.70	< .001	[0.178, 0.596]
AI Usage & Integration	0.406	0.087	.446	4.65	< .001	[0.232, 0.580]

Note. Dependent variable = Perceived Learning Outcomes.

As shown in Table 6, both predictors made statistically significant unique contributions to perceived learning outcomes: teacher NVC ($B = 0.387$, $SE = 0.105$, $\beta = .355$, $t = 3.70$, $p < .001$, 95% CI [0.178, 0.596]) and AI usage and integration ($B = 0.406$, $SE = 0.087$, $\beta = .446$, $t = 4.65$, $p < .001$, 95% CI [0.232, 0.580]). The fitted equation was Perceived Learning Outcomes = 0.717 + 0.387(NVC) + 0.406(AI Usage & Integration). These results are consistent with the hypothesized positive relationships, but the coefficients represent prediction of self-reported perceived outcomes rather than causal effects or objective proficiency gains.

Results of Qualitative Analysis:

A purposive maximum-variation sample of 12 pre-service teachers was drawn from the quantitative participants for the explanatory qualitative phase. Participants were selected to represent high, moderate, and low levels of perceived learning experience based on the quantitative results, thereby capturing contrasting perspectives rather than only typical or highly positive cases. The purpose of this sampling strategy was not statistical representation, but to explain why participants with different

quantitative profiles perceived teacher NVC and AI use differently. Interviews were analyzed iteratively, and data collection was considered sufficient when recurring patterns were well established and additional interviews were no longer generating substantively new themes. Thematic analysis identified three overarching themes that complemented and contextualized the quantitative findings.

Theme 1. Teacher Nonverbal Communication as a Source of Emotional Confidence

Most respondents (9 out of 12) thought that teachers' nonverbal communication played a more important role in their confidence in speaking a foreign language than AI. Participants repeatedly reported that the gestures, facial expressions, eye contact, and encouraging tone of voice of teachers were important sources of emotional support that reduced anxiety and increased their willingness to communicate. As one participant explained, "My teacher's gestures and facial expressions make me more confident to speak, as I know that mistakes are accepted and I receive immediate encouragement." (P3)

"A teacher is a real role model. They can tell me the pronunciation, correct my mistakes and encourage me in a way AI can't." (P8)

One participant viewed AI as having a greater influence, primarily because of concerns about the accuracy and consistency of AI-generated feedback, rather than a rejection of the teacher's role. These results, taken together, support the quantitative findings by indicating that teachers' nonverbal communication continues to be an important source of emotional confidence, even in learning environments where the use of AI is common.

Theme 2. Concerns about the accuracy of AI-generated information

A common theme across all interviews was the concern of participants about the accuracy and reliability of AI-generated information. Participants generally recognized AI as a useful learning support tool, but many also expressed doubts about the correctness of the explanations, translations, and language examples offered by AI. One of the participants said,

"Sometimes AI gives wrong explanations or translations, so I still need my teacher to check the answers." (P5)

Some participants also expressed concerns with over-reliance on AI or the use of AI without critical evaluation. The results indicate that although students appreciate the availability and instant feedback offered by AI, concerns about the accuracy of information are a major obstacle to its full integration into foreign language learning.

Theme 3: Teachers and AI Should Have Complementary Roles, Not Substitutive Ones

Most participants described an ideal learning environment where teachers and AI have complementary instead of competing roles. Teachers provided explanations, pronunciation feedback, emotional support, and classroom interaction, whereas AI was supposed to offer independent practice, immediate feedback, and learning beyond the classroom. One participant explained,

"The best learning experience is a blend of both. The teacher will explain and guide us, and the AI will help us practice anytime, anywhere." (P11)

Overall, the qualitative results reinforce the quantitative results by illustrating that students perceive teachers' nonverbal communication and AI as serving distinct yet mutually reinforcing functions. AI is mainly useful for constant practice and the availability of learning, but teachers continue to be crucial in developing emotional confidence, providing useful feedback, and critically analyzing the information generated by AI. These results are consistent with the quantitative evidence that teachers' nonverbal communication and the use of AI contribute to the perceived learning outcomes.

Table 7. Summary of Qualitative Themes

Theme	***Main Findings***	***Representative Quote***
Theme 1. Teachers' Nonverbal Communication as a Source of Emotional Confidence	Teachers' gestures, eye contact, facial expressions, and tone of voice enhanced learners' confidence and reduced communication anxiety.	*"My teacher's gestures and facial expressions make me feel more confident to speak."* (P3)
Theme 2. Concerns About the Accuracy of AI-Generated Information	Participants appreciated AI but questioned the accuracy and reliability of AI-generated information and emphasized the need for critical evaluation.	*"Sometimes AI gives wrong explanations or translations, so I still need my teacher to check the answers."*(P5)
Theme 3. Complementary Rather Than Substitutive Roles of Teachers and AI	Teachers and AI were viewed as serving complementary functions: teachers provided guidance and emotional support, while AI facilitated independent practice and accessibility.	*"The best learning experience is a blend of both. The teacher will explain and guide us, and the AI will help us practice anytime, anywhere."* (P11)

The qualitative results revealed three general themes: (1) the emotional confidence from teachers' nonverbal communication, (2) the anxiety of the accuracy of AI-generated information, and (3) the complementary roles of teachers and AI in foreign language learning. In general, teachers' nonverbal communication was appreciated by participants for emotional support and confidence building, while AI was appreciated mainly for independent practice and learning accessibility. The findings indicate different but mutually reinforcing roles of teachers and AI in supporting students' perceived learning outcomes.

DISCUSSION

Teachers' Nonverbal Communication and Embodied Multimodal Learning

The results of this study support the findings of Cao and Chen (2017), who found that teachers' gestures assist learners' comprehension and vocabulary memorization. They also confirm the findings of McCafferty and Stam (2008) that nonverbal communication functions as a "meaning enhancer," reducing the cognitive processing load of the learner and allowing for more effective communication in the second language classrooms. Furthermore, the results are consistent with the principles of embodied learning, according to which learners build meaning by combining visual, auditory, and motor experiences. These results, along with the findings, indicate that foreign language learning is more effective when verbal instruction is accompanied by teachers' nonverbal communication than when relying solely on spoken language.

AI-Assisted Language Learning

The findings are consistent with previous studies recognizing the benefits of AI in language learning, such as instant feedback, personalized learning, and opportunities for repetitive practice (Song & Song, 2023; Zhou, 2023). Wang et al. (2022) also support this by suggesting that AI promotes cognitive presence by encouraging learners to question, explore, and reflect during the learning process. In this study, AI usage and integration had a larger standardized regression coefficient than teacher NVC, but the qualitative findings showed that most participants still relied on teachers for emotional support, confidence building, and meaningful classroom interaction. Such findings imply that the increasing efficacy of AI does not diminish the importance of teachers. Instead, it points to an evolving role in which teachers move beyond knowledge transmitters to become facilitators of learning and learning designers. This points towards an interpretation consistent with Putkorn (2025), who argued that teachers should be increasingly learning designers, leading students towards meaningful and responsible learning and not just providers of knowledge.

Perceived Competence and Confidence

The findings also highlight perceived competence and confidence as important aspects of students' learning experience. Within the conceptual framework, perceived competence forms part of the broader perceived learning outcomes construct rather than a separate independent variable. The qualitative findings further contextualized this aspect by showing that teacher modeling, encouragement, and authentic interaction were valued for confidence building, while AI supported practice and immediate learning assistance. This pattern is consistent with Bandura's (1997) emphasis on mastery experiences, observational learning, and social encouragement.

Human-in-the-Loop AI Systems

The findings of this study follow previous research (Song & Song, 2023; Wang et al., 2022; Yuen & Schlote, 2024) suggesting that AI should be utilized with pedagogical guidance from teachers regarding

language learning and should not be used independently. The qualitative data, as noted above, indicated that accuracy of information was a predominant concern for over half of the interviewees in this study, thus supporting the point made above. Participants highlighted the pitfalls of AI-generated misinformation and insensitivity. Teachers were advised to validate AI content, learn the language and culture, and teach how to use AI ethically and critically. These findings align with the human-in-the-loop approach and teaching presence and suggest that the teacher remains relevant even with readily available AI-based tools to support learning.

Mixed Methods Integration and Pedagogical Implications

One of the key strengths of this study is the use of an explanatory sequential mixed-methods design, which allowed for the quantitative results to be interpreted in the context of students' lived experiences. Quantitative analysis suggested that AI usage and integration had a larger standardized coefficient than teacher NVC, while qualitative findings showed that students still valued the role of teachers in building confidence, providing emotional support, and interpreting linguistic and cultural contexts. The two strands of evidence are not contradictory findings but demonstrate that teachers and AI contribute to different but complementary dimensions of language learning. The study therefore presents a framework of complementary roles, where the main role of AI is to support cognitive processes through personalized practice and immediate feedback, and the role of the teacher is to provide social, emotional, and pedagogical support that AI cannot fully reproduce . These findings have important implications for pedagogy. AI should be a learning support tool under the guidance of teachers, not a replacement for language teachers. Teachers will still have to design learning experiences, lead classroom discussion, model appropriate use of language, and encourage ethical and critical use of artificial intelligence. At the same time, artificial intelligence is able to efficiently do individual practice, simulated communication, and immediate feedback and learning outside the classroom. Future research should examine instructional models that systematically combine teachers' nonverbal communication, AI-supported learning, peer interaction, and teacher feedback and their impact on objectively measured language proficiency.

Implications for Teaching

The results indicate that AI should be incorporated into foreign language education as an auxiliary aid for learning, not as a substitute for language teachers. Teachers should continue to be learning designers, facilitators, and ethical guides and should use nonverbal communication (e.g., facial expressions, eye contact, gestures, and vocal emphasis) to boost learners' comprehension, confidence, and emotional well-being. AI can also be effective in supporting individualized practice, simulated communication, immediate formative feedback, the development of learning materials, and learning beyond the classroom. The findings also emphasize the significance of fostering AI literacy, urging students to engage in critical evaluation, comparison, and verification of AI-generated information with the support

of teachers. The outcomes of this research suggest that the potentially effective teaching sequence might consist of teacher modeling, AI-supported practice, peer interaction, and teacher feedback. The integrated approach can contribute to students' perceived learning outcomes and their long-term language proficiency and confidence in the target language.

Limitations

This study has several limitations. First, the quantitative sample was modest (N = 72) and drawn from a single course context at one Thai open-admission university; therefore, the findings should not be generalized to all pre-service teachers, institutions, languages, or educational systems. Second, the outcome variable represents students' self-reported perceived course learning outcomes rather than objectively assessed language proficiency or achievement. Third, all main quantitative constructs were measured by self-report, leaving the findings vulnerable to social-desirability and common-method bias. Fourth, although the researcher-developed scales showed high internal consistency in this sample, scale development and validation were limited because the instrument was not a previously standardized measure and no separate pre-study pilot or formal expert content-validation procedure was conducted. Fifth, non-normality was observed for the composite variables; although residual normality, heteroscedasticity, linearity, autocorrelation, multicollinearity, and influential-case diagnostics supported the regression model, the relatively small sample still calls for cautious interpretation. Finally, the qualitative phase used purposive maximum-variation sampling to explain quantitative patterns rather than to achieve statistical representativeness; consequently, the interview findings provide contextual depth but should not be treated as prevalence estimates.

Future Research

Future research should replicate the study with larger, multi-institutional and more heterogeneous samples; use independently validated measures and stronger scale-development procedures; and include objective language-performance indicators alongside perceived course learning outcomes. Longitudinal or experimental designs could better examine temporal and causal relationships. Future studies should also distinguish among specific AI tools and AI-use purposes, and could further investigate ethical and critical AI awareness as a distinct supplementary AI-related construct alongside the main predictive model.

CONCLUSION

The study's findings demonstrate that both teachers' nonverbal communication and the application of AI were positively associated with students' perceived learning outcomes when learning a foreign language. While AI was statistically a stronger predictor on the margins, qualitative findings show that teachers still play an important role in providing a space where learners develop their emotional confidence, receive meaningful feedback, and critically evaluate information coming from AI. These findings are consistent with previous research on AI-assisted language learning, which emphasizes that

AI's educational value is dependent not only on technological capabilities but also on effective pedagogical guidance and support (Song & Song, 2023; Wang et al., 2022).

AI should be a learning support, not a replacement for language teachers. Nonverbal communication: Teachers should continue to use nonverbal communication as learning designers, facilitators, and ethical guides to stimulate learner engagement, confidence, and emotional safety. Artificial intelligence can provide personalized practice, immediate feedback, and learning beyond the classroom (Putkorn, 2025; Yuen & Schlote, 2024). The results confirm the importance of a human-in-the-loop approach to technology-enhanced language learning in which pedagogical decisions are made under the professional guidance of instructors.

This study contributes to the emerging literature on AI-assisted language acquisition by offering a complementary framework that combines the cognitive advantages of AI with the social and emotional roles of teachers. Furthermore, the explanatory sequential mixed-methods design illustrates how the integration of quantitative and qualitative information can offer a more complete understanding of technology-enhanced language acquisition than either technique in isolation (Creswell & Plano Clark, 2018). Additionally, the results of the present study are further supported by the mixed-methods approach and the high internal consistency of the measures employed. Combined, our findings contribute to the comprehension that the use of instructional AI tools and teacher non-verbal communication in the classroom can have a positive effect on the perceived learning outcomes of a course. These results require further replication in larger, multi-institutional samples and with more objective measures of achievement.

REFERENCES

Ajam, A., Rizal, A., Sahmadan, S., & Ridayani, R. (2023). The students' English achievement, perception and attitude in English language teaching. Journal of English Culture, Language, Literature and Education, 11(2).

Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman.

Baills, F., Suárez-González, N., González-Fuente, S., & Prieto, P. (2019). Observing and producing pitch gestures facilitates the learning of Mandarin Chinese tones and words. Studies in Second Language Acquisition, 41(1), 33–58.

Cao, N., & Chen, G. (2017). The role of gesture in the second language learning and teaching. American Journal of Applied Sciences, 14(12), 1070–1074.

Chniete, I., Kaddouri, M., Mhamdi, K., Marhraoui, M., & Khaldi, M. (2025). Language teaching in the age of AI. Advances in Computational Intelligence and Robotics Book Series, 151–172.

Gillette, S. (2017). The effects of hand gestures and traditional methods of teaching Mandarin Chinese tones.

Matthews, G. (2023). The teaching of nonverbal communication to EFL learners in Taiwan. International Journal of English Language Teaching, 11(4), 1–6.

McCafferty, S., & Stam, G. (2008). Gesture: Second language acquisition and classroom research. Routledge.

Putkorn, N. (2025). The role of Artificial Intelligence (AI) in Chinese language management. Journal of Humanities and Social Sciences Rajapruk University, 11(3), 21-39.

Song, C., & Song, Y. (2023). Enhancing academic writing skills and motivation: Assessing the efficacy of ChatGPT in AI-assisted language learning for EFL students. Frontiers in Psychology. https://doi.org/10.3389/fpsyg.2023.1260843

Wang, X., Pang, H. J., Wallace, M., Wang, Q., & Chen, W. (2022). Learners' perceived AI presences in AI-supported language learning: A study of AI as a humanized agent from community of inquiry. Computer Assisted Language Learning, 1–27.

Yuen, C. L., & Schlote, N. (2024). Learner experiences of mobile apps and artificial intelligence to support additional language learning in education. Journal of Educational Technology Systems.

Zhang, J., Hussin, M., & Abd Majid, M. Z. (2025). Artificial intelligence in language teaching in the context of higher vocational education: A bibliometric mapping of research trends (2000–2024). Forum for Linguistic Studies, 7(9).

Zhou, W. (2023). Chat GPT integrated with voice assistant as learning oral chat-based constructive communication to improve communicative competence for EFL learners. arXiv:2311.00718.

Zhu, M., & Wang, C. (2025). A systematic review of research on AI in language education: Current status and future implications. Language Learning & Technology, 29(1), 1–29.

Sub-Theme IV

Digital Transformation of Educational Efficiencies and Effectiveness: Roles of IR and IT Integration

P26008

Transforming Tutorial Interventions for Enhanced Interactive Learning in Writing and Speaking English among College Students

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ABSTRACT

The study conceptualized tutorial interventions for interactive learning among 40 male students, comprising 20 in the control group and 20 in the experimental group, from a college in Cagayan de Oro City, Philippines. A quasi-experimental design was used in between the pre-intervention and post-intervention measurements on non-randomly selected groups of male students aged 20–21 years. Google Beta LMS was utilized to give the online tutorial intervention to the experimental group. Descriptive statistics, independent- and paired-samples t-tests, mean gain analysis, and analysis of covariance (ANCOVA), with the level of significance set at $\alpha = .05$ were used to analyze the data. Results with p-values below .05 were considered statistically significant, warranting rejection of the null hypothesis. The results showed that the control and experimental groups had comparable pretest writing performance but differed significantly in their initial speaking performance. After the intervention, the experimental group exhibited significantly higher writing achievement and a moderate-to-large treatment effect compared with the control group. Although both groups improved in speaking, the gains could not be conclusively attributed to the intervention because the control group also displayed significant improvement during the same period. ANCOVA results further confirmed that the intervention positively influenced writing outcomes, with experimental-group students predicted to score approximately 10.5 points higher in posttest writing than their counterparts in the control group. However, the observed differences in speaking performance were largely influenced by pre-existing disparities rather than the intervention itself. In conclusion, online tutorials can effectively enhance students' English writing skills. Meanwhile, improving speaking skills requires more deliberate instructional support emphasizing the teachers' role in developing digital instructional materials to re-design online tutorials into more interactive and engaging learning environments, to enable students to achieve their intended learning outcomes.

Keywords: Learning Management System, Remedial Education, Learning Support

Introduction

English language proficiency is essential for Filipinos seeking employment in both local and international organizations, particularly in demonstrating competence in writing and speaking during recruitment processes. Teachers therefore play a critical role in diagnosing learners' difficulties and providing appropriate tutorial interventions to address identified needs. As tutors, teachers provide remedial support beyond regular classroom instruction, with feedback serving as a key component of the learning process Heron, et. al., 2021). Such feedback should be carefully designed to address students' academic and emotional needs across face-to-face, online, and asynchronous learning environments (Willis, et. al., 2025). As English instruction becomes increasingly digitally mediated, teachers must effectively integrate technology into tutorial practices, while students' growing technological competence enables them to access digital tools, online resources, and AI-supported applications. These technology-related skills not only facilitate language learning but also help prepare students for the challenges at work.

The integration of tools, such as computers, telephones, and software, has resulted in increased use of e-mail, voice mail, videoconferencing, and voice recognition to deliver messages all over the world. This phenomenon highlights the role, influence and importance of technology in the society today. Technological application plays a big role in the world outside the classroom; hence students expect to find it used within the classroom. Likewise, audiovisual materials afford students with content, meaning and guidance plus they enhance genuineness to the classroom situation. Bringing technology into the classroom increases students' exposure to various references while reducing the risk of students' dependence on the teacher's personal use of a language. Thus, it provokes students' stimuli helping them to process information effortlessly. The COVID19 outbreak compelled teachers and students to use technology and online tools. Academic institutions used Google LMS and Microsoft Teams for Education during COVID.

The post-COVID-19 pandemic period presented significant challenges to the educational sector. Reports published in 2021 linked the learning crisis in the Philippines to the disruptions caused by the COVID-19 pandemic (Abadilla, 2021). In higher education, faculty members observed that students' academic performance frequently fell below established learning benchmarks and expected competency standards. Educational administrators likewise recognized the limitations of online learning in fostering academic competence, particularly when compared with more interactive, collaborative, and guided learning environments.

The Commission on Higher Education (CHED) issued CHED Memorandum Order (CMO) No. 16, Series of 2022, which mandated the resumption of physical campus-based learning. However, many higher education institutions in the Philippines were unable to immediately transition to full in-person

instruction due to logistical, infrastructural, and health-related considerations (Lu, 2023). Consequently, institutions approached the continued implementation of online and hybrid learning modalities with caution, recognizing both their benefits and limitations in achieving desired learning outcomes. Studies related to distance learning, e-learning, distance education, microcredentials, MOOCs and others offer varying views about it. Bhatia et. al. (2024) emphasized that educational technology platforms while highly promoting self-responsibility, lacks teacher-student autonomy and shows deterioration of the robust, two-way interaction between human societies and their physical environments critical for developing place-based critical pedagogies as students and teachers use these modalities from within their respective socio-technical and cultural realities. They claimed further that there is a need to reimagine education using edtech to be inclusive of learning and digital features. On the other hand, Horvath & Steinberg (2023) claimed that the success in the use of technology or digital learning is dependent on how students, teachers, and others envisage and establish boundaries and orders of learning. Negative perspectives about the use of digital education exists because there are many opposing ideas of what makes good and fair school education. Within this context, the institution under study adopted a hybrid learning modality during the second semester of Academic Year 2022–2023 as part of its strategy to facilitate learning continuity while gradually transitioning toward face-to-face instruction.

Tutoring is one of the personalized academic guidance a university may provide to its students. The tutorial program may boost student's confidence to do better in the academic tasks. However, it may be an added burden to students' schedule due to extra time commitment and performance pressure. Thus, the shift toward student-centered learning in higher education has accentuated the importance of interactive and engaging instructional strategies. Traditional lecture-based and passive tutorial sessions may no longer meet the evolving needs of college students, particularly in developing critical thinking, collaboration, and sustained engagement. With the integration of digital tools, collaborative activities, and learner-centered approaches, tutorial interventions can be redesigned to promote active participation and deeper learning. This study aimed to evaluate students' engagement, interaction, and academic performances through a redesigned tutorial intervention.

Theoretical Framework

The study is anchored on two complementary theories: Vygotsky's Social Constructivist Theory, the Zone of Proximal Development (ZPD), and the theory of automaticity in second language acquisition. Vygotsky's ZPD explains learning as a socially mediated process in which learners develop knowledge and skills through interaction with more knowledgeable adults or capable peers, supported by appropriate instructional and cognitive tools (America et al., 2021, as cited in Chand, 2023). In this study, the ZPD is the theoretical basis for the structured online tutorial intervention through the use of tutor guidance, scaffolding, feedback, and gradually reduced assistance. These would move learners

from supported performance toward greater independence in writing and speaking. The tutor provided explicit instruction and demonstrated the theoretical and practical aspects of the target language skills in the initial sessions. The next sessions included guided writing and speaking activities in which students completed tasks, recorded their oral responses, reviewed their performance, responded to reflection questions, and received individualized feedback. As learners progressed through the intervention, opportunities for independent task completion, revision, and resubmission increased while direct assistance was gradually reduced. Thus, the intervention operationalized the principles of ZPD by providing learners with support appropriate to their current level of competence and progressively transferring responsibility for learning to the students.

The second theoretical perspective is automaticity in second language acquisition, which refers to the ability to process and produce language with increasing efficiency and reduced conscious effort as a result of repeated practice, proceduralization, and continued exposure (Suzuki, 2025; Shahini, 2025). This theory complements ZPD by explaining the cognitive process through which skills initially requiring considerable attention and external support can become increasingly efficient and accessible through practice. The online tutorial intervention was specifically structured to promote this process through repeated and purposeful engagement with writing and speaking tasks. Across the intervention sessions, students repeatedly perform tasks based on target skills, recorded and reviewed their oral responses, received instructor feedback, reflected on their performance, and revised and resubmitted their outputs. The learners go through the cycles of practice, feedback, reflection, and revision which provided opportunities for them to reinforce language forms and procedures and progressively perform tasks with greater fluency and less reliance on external assistance. The self-paced nature of the LMS also allowed students to revisit learning materials and practice tasks according to their individual needs.

ZPD and automaticity can therefore be viewed as complementary. ZPD illustrates the educational procedure involving the tutor scaffolding, guided practice, feedback, and gradual withdrawal of support help learners accomplish tasks beyond their initial independent capability. Automaticity shows the cognitive outcome of systematic practice, where repeated execution of tasks and feedback facilitate the transition from effortful processing to increasingly fluent and efficient language use. The framework consequently positions the LMS not merely as a platform for delivering tutorial materials but as an interactive learning environment through which scaffolding, practice, feedback, reflection, and revision are systematically integrated to support language development.

Conceptual Framework

This paper aims to redesign tutorials to accommodate the use of technology in providing remediation to students. Innovation leading to changes is sought to improve students' proficiency in English. The

innovation envisioned focuses on the development of educational materials through digital media in the Learning Management System (LMS).

The study examines the effectiveness of the tutorial intervention for enhanced interactive learning in improving students' English writing and speaking skills. The framework focuses on the comparison of the mean gains between the pre-test and post-test scores of the control group and the experimental group. The control group follows the conventional tutorial while the experimental group immerses in the tutorial intervention for enhanced interactive learning. Figure 1 shows the flow of the study.

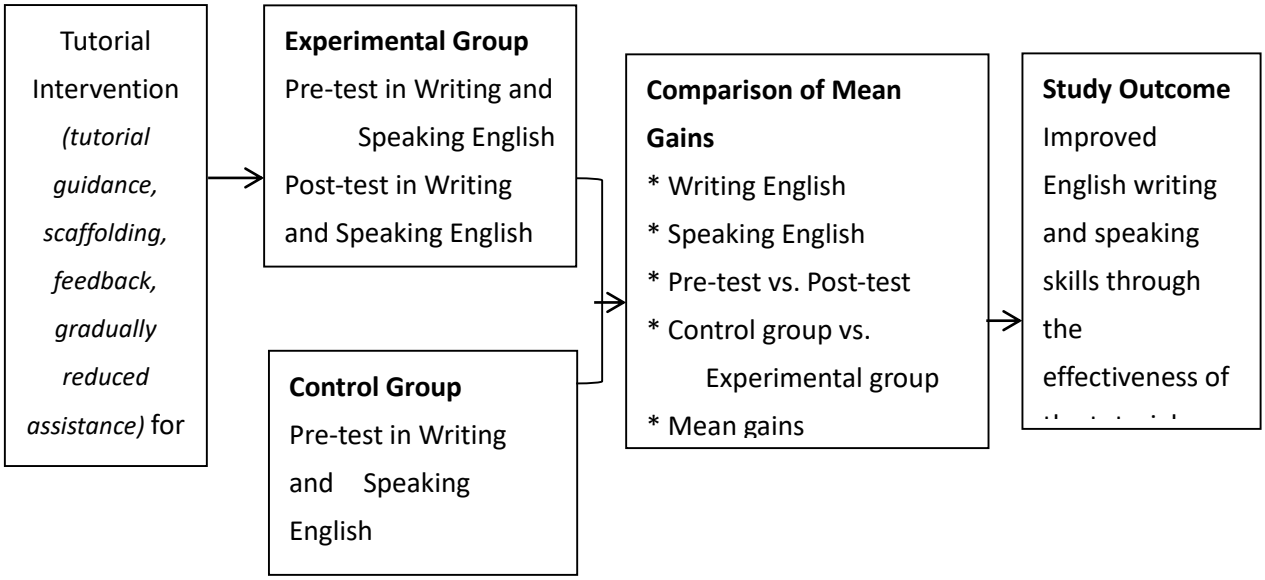


Figure 1. Schematic Diagram of the Tutorial Intervention for Enhanced Interactive Learning

Objectives of the Study

The chief purpose of the study is to examine the effectiveness of the design of the tutorials for interactive learning among selected students. The specific objectives are as follows:

1. to determine the significant differences in the performance of the students (control and experimental groups) in the pretest mean scores in terms of writing and speaking skills;
2. to determine the significant differences in the performance of the students (control and experimental groups) in posttest mean scores in terms of writing and speaking skills;
3. to determine the significant mean gains in the pretest and posttest mean scores of students in the experimental group and the control group considering writing and speaking skills; and,
4. to determine the significant difference in the performance of the experimental group in terms of writing and speaking before and after the treatment.

Below were the null hypotheses tested at 0.05 level of significance:

1. There are no significant differences in the performance of the students (control and experimental groups) in the pretest mean scores in terms of writing and speaking skills.
2. There are no significant differences in the performance of the students (control and experimental groups) in the posttest mean scores in terms of writing and speaking skills.
3. There are no significant mean gains in the pretest and posttest mean scores of students in the experimental group and the control group in terms of writing and speaking skills.
4. There is no significant difference in the performance of the experimental group in terms of writing and speaking skills before and after the treatment.

Research Methodology

The study employed a quantitative research approach using a quasi-experimental design to examine the effects of an online tutorial intervention on students' writing and speaking performance. The study utilized a non-probability sampling procedure and involved non-randomly selected participants who were assigned to control and experimental groups. The college had 222 third-year students enrolled in the face-to-face tutorial program called Enhancement and Assessment Program (EAP), 120 qualified to take the Maritime School Assessment Program (MSAP) which required them to attend an intensive two-month review of Maritime Professional Subjects, Applied Mathematics, Physics, and English in addition to their required EAP attendance. Following the established eligibility criteria and the completion of the initial assessment, the study focused on the 102 students who remained eligible for participation in the tutorial intervention. However, only 40 students voluntarily completed the intervention and provided complete pretest and posttest data. These participants were equally distributed into two groups: 20 students in the control group and 20 students in the experimental group. The control group participated in the conventional face-to-face tutorial sessions, while the experimental group received the online tutorial intervention through the Learning Management System (LMS). The equal number of participants in the two groups provided a balanced basis for comparing their pre-intervention and post-intervention performance.

The tutorial materials and assessment procedures for speaking and writing were adapted from *Cambridge English for Job Hunting* (Downes, 2009). The materials have significant learning value as these provide the respondents with a structured and practical foundation for developing general English proficiency and fluency, while supporting the acquisition, reinforcement, and application of essential language skills. The experimental group completed equivalent two-hour weekly sessions through the LMS. The intervention included theoretical discussions, writing and speaking tasks, audio/video recording, self-reflection, instructor feedback, revision, and resubmission. The LMS-based intervention emphasized self-paced learning, documented learner progress, reflective practice, personalized

feedback, and multiple opportunities for revision. The final two sessions focused on revising and completing the students' writing and speaking outputs.

A pilot test was conducted with 30 third-year college students who were not included in the main study. The instruments yielded a Cronbach's alpha reliability coefficient of 0.72, indicating acceptable internal consistency and supporting their suitability for the main data collection. Furthermore, the writing and speaking pretest and posttest performances were independently evaluated by three interraters to ensure objectivity and consistency in the assessment of the participants' performance. The interraters were experienced college English language instructors who had taught English Grammar, Speech and Oral Communication, and Technical Writing for more than ten years. Their extensive teaching experience and familiarity with the target competencies qualified them to assess the students' writing and speaking performances using the established scoring criteria.

The data were analyzed using descriptive statistics, independent- and paired-samples *t*-tests, mean gain analysis, and analysis of covariance (ANCOVA). The level of significance was set at $\alpha = .05$, with $p < .05$ considered statistically significant and interpreted as grounds for rejecting the null hypothesis. The control and experimental groups were treated as independent samples. For posttest speaking scores, the Welch independent-samples *t*-test was employed because the assumption of equal variances was not met. ANCOVA was additionally conducted for speaking performance to account for the significant difference between the groups at pretest and to provide a more appropriate estimate of the intervention effect after controlling for baseline differences.

The limitation of the study is its relatively small final sample size which restricts the generalizability of its findings to the broader student population. The results were interpreted within the context of the participating institution and the specific characteristics of the respondents. Meanwhile, the findings may provide useful insights and potentially transferable practices for similar educational settings, specifically institutions using technology-supported tutorial interventions for students requiring additional academic support.

Results and Discussion

Two tests, the pretest and posttest, were conducted to evaluate the respondents' level in their English skills in writing and speaking.

Table 1

Difference in the Pretest Performance of the Control and Experimental Groups

Skill	Group	Mean	SD	t	df	p-value	Decision on H_0	Interpretation
Writing	Control	43.80	14.38	0.61	38	.547	Fail to Reject	Not Significant

Skill	Group	Mean	SD	t	df	p-value	Decision on H₀	Interpretation
	Experimental	46.65	15.25					
Speaking	Control	1.80	0.81	2.32	38	.026	Reject	Significant
	Experimental	2.55	1.19					

Table 1 shows that the control group obtained a pretest mean writing score of 43.80 (SD = 14.38)**,** while the experimental group obtained 46.65 (SD = 15.25)**.** The independent-samples t-test revealed no statistically significant difference between the two groups, $t(38) = 0.61$, $p = .547$. Since the probability value is greater than .05, the null hypothesis is not rejected. One can infer that regardless of their age, course, and their high school background, the respondents' outcomes are the same at the beginning of their collegiate semester. This finding indicates that the control and experimental groups had relatively comparable writing performance prior to the intervention.

In speaking, however, the control group obtained a mean pretest score of 1.80 (SD = 0.81)**,** whereas the experimental group obtained a higher mean of 2.55 (SD = 1.19)**.** The difference was statistically significant, $t(38) = 2.32$, $p = .026$. Thus, the null hypothesis is rejected for speaking. This indicates that the two groups were not statistically equivalent in their initial speaking performance, with the experimental group already performing better before the treatment was introduced. A supplemental analysis using ANCOVA would shed light about the results as the groups differed in speaking at pretest.

Table 2

Difference in the Posttest Performance of the Control and Experimental Groups

Skill	Group	Mean	SD	t	df	p-value	Decision on H₀	Interpretation
Writing	Control	48.70	11.16	3.91	31.30	<.001	Reject	Significant
	Experimental	60.10	6.77					
Speaking	Control	2.52	1.45	1.74	38	.090	Fail to Reject	Not Significant
	Experimental	3.22	1.07					

As shown in Table 2, the experimental group obtained a substantially higher posttest writing mean of 60.10 (SD = 6.77) compared with the control group's mean of 48.70 (SD = 11.16)**.** The difference was statistically significant, $t(31.30) = 3.91$, $p < .001$. The null hypothesis is therefore rejected. This finding indicates that the experimental group demonstrated significantly better writing performance after the intervention than the control group. The magnitude of the difference was also large, with an estimated Cohen's d = 1.23, suggesting that the difference was not only statistically significant but also educationally substantial.

The results entail that the respondents in the experimental group were able to make more improvement in their writing performance compared to the control group. One can deduce that the online tutorial intervention may have contributed to the development of the experimental group's writing skills. The

respondents in the experimental group probably were able to control their pace in learning the writing skills compared to the respondents of the control group who were dependent on the face-to-face tutorials. As indicated, the respondents were able to examine their written outputs which afforded them the opportunity to correct their mistakes. In one of the interactive tutorial sessions, some expressed their thoughts about their thought processes, their answers and their style of writing. In this regard, self-consciousness and awareness of one's limitations allowed one to find ways and opportunities to improve his writing skills. More importantly, it made the participants to think, reflect and revise their thought processes for them to speak better.

For speaking, the experimental group likewise obtained a higher posttest mean of 3.22 (SD = 1.07) than the control group, which obtained 2.52 (SD = 1.45)**.** However, the difference did not reach statistical significance, $t(38) = 1.74$, $p = .090$. The null hypothesis is therefore not rejected. Although the experimental group had a numerically higher speaking score, the evidence is insufficient to conclude that its posttest speaking performance was significantly better than that of the control group.

Table 3

Mean Gains of the Control and Experimental Groups

Skill	Group	Pretest Mean	Posttest Mean	Mean Gain	SD of Gain
Writing	Control	43.80	48.70	4.90	10.54
	Experimental	46.65	60.10	**13.45**	15.15
Speaking	Control	1.80	2.52	**0.72**	1.32
	Experimental	2.55	3.22	0.67	1.21

For Table 3, the control group increased by an average of 4.90 points in writing, whereas the experimental group increased by 13.45 points. Thus, the experimental group's writing improvement was almost three times the mean improvement observed in the control group. An independent-samples t-test comparing the writing gain scores showed that the difference in gains was statistically significant, $t(38) = 2.07$, $p = .045$. Therefore, the null hypothesis is rejected. This finding suggests that the improvement in writing was significantly greater among students exposed to the intervention. The effect size for the difference in writing gains was approximately Cohen's d = 0.66, which indicates a moderate-to-large treatment effect.

This finding implies that the experimental group had progressed with the tutorials conducted online for the writing skill. Based on the material used, the respondents were able to develop their skills using the language effectively in writing cover letters and curriculum vitae. Results indicated their capability to articulate their knowledge and insights about their career trajectory or prospective profession. Specifically, they could expound about their background, interests, and technical knowledge with reasonable ease. They had control of structure and spelling; and general vocabulary was adequate to

convey their message accurately. They showed consistency in control of compound and complex sentences. On the other hand, the respondents displayed only few errors in basic grammar structures, occasional errors using compound sentences, and somewhat more frequent in the highly formal, specialized or idiomatic sentence structures. The study of Li (2023) showed that online tutorials were effective as reflected in the expert assessment and participants' self-assessment. The tutorial covered among others, logic of structure, cohesion, academic writing and grammar. The positive findings were attributed to study's design principles which encompassed several academic genres and corpus linguistics. On the other hand, writing tutorials according to Cho (2023) showed that interactional level tutorial worked better than online tutorials. The reason for this was the technical limitations attributed to online communication. Hence, some sought to establish another alternative to deliver English tutorial to the students.

In speaking, the control group recorded a mean gain of 0.72, whereas the experimental group recorded a mean gain of 0.67. The gains were nearly identical. The difference between the two groups was not statistically significant, $t(38) = 0.12$, $p = .903$. Thus, the null hypothesis is not rejected for speaking gain scores. This means that although the students in the experimental group improved in speaking, their improvement was not significantly greater than the improvement demonstrated by students who did not receive the intervention. Consequently, the speaking gains cannot be attributed specifically to the treatment based on these data.

Table 4

Pretest–Posttest Performance of the Experimental Group

Skill	Pretest Mean	Posttest Mean	Mean Difference	t	df	p-value	Decision on H_0	Interpretation
Writing	46.65	60.10	13.45	3.97	19	<.001	Reject	Significant
Speaking	2.55	3.22	0.67	2.47	19	.023	Reject	Significant

Table 4 reveals that the experimental group's writing mean increased from 46.65 in the pretest to 60.10 in the posttest, representing an average increase of 13.45 points. The paired-samples t-test showed that this improvement was statistically significant, $t(19) = 3.97$, $p < .001$. Therefore, the null hypothesis is rejected. The corresponding paired-samples effect size was approximately Cohen's dz = 0.89, indicating a large improvement in writing following the intervention. This finding provides evidence that the students' writing performance improved substantially during the intervention period. The experimental group's speaking mean likewise increased from 2.55 to 3.22, corresponding to an average gain of 0.67. The difference was statistically significant, $t(19) = 2.47$, $p = .023$. Thus, the null hypothesis is also rejected for the experimental group's within-group speaking comparison.

While this finding confirms that the experimental students improved significantly in speaking from pretest to posttest, it should not by itself be interpreted as proof that the intervention caused the

improvement. The control group also demonstrated a statistically significant speaking improvement during the same period. For comparison, the control group's speaking score increased significantly from 1.80 to 2.52, $t(19) = 2.43$, $p = .025$. Its average speaking gain of 0.72 was actually slightly higher than the experimental group's gain of 0.67. Therefore, the within-group improvement observed in the experimental group must be considered together with the between-group comparison. Because the experimental group already performed significantly better than the control group in speaking during the pretest, ANCOVA was conducted to determine whether group membership significantly predicted posttest performance after controlling for the corresponding pretest score.

Table 5

ANCOVA Results for Posttest Performance Controlling for Pretest Scores

Outcome	Adjusted Group Effect	p-value	Decision	Interpretation
Posttest Writing	10.53	<.001	Significant	Experimental group remained significantly higher
Posttest Speaking	0.32	.432	Not Significant	No significant treatment-related group difference

After controlling for pretest writing scores, membership in the experimental group remained a statistically significant predictor of posttest writing performance, $p < .001$. The adjusted coefficient of approximately 10.53 points indicates that, after accounting for initial writing performance, students in the experimental group were predicted to score about 10.5 points higher in posttest writing than students in the control group.

For speaking, however, after controlling for the initial speaking score, the adjusted group effect was not statistically significant, $p = .432$. This result provides further evidence that the higher speaking scores observed among experimental students cannot confidently be attributed to the intervention. Rather, part of the observed difference can be explained by their higher speaking performance prior to the treatment. The lack of improvement in the speaking skills among the experimental group could be attributed to several factors. Previous studies have shown that students claimed limited ability to speak or were not able attain academic benchmarks in speaking due to lack of time to practice, fear of being scolded, and peer pressure (Khan, N., and Ali, A., 2010). Another study enumerated students' perceived speaking problems such as lack of vocabulary knowledge, pronunciation difficulties, incorrect grammar, inability to connect sentences and paragraphs, and lack of confidence (Riaz, Y. Kausar, G., 2024).

Overall Statistical Interpretation

The overall findings showed evidence the intervention's effectivity in improving writing skillsThe experimental and control groups had a statistically comparable writing performance at the onset, but

the experimental group subsequently obtained significantly higher posttest scores and significantly greater writing gains. The experimental students also manifested a large and statistically significant pretest-to-posttest improvement in writing. Importantly, the advantage in writing remained statistically significant even after controlling for initial writing ability through ANCOVA. However, the evidence for an intervention effect on speaking was considerably weaker. Although the experimental group demonstrated a statistically significant improvement from pretest to posttest, the control group demonstrated a comparable improvement. Moreover, the experimental group's significantly higher speaking performance before the intervention made the difference in speaking gain scores between the two groups not significant. Furthermore, the use of ANCOVA showed no significant adjusted treatment effect on posttest speaking. Thus, the results indicate that the intervention had a pronounced and statistically supported effect on students' writing performance but did not demonstrate a distinct treatment effect on speaking performance.

The intervention is deemed effective for developing writing skills. The findings elucidate that the respondents demonstrated the principles of Vygotsky's Zone of Proximal Development (ZPD) in their writing performance. The tutorial intervention facilitated the development of automaticity in second language acquisition based on the observed gains. This enables learners to perform writing tasks independently with reduced external support. The substantial improvement in writing further implies that scaffolded learning experiences effectively assisted learners in progressing from assisted performance to self-regulated task completion.

Meanwhile, the significant within-group speaking improvement demonstrates developmental progress among the experimental students in speaking. The respondents may have exhibited evidence of ZPD in speaking, as reflected in their improved post-intervention performance. However, the available statistical evidence does not establish that this progress exceeded what occurred under the control condition. This finding suggests that the development of automaticity in oral language production may require more sustained exposure, repeated practice, and authentic communicative interactions. Consequently, learners may benefit from additional speaking opportunities and structured oral activities designed to reinforce fluency, confidence, and spontaneous language use. These findings underscore the importance of continuous scaffolding and meaningful practice in facilitating learners' progression toward greater communicative competence.

Conclusion

The findings provide diverse opportunities in the development of appropriate strategies in delivering tutorial interventions to the respondents and other students needing such assistance. The emphasis of this study is on giving premium on assisting students to varying forms of learning to assure students continued success not only in their academic life, but also in their preparation for future employment. As disclosed, the improved writing performance of the respondents shows the usefulness of online

tutorial interventions to enhance English writing skills. This finding is supported by various literatures indicating that the students' writing skills are learned and will go through a process in which learners progressively acquire and refine skills through practice, feedback, and revision. Accordingly, writing instructors should provide systematic support in areas such as content development, organization, grammar, and language use. Interactive online tutorials and technology-enhanced applications may therefore be strategically integrated into language instruction to provide engaging, flexible, and meaningful opportunities for students to practice and improve their writing skills. The use of such platforms can also provide authentic and learner-centered experiences that complement, rather than simply replicate, traditional face-to-face tutorials.

Although the findings did not provide conclusive evidence that the speaking intervention produced significant treatment-related gains, this result should not be interpreted as evidence that online tutorials are inherently ineffective for developing speaking skills. Rather, the findings suggest that speaking proficiency may require more sustained exposure, repeated practice, authentic communicative interaction, and more intensive instructional scaffolding. Given the evidence reported in previous studies on technology-supported language learning, further research is recommended to examine how redesigned and more interactive online tutorials can effectively facilitate the development of speaking skills. Also, future studies may consider longer intervention periods, more frequent speaking activities, authentic communicative tasks, peer interaction, individualized feedback, and technology-supported opportunities for repeated oral practice.

Future researchers may also explore hybrid tutorial models that combine the accessibility and flexibility of technology-mediated instruction with the interpersonal support provided by face-to-face tutorials. Such models may accommodate students who prefer traditional classroom interaction while extending tutorial support beyond the physical classroom. Technology alone does not guarantee successful learning. Language teachers should foster students' sense of responsibility, self-regulation, and active participation in their own learning. Although online tutorials can promote self-directed and self-regulated learning, students may also encounter competing distractions, including social networking platforms, entertainment, and online gaming, which can reduce the time and attention devoted to academic tasks. Thus, the role of the teacher, tutor, or facilitator remains essential. Effective tutorial intervention ultimately depends on the complementary relationship between purposeful instructional design, innovative technology, competent facilitation, and students' active engagement in the learning process.

References:

Abadilla, D. D. (2021, October 1). Int'l study notes worst 'learning loss' among poorest PH kids. *Philippine Daily Inquirer*. https://globalnation.inquirer.net/199341/intl-study-notes-worst-learning-loss-among-poorest-ph-kids

Alamri, W., & Qasem, F. (2024). Foreign language speaking anxiety in relation to gender: students and teachers' perceptions. Cogent Education, 11(1). https://doi.org/10.1080/2331186X.2024.2423440

Bhatia, K. V., Arora, P. & Gupta, S. (2025). Edtech platforms from below: a family ethnography of marginalized communities and their digital learning post-pandemic. *Learning, Media and Technology*, *50*(4), 482–496. https://doi.org/10.1080/17439884.2024.2328693

CHED Memorandum Order No. 16, Series of 2022,

CHED Memorandum Order No. 12, Series of 2025.

Cho, S. (2023). Online vs. Offline Interactions During Writing Tutorials: Focusing on Korean Learners of English. 영어학, 23, 160-174. DOI: DOI: 10.15738/kjell.23..202302.160

Dinh, C. T., & Phuong, H. Y. (2024). MOOC learners' perspectives of the effects of self-regulated learning strategy intervention on their self-regulation and speaking performance. Cogent Education, 11(1). https://doi.org/10.1080/2331186X.2024.2378497

Downes, Colm, (2009) Cambridge English for Job Hunting. Cambridge University Press. UK.

Hartono, D., Basthomi, Y., Widiastuti, O., & Prastiyowati, S. (2022). The Impacts of Teacher's Oral Corrective Feedback to Students' Psychological Domain:A Study on EFL Speech Production. Cogent Education, 9(1). https://doi.org/10.1080/2331186X.2022.2152619

Heron, M., Dippold, D., Aksit, N., Aksit, T., Doubleday, J., & McKeown, K. (2024). Tutors' beliefs about language and roles: practice as language policy in EMI contexts. *Teaching in Higher Education, 29* (1), 251–265. https://doi.org/10.1080/13562517.2021.1973410

Horvath, K., & Steinberg, M. (2023). Social classification and the changing boundaries of learning. A neopragmatic perspective on social sorting in digital education. *Learning, Media and Technology*, *48*(4), 566–580. https://doi.org/10.1080/17439884.2023.2219900

Khan, N. & Arshal Ali (2010). Improving the speaking ability in English: The students' perspective. *Procedia - Social and Behavioral Sciences*, *2*(2). https://doi.org/10.1016/j.sbspro.2010.03.554

Li, Z., Makarova, V., & Wang, Z. (2023). Assessment of academic esl writing in an online tutorial for graduate students. In 22nd European Conference on e-Learning: ECEL 2023. Academic Conferences and publishing limited.

Lu, B. J. (2023, June 16). Addressing effects of COVID-19 among Filipino learners. *Philippine News Agency*. https://www.pna.gov.ph/opinion/pieces/704-addressing-effects-of-covid-19-among-filipino-learners

Riaz, Y., & Kausar, G. (2024). Improving Pakistani college students' speaking skills using AI-driven linguistic input: An experimental study. *Journal of Asian Development Studies, 13*(4), 853-870.

Shahini, A. (2025). Automaticity in Language Learning. In: Language Learning Theories. Palgrave Macmillan, Cham. https://doi.org/10.1007/978-3-031-92210-7_8

Suzuki, Y. Maie, R., & Hui, B. (2025). Research timeline: Automatization in second language learning. Language Teaching, 1-20. https://doi. org/10.1017/S026144482500059X.

Willis, A., Sempowicz, T., & Robertson, A. (2025). University student experiences of feedback: timing and credibility are key. *Teaching in Higher Education*, 1–18. https://doi.org/10.1080/13562517.2025.2605679

P26016

A Data-Driven Competency Training Evaluation Framework for the Public Sector: Integrating Learning Analytics, Kirkpatrick Model, IPA, and IR–IT Collaboration

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ABSTRACT

As governments advance digital transformation and evidence-based decision making, public sector training management is shifting from administrative record-keeping toward data-informed governance. However, many training evaluation practices still rely heavily on post-training satisfaction surveys and lack integrated approaches for examining learning outcomes, workplace application, and longer-term organizational relevance across multiple years. This study aimed to develop a data-driven competency training evaluation framework by integrating Learning Analytics, the Kirkpatrick Four-Level Evaluation Model, Institutional Research (IR), Information Technology (IT), and dashboard-based decision support.

A case study with secondary data analysis was conducted using de-identified training data from the Waste Management Supervisor Training Program organized by Taiwan's Environmental Management Administration during 2023–2024. The framework was mapped to the four levels of the Kirkpatrick model. Individual-level administrative data were available for Level 1 reactions and Level 3 self-reported workplace effectiveness, while publicly reported aggregate learning-gain statistics and follow-up summaries provided supplementary contextual evidence related to Levels 2 and 4. Descriptive statistics, cross-year comparisons, reliability analysis, and dashboard visualization were used to examine training effectiveness, and an Importance–Performance Analysis (IPA) dashboard prototype was developed as a proof of concept for future competency-gap analysis.

The findings showed that learner satisfaction remained consistently high, while cross-year differences in the available composite indicators were modest and not statistically significant.

[1] **Disclaimer:** The content and views expressed in this study represent the authors' independent academic research and do not represent the position of the commissioning agency, the Environmental Management Administration, Ministry of Environment, Taiwan.

Publicly reported Level 2 learning-gain statistics and post-training follow-up summaries provided supplementary contextual evidence concerning learning patterns, reported workplace application, implementation conditions, and suggestions for course improvement.

This study contributes by proposing a practical Data-Driven Competency Training Evaluation Framework that integrates training evaluation, Learning Analytics, IR–IT collaboration, and dashboard visualization. Rather than claiming a fully validated governance system, the study offers an empirically grounded proof of concept for transforming fragmented training records into actionable evidence for continuous improvement and competency-oriented decision support.

Keywords: Learning Analytics, Competency-Based Training, Digital Transformation, Evidence-Based Decision Making

Introduction

The rapid development of artificial intelligence (AI), digital transformation, and evidence-based decision making has fundamentally changed how governments manage organizational learning and human resource development. Rather than relying solely on administrative records or post-training satisfaction surveys, public sector organizations are increasingly expected to transform training data into actionable evidence that supports policy formulation, resource allocation, and competency development.

Despite this trend, training evaluation in many public organizations remains limited to measuring participants' immediate reactions. Most evaluation practices focus on course satisfaction and annual reports, while cross-year comparisons, competency development, workplace application, and organizational outcomes receive relatively limited attention. Consequently, training managers often lack sufficient evidence to identify competency gaps, evaluate long-term training effectiveness, or support continuous improvement through data-driven decision making.

The theme of SEAAIR 2026, Digital Transformation of Educational Efficiencies and Effectiveness: Roles of IR and IT Integration, highlights the importance of integrating Institutional Research (IR) and Information Technology (IT) to support digital transformation in educational and organizational contexts. Within public sector training, IR provides evidence generation through data analysis and evaluation, whereas IT enables data integration, system management, and visualization. Effective collaboration between IR and IT therefore offers an

opportunity to transform fragmented training records into meaningful governance information that supports evidence-based decision making.

To address this gap, this study proposes a Data-Driven Competency Training Evaluation Framework by integrating Learning Analytics, the Kirkpatrick Four-Level Evaluation Model, Importance–Performance Analysis (IPA), and IR–IT collaboration. Using the Waste Management Supervisor Training Program organized by Taiwan's Environmental Management Administration during 2023–2024 as a case study, this research combines secondary data analysis with dashboard-based visualization to examine training effectiveness from multiple perspectives.

Specifically, this study pursues three objectives: (1) to develop a competency-based training evaluation framework integrating Learning Analytics and the Kirkpatrick model; (2) to examine training effectiveness through cross-year analyses of learning satisfaction and self-reported workplace effectiveness, supplemented by publicly reported learning-gain evidence; and (3) to demonstrate how IR–IT integration and dashboard visualization can support evidence-based decision making and digital governance in public sector training.

This study contributes to the literature in three ways. First, it extends the application of Learning Analytics and the Kirkpatrick model to the context of public sector competency training. Second, it proposes a governance-oriented framework that integrates training evaluation, competency analysis, and dashboard visualization. Third, it illustrates how IR–IT collaboration can transform fragmented training records into decision-support information for continuous improvement and digital transformation.

Literature Review

2.1 Digital transformation and IR–IT integration

Digital transformation has become a key strategy for improving organizational effectiveness and evidence-based decision making in the public sector. Taiwan's digital governance policies emphasize data governance, cross-agency data integration, and the application of digital technologies to enhance public value and administrative efficiency (National Development Council, 2021; Ministry of Digital Affairs, 2024). In the education sector, the Ministry of Education (2022) also highlights that data-driven governance requires integrated data collection, management, analysis, and application to support policy development and continuous improvement.

From a governance perspective, digital transformation extends beyond technology adoption. Chen (2021) argues that successful digital transformation requires organizational change, process redesign, and governance innovation, enabling institutions to transform fragmented information into strategic decision-support resources.

Within this context, Institutional Research (IR) and Information Technology (IT) play complementary roles. IR focuses on defining evaluation questions, constructing analytical indicators, and interpreting evidence for decision making, while IT provides data integration, system maintenance, and information security. Effective collaboration between IR and IT therefore enables organizations to establish a data governance framework that supports evidence-based management rather than routine administrative reporting.

Building upon this perspective, this study applies the concept of IR–IT integration to public sector training management and proposes a governance framework that transforms training records into decision-support information for competency development and continuous improvement.

2.2 Learning Analytics and Training Evaluation

Learning Analytics has emerged as an important approach for supporting educational decision making through the systematic collection, analysis, and interpretation of learning data. Long and Siemens (2011) define Learning Analytics as the measurement, collection, analysis, and reporting of learner data and learning contexts for the purpose of understanding and optimizing learning and the environments in which it occurs.

Previous studies have shown that Learning Analytics can support curriculum improvement, learner monitoring, organizational planning, and quality enhancement (Wong, 2017). Effective Learning Analytics, however, depends not only on analytical techniques but also on integrated data management throughout the data lifecycle, including data collection, storage, integration, analysis, and decision support (Alblawi, 2018).

While Learning Analytics has been widely applied in higher education, its application in public sector training remains limited. Most government training programs continue to rely primarily on satisfaction surveys and descriptive statistics, making it difficult to evaluate long-term learning outcomes or support evidence-based governance.

To address this limitation, this study integrates Learning Analytics with the Kirkpatrick Four-Level Evaluation Model. The framework evaluates training effectiveness across four

dimensions: reaction (L1), learning (L2), behavior (L3), and organizational outcomes (L4). By combining multiple sources of training data, Learning Analytics provides a foundation for continuous evaluation rather than one-time course assessment.

2.3 Competency Gap Analysis Using IPA

Importance–Performance Analysis (IPA), originally proposed by Martilla and James (1977), evaluates organizational performance by comparing perceived importance with actual performance, allowing managers to identify priorities for improvement and resource allocation. Because of its simplicity and practical value, IPA has been widely applied in business management, education, public services, and nonprofit organizations.

In training evaluation, IPA has been extended to competency development by comparing the perceived importance of competencies with current competency levels. Wen and Lin (2018) demonstrated that IPA can effectively identify priority improvement areas and support strategic resource allocation in nonprofit organizations.

Despite its wide application, IPA has rarely been integrated with Learning Analytics and public sector training evaluation. Accordingly, this study applies IPA as a competency governance tool to complement Learning Analytics and the Kirkpatrick evaluation framework. The IPA dashboard presented in this study serves as a proof of concept, illustrating how competency gap analysis can support future training planning and resource allocation. Because competency importance ratings were not available during the study period, the prototype uses simulated data to demonstrate the analytical framework rather than actual competency gaps.

Government policy documents and practitioner reports are cited in this section primarily to illustrate the policy context for digital governance in Taiwan rather than as primary theoretical sources.

Kirkpatrick defines what training outcomes should be evaluated; Learning Analytics provides the data and analytical processes for longitudinal evaluation; IPA extends the framework toward competency-priority identification; and IR–IT collaboration provides the organizational and technological infrastructure required to operationalize these components as a continuous decision-support system.

Methodology

3.1 Research design

This study adopted a case study approach combined with secondary data analysis to examine how public sector training data can support evidence-based decision making through Learning Analytics and digital governance. The case examined a management-level training program implemented under projects commissioned by the Environmental Management Administration, Ministry of Environment, Taiwan, during 2023–2024.

The case study approach is appropriate for investigating complex organizational phenomena within real-world contexts (Yin, 2018). The study combined secondary analysis of de-identified administrative training data with documentary analysis of publicly available project reports. The administrative records and publicly reported training results were generated through routine government training activities rather than collected specifically for this research.

Based on Learning Analytics, this study integrates the Kirkpatrick Four-Level Evaluation Model, competency analysis, and dashboard visualization to develop a Data-Driven Competency Training Evaluation Framework for public sector training governance.

3.2 Data sources, participants, and indicators

The individual-level administrative dataset used for quantitative analysis included de-identified trainee background information, Level 1 course and activity satisfaction survey responses, and Level 3 self-reported workplace-effectiveness responses. These data were used solely for the approved academic research purpose and were analyzed and reported only in aggregate form. Evidence for Level 2 learning outcomes and Post-training follow-up evidence related to Level 4 was drawn from publicly available project reports issued by the Environmental Management Administration, Ministry of Environment, Taiwan. The Level 2 materials consisted of publicly reported pre- and post-training learning-gain statistics. The Level 4 materials consisted of published thematic summaries concerning workplace application, perceived changes in work practices, implementation facilitators and barriers, and suggestions for course improvement. The present study used these published materials as contextual and supplementary evidence; it did not access or analyze individual-level pre- and post-test records, individual interview records, or original interview transcripts.

The quantitative administrative dataset included 408 trainees (N = 408) enrolled in the Waste Management Supervisor Training Program across five course categories: foundational legal courses (n = 237, 58.1%), advanced legal courses (n = 64, 15.7%), communication and

coordination courses (n = 61, 15.0%), supervisory leadership courses (n = 36, 8.8%), and environmental practice courses (n = 10, 2.5%). In terms of gender, 243 participants (59.6%) were male and 165 participants (40.4%) were female. The sample included participants across multiple age groups and years-of-service categories; nearly half of the participants had less than five years of service in cleaning teams.

To improve interpretability, three composite indicators already embedded in the administrative dataset were used in the analysis: course planning satisfaction, facilities and service satisfaction, and self-rated workplace effectiveness. Course planning satisfaction summarized participants' perceptions of instructional design and teaching-related arrangements (content, duration, instructor, and course organization), facilities and service satisfaction summarized venue- and service-related experiences (catering, venue, and equipment), and self-rated workplace effectiveness summarized the five workplace application items. These composite indicators served as the principal variables for cross-year inferential comparison in this study.

Table 1: Training evaluation indicators

Level	Data source	Indicator	Analysis
Basic information	De-identified administrative training dataset	Year, course type, participant characteristics	Descriptive statistics
L1	De-identified administrative training dataset	Course content, instructor, duration, course arrangement, catering, venue, and equipment	Reliability analysis, descriptive statistics, and cross-year comparisons
L2	Publicly available project reports	Reported pre- and post-training learning-gain statistics	Documentary synthesis / descriptive contextual interpretation
L3	De-identified administrative training dataset	Self-rated workplace usefulness, knowledge application, perceived performance improvement, acceptance of new challenges, and proactive work attitude	Reliability analysis, descriptive statistics, independent-samples t-tests, and one-way ANOVA
L4	Publicly available project reports	Published summaries of workplace application, facilitators and barriers, and course-improvement suggestions	Documentary synthesis of published thematic summaries

3.3 Data preparation and analysis procedures

The analysis proceeded in four stages.

First, the de-identified 2023 and 2024 administrative datasets containing Level 1 and Level 3 measures were integrated into a unified database for cleaning and standardization. Data

preparation included checking variable consistency, identifying missing values, confirming course-type coding, and reviewing the structure of derived composite indicators already recorded in the administrative data file.

Second, descriptive statistics were used to summarize participant characteristics and the overall distribution of training evaluation indicators. Frequencies and percentages were calculated for year, course type, and gender, while available information on age and years of service was used to provide descriptive participant context. Means and standard deviations were also examined for the three composite indicators: course planning satisfaction, facilities and service satisfaction, and self-rated workplace effectiveness.

Third, inferential analyses were conducted to strengthen cross-year comparison. Independent-samples t-tests were performed to examine whether the 2023 and 2024 cohorts differed significantly in course planning satisfaction, facilities and service satisfaction, and self-rated workplace effectiveness. Levene's tests were used to assess homogeneity of variance before interpreting the t-test results. In addition, a one-way analysis of variance (ANOVA) was conducted to examine whether self-rated workplace effectiveness differed across the five course categories.

Fourth, competency-gap analysis and dashboard visualization were used as supplementary demonstration modules rather than full validation components. A prototype of Importance–Performance Analysis (IPA) was constructed to illustrate how competency importance and performance data could eventually be integrated into decision support. Because direct competency-importance ratings were not available in the study period, the IPA component used simulated values solely for proof-of-concept purposes and therefore should not be interpreted as empirical evidence of actual competency gaps. The dashboard prototype integrated descriptive results, cross-year comparisons, and the conceptual IPA module to demonstrate how IR–IT collaboration can support training governance through data integration and visualization.

3.4 Reliability of composite scales

The internal consistency of the composite scales was assessed using Cronbach's alpha, a commonly used indicator for evaluating the reliability of multi-item measures. Table 2 summarizes the reliability estimates for the three scales used in this study. The results indicated satisfactory to excellent internal consistency across all constructs, with Cronbach's alpha coefficients of .945 for course planning satisfaction, .889 for facilities and service satisfaction, and .965 for self-rated workplace effectiveness. These findings suggest that the items included

in each scale were sufficiently consistent to justify their aggregation into composite indicators for further analysis.

Table 2 Internal consistency of composite scales (Cronbach's alpha)

Construct	Number of items	Example item content (summary)	Cronbach's α
Course planning satisfaction	4	Satisfaction with content, course duration, instructor quality, course arrangement	.945
Facilities and service satisfaction	3	Satisfaction with catering, venue, equipment	.889
Self-rated workplace effectiveness	5	Perceived usefulness for work, application of new knowledge, improved performance, new challenges, proactive attitude	.965

3.5 Statistical analysis strategy

All quantitative analyses were conducted using SPSS. Descriptive statistics and inferential results are summarized in Tables 3 and 4. As shown in Table 3, independent-samples t-tests indicated no statistically significant cross-year differences in the three composite indicators.

Table 3 Cross-year comparisons of composite indicators (independent-samples t-tests)

Composite indicator	Year	n	M	SD	t(df)	p
Self-rated workplace effectiveness	2023	249	4.372	0.728	−0.212 (406)	.832
	2024	159	4.387	0.711		
Facilities and service satisfaction	2023	249	4.249	0.803	−0.547 (406)	.585
	2024	159	4.292	0.770		
Course planning satisfaction	2023	249	4.393	0.736	−1.690 (406)	.092
	2024	159	4.517	0.713		

Table 4 Differences in self-rated workplace effectiveness by course type (one-way ANOVA)

Outcome	Source	SS	df	MS	F	p
Self-rated workplace effectiveness	Between groups	0.474	4	0.119	0.227	.923
	Within groups	210.887	403	0.523		
	Total	211.361	407			

3.6 Publicly Reported Level 2 and Level 4 Supplementary Evidence

Evidence concerning Level 2 learning outcomes and Post-training follow-up evidence related to Level 4 was drawn from publicly available project reports issued by, or made publicly available through, the Environmental Management Administration, Ministry of Environment, Taiwan.

The present study did not access or analyze individual-level pre- and post-test records, individual interview records, or original interview transcripts. Instead, the published aggregate statistics and thematic summaries were used as contextual evidence to complement the quantitative analysis of de-identified Level 1 and Level 3 administrative training data. Accordingly, the Level 2 and Level 4 evidence should be interpreted as supplementary and descriptive rather than as independently reanalyzed individual-level evidence.

Because the publicly available reports did not provide sufficient information to independently verify the measurement properties and calculation procedures of the learning-gain indicators, these values were used only for descriptive contextual comparison.

3.7 Dashboard Prototype

A dashboard prototype was developed to demonstrate the practical application of the proposed framework in a visual decision-support environment. The dashboard prototype was developed as a web-based interactive visualization using HTML, CSS, and JavaScript, based on the integrated administrative dataset described in Sections 3.2 and 3.3. Within this process, IR guided indicator development, analytical interpretation, and dashboard design, while the technical implementation supported data presentation, interaction, and visualization.

The development process followed three main steps. First, key indicators were selected and grouped according to the four levels of the Kirkpatrick model (L1–L4) and the three composite scales (course planning satisfaction, facilities and service satisfaction, and self-rated workplace effectiveness). Second, these indicators were organized into a modular dashboard structure that allows users to switch between overall trends, cross-year comparisons, and course-level views. Third, interactive charts and summary panels were configured to support basic filtering by year and course category, providing training managers with an accessible interface for exploratory review.

The dashboard consists of four functional modules: (1) a training effectiveness module displaying L1–L3 indicators and composite scores; (2) a contextual evidence module summarizing publicly reported post-training follow-up themes relevant to Level 4; (3) a competency-gap module presenting the IPA prototype; and (4) a cross-year comparison module for reviewing longitudinal patterns. Rather than serving as a production information system, the dashboard functions as a proof of concept, illustrating how IR–IT collaboration can integrate administrative training data into a visual decision-support platform for competency development and continuous improvement.

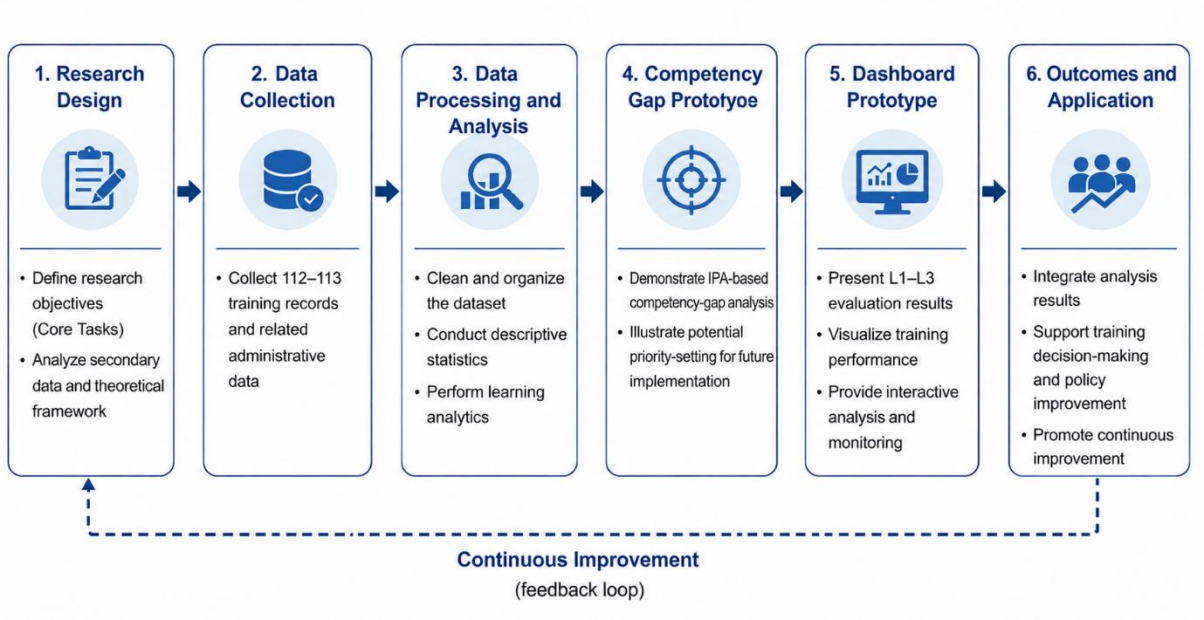


Figure 1: Research Framework

Discussion

4.1 Training Effectiveness Across Kirkpatrick Levels

The results revealed different but complementary patterns across the Kirkpatrick evaluation levels. At the reaction level (L1), participants reported consistently high levels of satisfaction with course planning and facilities and services in both 2023 and 2024. Cross-year comparisons further indicated that these differences were not statistically significant, suggesting that participants' immediate reactions to the training remained relatively stable across the two cohorts.

At the behavior level (L3), self-rated workplace effectiveness also remained high in both years. Although the 2024 cohort showed a slightly higher mean score than the 2023 cohort, the difference was not statistically significant. These findings suggest that, within the available participant-level data, the training program maintained a generally positive pattern of perceived workplace applicability across the two program years.

For the higher levels of evaluation, the available evidence was more mixed and should be interpreted cautiously. Publicly reported Level 2 learning-gain statistics and Level 4 follow-up summaries provided supplementary contextual information; these materials were not subjected to individual-level inferential analyses in the present study.

Because the Level 2 evidence consisted of publicly reported aggregate learning-gain statistics rather than individual-level pre- and post-test records, it was interpreted descriptively and was not subjected to inferential analysis in the present study. Accordingly, conclusions regarding learning outcomes and post-training follow-up should be interpreted with appropriate caution.

Taken together, the findings support the broader Kirkpatrick argument that training evaluation should not rely solely on immediate satisfaction measures, but should instead combine multiple sources of evidence across evaluation levels.

Figure 2 illustrates how the proposed dashboard integrates indicators across the four Kirkpatrick levels. The dashboard combines L1–L4 evidence into a unified monitoring interface to support evidence-based decision making in public sector training.



Figure 2 Four-Level Training Evaluation Dashboard for Public Sector Competency Training (L1–L4)

4.2 Course-Level Differences and Learning Analytics

Cross-course comparisons showed some descriptive variation across course categories; however, these patterns were exploratory and should not be interpreted as evidence of differential course effectiveness. Consistent with this interpretation, the one-way ANOVA did not indicate a statistically significant difference in self-rated workplace effectiveness across course categories.

This result suggests that any apparent differences across course types were modest within the current sample and were not strong enough to support firm claims of differential effectiveness. Rather than demonstrating clear superiority of one course type over another, the results indicate that course-level variation may be better interpreted as a practical signal for ongoing monitoring and instructional refinement. From a Learning Analytics perspective, this is still valuable because it allows training managers to move beyond single-session satisfaction summaries and begin identifying where deeper follow-up or redesign may be warranted.

The dashboard prototype therefore serves less as a tool for making definitive comparative judgments and more as an integrative monitoring interface. By bringing together satisfaction, learning, and workplace application indicators across years and course categories, it supports pattern recognition, longitudinal review, and data-informed discussion among training managers and system developers.



Figure 3: Cross-Year Dashboard Prototype Showing Training Indicators and Reported Level 2 Learning-Gain Statistics

Note. Level 2 values are based on aggregate learning-gain statistics reported in publicly available project reports and are presented for contextual illustration only; no individual-level inferential analysis was conducted.

4.3 Competency Governance Through IPA and Qualitative Follow-Up

To extend the framework beyond the individual-level Level 1 and Level 3 analyses, this study incorporated publicly reported Level 2 learning-gain statistics and Level 4 follow-up summaries, together with an IPA-based competency-governance prototype. The publicly available project reports described follow-up activities conducted after training and presented thematic summaries concerning the reported application of course content, perceived changes in work practices, implementation facilitators and barriers, and suggestions for course improvement.

These published Level 4 summaries provided contextual evidence that complemented the quantitative findings. They should not be interpreted as the results of a new qualitative study conducted by the present authors, because the study did not access individual interview records or original transcripts and did not perform primary qualitative coding. Rather, the value of the publicly reported follow-up evidence lies in illustrating how training evaluation can connect participant-reported workplace application with continuing program improvement.

The IPA module should be understood more cautiously. Because direct competency-importance ratings were unavailable during the study period, simulated data were used to construct the IPA dashboard as a proof of concept rather than as a validated empirical model of actual competency gaps. Accordingly, the contribution of this component lies in demonstrating a feasible analytical architecture for future governance use, not in claiming that the present study has identified verified competency priorities.

Taken together, the publicly reported Level 4 follow-up summaries and the IPA prototype illustrate how the proposed framework can evolve from post-training reporting toward more comprehensive competency governance. However, the current study should be understood as an initial demonstration of this integrative approach, and future research will need to incorporate actual competency-importance data, more systematic qualitative coding procedures, and broader organizational outcome measures to validate the framework more fully.

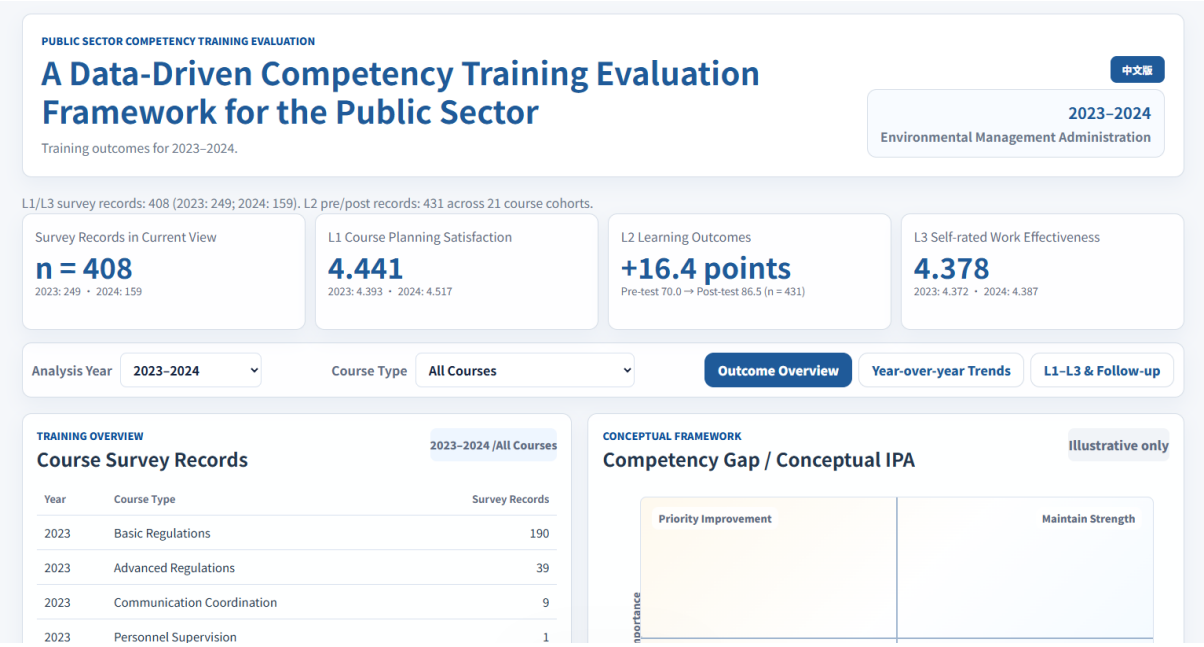


Figure 4: Prototype Dashboard of Training Outcomes and Competency-Gap IPA Analysis Using Simulated Importance Values

4.4 IR–IT Integration for Data-Driven Governance

One of the major contributions of this study is the integration of Institutional Research (IR) and Information Technology (IT) into public sector training governance. As illustrated by the dashboard prototype, the proposed framework distinguishes complementary IR and IT functions: IR focuses on indicator construction and analytical interpretation, whereas IT functions support data integration, system implementation, and visualization.

Within the proposed framework, Within the proposed framework, IR is responsible for defining evaluation indicators and interpreting analytical findings, whereas From the perspective of the proposed IR–IT framework, IR functions include indicator development and analytical interpretation, whereas IT functions include data integration, system implementation, and visualization. Through continuous collaboration between IR and IT, fragmented training records can be transformed into governance resources that support evidence-based decision making, competency development, and continuous improvement.

Overall, this study demonstrates that integrating Learning Analytics, the Kirkpatrick evaluation model, dashboard visualization, and IR–IT collaboration provides a practical approach for advancing digital transformation in public sector training management.

Conclusion

This study developed a Data-Driven Competency Training Evaluation Framework for public sector training by integrating Learning Analytics, the Kirkpatrick Four-Level Evaluation Model, Importance–Performance Analysis (IPA), and IR–IT collaboration. Using the Waste Management Supervisor Training Program of Taiwan's Environmental Management Administration as a case study, the research demonstrated how administrative training records can be organized into a more systematic evidence base for competency development, longitudinal review, and data-informed governance.

The empirical findings showed that learner satisfaction remained high across the two-year period and that the three composite indicators examined in the quantitative analysis were relatively stable across cohorts. Cross-year differences in course planning satisfaction, facilities and service satisfaction, and self-rated workplace effectiveness were not statistically significant, suggesting that the observed variations should be interpreted cautiously. At the same time, publicly reported follow-up summaries added contextual insight into how trainees perceived the practical application of course content and where further instructional refinement may be needed.

Taken together, the study suggests that training evaluation in the public sector benefits from combining satisfaction measures, workplace-related self-assessments, follow-up qualitative evidence, and visualization tools rather than relying on any single source of data. The framework therefore contributes less as a claim of completed governance transformation and more as a practical and research-based model for structuring future evidence-based training management.

5.1 Conceptual and Integrative Contributions

This study makes three conceptual and integrative contributions. First, it extends the application of the Kirkpatrick Four-Level Evaluation Model by embedding it within a Learning Analytics perspective that emphasizes longitudinal integration of multiple administrative and evaluative data sources rather than one-time post-course assessment. In this sense, the study contributes to the literature not by introducing an entirely new theory, but by clarifying how existing evaluation concepts can be systematically connected in the context of public sector competency training.

Second, the study proposes a more explicitly governance-oriented interpretation of training evaluation. By linking training satisfaction, workplace application, qualitative follow-up, and

dashboard-based monitoring, the framework repositions evaluation as an ongoing evidence infrastructure for managerial reflection and program refinement rather than merely an end-of-course reporting exercise.

Third, the study contributes to discussions of IR–IT integration by illustrating how analytical interpretation and technical implementation can be brought together in public sector training governance. Although the framework remains an integrative model rather than a wholly novel theory, its value lies in articulating a structured bridge between Learning Analytics, training evaluation, and digital governance in a field where such integration has rarely been operationalized in a coherent case-based design.

5.2 Practical Implications

From a practical perspective, the proposed framework offers a feasible approach for public organizations seeking to strengthen evidence-based training management. Rather than relying solely on post-training satisfaction surveys, agencies can combine participant background information, composite satisfaction measures, workplace-related follow-up indicators, and qualitative feedback to obtain a more comprehensive view of training effectiveness.

The study also provides a practical model for staged implementation. As an initial step, organizations can standardize training records and develop reliable composite indicators; as a second step, they can introduce cross-year comparisons and follow-up interviews; and as a further development, they can integrate these results into dashboard-based monitoring for internal review and decision support. This staged approach is especially relevant for public organizations that are interested in digital transformation but still operate with fragmented administrative datasets.

In addition, the dashboard prototype illustrates how IR–IT collaboration can support communication between training managers, analysts, and system developers. Even in its proof-of-concept form, the prototype demonstrates how visualized data can facilitate discussion about program consistency, course refinement, and future competency tracking without overstating the maturity of the current system.

5.3 Limitations and Future Research

Several limitations should be acknowledged. First, this study examined a single government training program, and the findings therefore should not be generalized uncritically to other

public sector training contexts. Future studies may test the framework in other administrative domains, levels of government, or professional training systems.

Second, the IPA module was developed using simulated data because competency-importance ratings were unavailable during the study period. As a result, the IPA component should be understood as a proof of concept rather than a validated empirical assessment of actual competency gaps. Future research should incorporate direct competency-importance measures and examine whether the proposed competency-gap model yields stable and actionable results in real implementation settings.

Third, the Level 2 component was based on publicly reported aggregate pre- and post-training learning-gain statistics. Because individual-level pre- and post-test records were not available for reanalysis, the present study could not independently assess individual learning change, measurement quality, or comparability across course categories.

Fourth, the Level 4 component relied on thematic summaries of post-training follow-up interviews reported in publicly available project documents. Although these summaries provided useful contextual evidence regarding workplace application, the present study did not access original interview transcripts, conduct primary qualitative coding, or examine a broader set of organizational performance indicators. Future research could strengthen the framework by incorporating richer qualitative evidence, broader organizational outcome measures, user evaluation of the dashboard itself, and more systematic validation of relationships among the four Kirkpatrick levels.

Ethics, Data Governance, and Disclaimer

This study involved secondary analysis of administrative training records generated through routine program implementation. The use of the records for academic research, degree-related research, and scholarly dissemination was conditionally authorized by the Environmental Management Administration, Ministry of Environment, Taiwan. All data were de-identified before analysis, and findings are reported only in aggregated form to protect the confidentiality of individual participants and non-public operational information.

The underlying administrative dataset is not publicly available because it contains government-commissioned training records subject to personal-data protection, confidentiality obligations, and institutional data-governance requirements. Any request for access must be reviewed by the relevant data controller and commissioning authority.

The data source for this study was the Environmental Management Administration, Ministry of Environment, Taiwan. The content and views expressed in this study represent the authors' independent academic research and do not represent the position of the commissioning agency, the Environmental Management Administration, Ministry of Environment, Taiwan.

References

Alblawi, A. S. (2018). *Big data and learning analytics in higher education: Demystifying variety, acquisition, storage, NLP and analytics*. arXiv. https://doi.org/10.48550/arXiv.1801.06052

Ferguson, R. (2012). The State of Learning Analytics in 2012: A Review and Future Challenges. Technical Report, Knowledge Media Institute, The Open University, UK. http://kmi.open.ac.uk/publications/pdf/kmi-12-01.pdf

Kirkpatrick, D. L. (1994). *Evaluating training programs: The four levels*. Berrett-Koehler.

Kirkpatrick, D. L., & Kirkpatrick, J. D. (2006). *Evaluating training programs: The four levels* (3rd ed.). Berrett-Koehler.

Kirkpatrick, J. D., & Kirkpatrick, W. K. (2016). *Kirkpatrick's four levels of training evaluation*. ATD Press.

Lester, J., Klein, C., Johri, A., & Rangwala, H. (Eds.). (2018). *Learning analytics in higher education: Current innovations, future potential, and practical applications* (1st ed.). Routledge. https://doi.org/10.4324/9780203731864

Long, P., & Siemens, G. (2011, September 12). Penetrating the fog: Analytics in learning and education. *EDUCAUSE Review*. https://er.educause.edu/articles/2011/9/penetrating-the-fog-analytics-in-learning-and-education

Martilla, J. A., & James, J. C. (1977). Importance-performance analysis. *Journal of Marketing, 41*(1), 77–79. https://doi.org/10.1177/002224297704100112

Stewart, D. W., & Kamins, M. A. (1993). *Secondary research: Information sources and methods* (2nd ed.). SAGE Publications.

Viberg, O., Hatakka, M., Balter, O., & Mavroudi, A. (2018). The Current Landscape of Learning Analytics in Higher Education. Computers in Human Behavior, 89, 98-110. https://doi.org/10.1016/j.chb.2018.07.027

Wong, B. T. M. (2017). Learning analytics in higher education: An analysis of case studies. *Asian Association of Open Universities Journal*, *12*(1), 21–40. https://doi.org/10.1108/aaouj-01-2017-0009

Yin, R. K. (2018). *Case study research and applications: Design and methods* (6th ed.). SAGE Publications.

呂育誠、許峻嘉（2015）。公務人員管理核心能力實施規劃之研究———藉由行為指標整合學習路徑圖與課程模組的設計理念。人事月刊，（363），17-27。https://www.dgpa.gov.tw/Uploads/public/Attachment/65101622994.pdf

國家科學及技術委員會（編）。（2025 年 2 月）。*智慧國家方案（2021–2025 年）2024 年階段成果報告*。行政院智慧國家 2.0 推動小組。https://digi.nstc.gov.tw/Page/B2D91A1F577ABE3

國家發展委員會。（2021）。*服務型智慧政府 2.0 推動計畫（110–114 年）*。https://ws.ndc.gov.tw/001/administrator/10/relfile/0/14037/cb1d46fd-ff72-495f-b852-b9cf2f978669.pdf

教育部。（2022 年 6 月 23 日）。*中小學課程師資教學與評量跨系統協作資料驅動決策治理跨系統工作圈第五次會議紀錄*。https://ws.moe.edu.tw/001/Upload/23/relfile/0/6951/24cfdc58-b98c-4d13-bcc1-57b9b2d1e7a4.pdf

陳泓逸。（2025）。*企業數位轉型治理框架：從戰略規劃到執行落地的系統性方法論*。https://www.hungyichen.com/insights/digital-transformation-governance-framework

陳敦源（2021 年 4 月 7 日）。〈政府數位轉型：創新變革？還是追新而已？〉。*指南新政電子報雙周刊*（第 20 期）。https://css.nccu.edu.tw/wp-content/uploads/2021/04/1_%E9%99%B3%E6%95%A6%E6%BA%90_%E6%94%BF%E5%BA%9C%E6%95%B8%E4%BD%8D%E8%BD%89%E5%9E%8B%EF%BC%9A%E5%89%B5%E6%96%B0%E8%AE%8A%E9%9D%A9%EF%BC%9F%E9%82%84%E6%98%AF%E8%BF%BD%E6%96%B0%E8%80%8C%E5%B7%B2%EF%BC%9F.pdf

陳敦源。（2021 年 4 月 8 日）。*數位政府與數位轉型*〔演講簡報〕。國立政治大學社會科學學院數位轉型推動研究中心。https://css.nccu.edu.tw/wp-content/uploads/2021/04/%E6%95%B8%E4%BD%8D%E8%BD%89%E5%9E%8B%E8%88%87%E7%99%BC%E5%B1%95_%E6%94%BF%E5%A4%A7%E7%A4%BE%E7%A7%91%E9%99%A2_20210408.pdf

溫玲玉、林德勳（2018）。應用 IPA 模式分析非營利組織之服務策略。全球管理與經濟，14（1），15-32。https://doi.org/10.6565/JGME.201806_14(1).0002

數位發展部（2024 年 1 月 31 日）。*智慧政府發展策略*。數位發展部全球資訊網。https://moda.gov.tw/digital-affairs/digital-service/operations/120

環境部環境管理署（2023）。全國執行機關清潔隊人力資源管理精進計畫。

環境部環境管理署（2024）。清潔隊人力資源管理精進計畫。

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NARRATIVES OF FILIPINO STUDENTS NAVIGATING DIFFERENT LEARNING MODALITIES IN A PANDEMIC: INSIGHTS FOR DIGITAL TRANSFORMATION IN HIGHER EDUCATION

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ABSTRACT

This study explored the lived experiences of college students navigating different learning modalities during the COVID-19 pandemic. Using narrative analysis grounded in Murray's three levels of meaning (personal, positional, and ideological), the study examined student adaptation across three chronological phases: the migration to online learning, the transitional shift to hybrid learning, and the post-pandemic resumption of full face-to-face operations. Data were gathered from students enrolled in private higher education institutions in Cagayan de Oro City. The analysis reveals a complex evolution in student identity and adaptability, including *online learning as a mirror of socioeconomic disparities, hybrid learning as a hope for quality education and interaction, and face-to-face learning modality as a catalyst for personal growth and academic success.* The findings demonstrate that these transitions require positional and pedagogical adjustments rather than simple adherence to protocols. In the context of ongoing digital transformation, these student narratives offer critical insights for enhancing institutional resilience, optimizing digital learning environments, and designing inclusive, student-centered learning environments.

Keywords: Higher Education, Narrative Analysis, Learning Modalities, Digital Transformation, Institutional Resilience

Introduction

The COVID-19 pandemic triggered unprecedented disruptions in higher education, compelling Philippine higher education institutions (HEIs) to rapidly shift from face-to-face instruction to online learning to sustain educational continuity (Commission on Higher Education, 2020). As

conditions changed, students encountered successive shifts from online to hybrid and eventually to full face-to-face instruction. These shifts represented more than changes in the mode of instructional delivery; they also required students to continuously adjust their routines, participation, relationships, and ways of engaging with learning.

During the initial shift to online learning, digital platforms provided a means of sustaining educational participation amid pandemic-related disruptions, while students also had to negotiate new forms of academic and peer interaction (Giray et al., 2022; Tuguic & Bilan, 2023). However, students also encountered isolation, difficulties with concentration and self-regulation, and unequal access to devices and stable internet connectivity (Baticulon et al., 2021; Giray et al., 2022; Jose et al., 2023; Tuguic & Bilan, 2023). As institutions introduced hybrid arrangements, students encountered a different set of expectations as online and in-person activities were combined. Although hybrid learning offered opportunities for social interaction and flexibility, it also required students to adjust how they participated in academic activities (Alfiras et al., 2021; Villanueva et al., 2023). The eventual return to full face-to-face instruction likewise brought opportunities for social reconnection while requiring students to readjust to classroom routines and academic demands (Azila-Gbettor et al., 2023; Zheng & Zheng, 2023).

Existing literature has documented the challenges, opportunities, and student responses associated with particular learning modalities during and after the pandemic (Giray et al., 2022; Villanueva et al., 2023; Lewohl, 2023; Azila-Gbettor et al., 2023). Studies have examined online learning in relation to student isolation, digital inequality, and self-regulation (Baticulon et al., 2021; Giray et al., 2022; Jose et al., 2023), hybrid learning in relation to technological literacy and social connectedness (Alfiras et al., 2021; Villanueva et al., 2023), and face-to-face learning in relation to social interaction, engagement, and adjustment (Zhang, 2022; Lewohl, 2023; Azila-Gbettor et al., 2023). However, much of the literature reviewed here examines these modalities as distinct learning environments rather than as successive experiences within a student's educational trajectory. Less attention has been given to how students make sense of themselves, their roles within the academic environment, and their relationships with faculty and peers as they move across successive learning modalities.

Examining these transitions as a continuous narrative may therefore provide a different understanding of student adaptation. Students' accounts were examined at the personal, positional, and ideological levels described by Murray (2000), providing a framework for considering individual experiences, academic relationships, and broader assumptions and practices surrounding learning.

Accordingly, this study explored the narratives of Filipino college students who experienced online, hybrid, and full face-to-face learning across the pandemic and its aftermath. It examined how students experienced and navigated these transitions at the personal, positional, and ideological levels. By tracing these experiences across successive learning environments, the study seeks to contribute a student-centered understanding of how meanings, roles, and expectations are renegotiated during educational transitions, with implications for how HEIs may approach future changes in learning delivery and institutional support.

Literature Review

The COVID-19 pandemic forced an abrupt global migration to online platforms, exposing existing structural and socioeconomic inequalities in the Philippines. Under these emergency remote setups, students experienced isolation, exhaustion, and negative perceptions of instructional quality, with some describing online learning as more focused on task compliance than meaningful learning (Giray et al., 2022).

Furthermore, digital exclusion and socioeconomic inequalities constrained students' ability to participate effectively in online learning, particularly among those lacking stable internet or adequate hardware (Giray et al., 2022; Jose et al., 2023), while extended device usage triggered physiological fatigue and psychological stressors like anxiety and isolation (Baticulon et al., 2021). Despite these barriers, online learning gave students greater control over their study time and pacing of academic work, reflecting greater autonomy in managing their learning (Limniou et al., 2021; Tullis & Benjamin, 2010). This persistence was driven by motivational factors, including loss aversion regarding academic delays (Jose et al., 2023; Yechiam, 2019) and determination to continue education despite pandemic challenges (Tuguic & Bilan, 2023). Taken together, these studies suggest that online learning was experienced not simply as a technological shift but as a reorganization of students' access, autonomy, and responsibility for learning.

By 2022, hybrid learning offered a compromise between remote and in-person instruction, requiring institutions and students to negotiate both digital and physical learning environments. Combining traditional classrooms with Learning Management Systems stimulated critical thinking and motivation through diverse assessments (Villanueva et al., 2023). However, students often had to seek supplementary electronic resources independently, highlighting the importance of technological literacy and confidence in navigating hybrid learning (Tuguic & Bilan, 2023). Crucially, the hybrid model reintroduced physical interaction into students' learning trajectories, providing opportunities for campus participation and social connectedness through co-curricular engagement (Villanueva et al., 2023).

Lastly, the post-pandemic resumption of face-to-face instruction served as an important context for rebuilding opportunities for social interaction and connection (Zhang, 2022). It also highlighted changes in student expectations: modern learners increasingly prefer traditional lectures to be systematically augmented with the electronic and universal learning resources that gained popularity during the remote era (Zhu et al., 2022). In-person instructional strategies improved content comprehension and student attendance (Lewohl, 2023). However, the complete physical return exposed infrastructural challenges reported in the Philippine context, characterized by inadequate classroom ventilation, insufficient physical spaces, and difficulties enforcing campus health protocols (Toquero & Maboloc, 2023).

While existing literature extensively explores student experiences within individual learning modes, fewer studies examine how these experiences unfold across successive modality shifts within the same educational trajectory. Examining these experiences as a connected trajectory may clarify how students' needs, roles, and expectations change as learning environments shift, providing a basis for student-informed institutional planning and support.

Specifically, this study sought to answer the following questions:

1. How did Filipino college students experience and make sense of online learning at the personal, positional, and ideological levels?
2. How did Filipino college students experience and make sense of hybrid learning at the personal, positional, and ideological levels?
3. How did Filipino college students experience and make sense of face-to-face learning at the personal, positional, and ideological levels?

Methodology

This qualitative study used narrative analysis to examine participants' experiences across the three learning modalities.

Theoretical and Methodological Framework

This study is grounded in narrative theory, which views individuals as constructing meaning about themselves and their environments through culturally and socially mediated interactions (Uzun & LeBlanc, 2017). A narrative approach was used to examine students' experiences as

connected accounts of change across successive learning modalities, rather than as isolated experiences within a single mode of learning.

Murray's (2000) three-level framework guided the interpretation of these narratives. At the personal level, the analysis examined how students understood and evaluated their own experiences, feelings, and responses to changes in learning conditions. At the positional level, it examined how students understood their roles and interactions within the academic environment, including their relationships with other members of the learning community. At the ideological level, it examined broader assumptions, institutional practices, and beliefs about learning that emerged from students' accounts.

The framework therefore provided an interpretive structure for examining how students' meanings, roles, and expectations changed as they moved from online to hybrid and then to face-to-face learning.

Participants and Sampling

Seven college students were purposively selected based on predefined eligibility criteria. Participants were required to: (a) be enrolled in a private university or college within Cagayan de Oro City; (b) have experienced all three learning modalities examined in the study—online, hybrid, and face-to-face learning; and (c) be currently residing in Cagayan de Oro City and willing to participate in an audio-recorded interview. Students who had not experienced all three modalities or who resided outside Cagayan de Oro City were excluded.

The seven participants ranged in age from 21 to 24 years and included students from the third and fourth year levels, with four males and three females. The criterion requiring experience across all three modalities was central to the sampling strategy, as the study examined students' experiences across successive changes in learning environments rather than within a single modality.

Data Collection and Analysis

The interview guide was developed as an open-discussion guide to elicit participants' thoughts, feelings, challenges, coping experiences, and insights across the three learning modalities. It was reviewed with the thesis adviser, externally validated, pilot-tested, and subsequently reviewed and approved by the academic panel. Following approval from the Xavier University Research Ethics Board, participants were recruited through social media notices and formal invitations. Eligibility was verified through a demographic questionnaire, after which

participants provided informed consent. One-on-one, face-to-face interviews were audio-recorded, with interview duration varying according to participants' responses.

Audio recordings were transcribed verbatim using oTranscribe. The analysis proceeded through five stages: (1) organization and preparation of the data, (2) familiarization with the transcripts, (3) initial coding, (4) grouping codes into categories and themes, and (5) interpretation of the data. Thematic coding was used to identify recurring patterns across participants' accounts, while Murray's (2000) framework guided the subsequent interpretation of these patterns at the personal, positional, and ideological levels. The researcher examined significant turning points within individual narratives to trace the progression from online to hybrid and face-to-face learning, categorized emerging themes according to Murray's levels, and then compared accounts across participants to develop the final cross-participant narrative.

Trustworthiness and Reflexivity

Trustworthiness was addressed through sensitivity to context, commitment and rigor, impact and importance, and reflexivity, following Yardley's (2015) principles. The interview guide was externally validated, pilot-tested, and reviewed by the academic panel, while verbatim transcription and systematic coding supported consistency in handling the participants' accounts. The researcher also maintained reflexive awareness throughout the analysis. An initial expectation that students would report substantial difficulties during the transition to hybrid learning was reconsidered as recurring participant accounts did not consistently support this expectation. Rather than treating these accounts as exceptions, the researcher allowed the participants' narratives to guide the developing interpretation. This reflexive process helped reduce the influence of pre-existing assumptions on the identification and interpretation of themes.

Results and Discussion

The narratives were examined as connected accounts of change across online, hybrid, and face-to-face learning, tracing how students' experiences, roles, and expectations shifted across these successive learning environments.

The Beginning Chapter: The Online Migration

The transition to online learning disrupted students' academic routines, relationships, and sense of participation, requiring new ways of managing learning and maintaining connection.

Personal Level: Navigating Technical and Psychological Strains. Participants described difficulties with platform usability and access to specialized software. Mac shared, *"We had a website in the university, but it was not a friendly website,"* while Carms described difficulties with specialized course software. Internet instability, limited devices, and differences in digital literacy also disrupted learning continuity among Jake, Bret, and Je, consistent with Ilias et al. (2020).

The home-based learning environment also introduced new sources of distraction. Mac observed, *"with our generation now... it is easy for us to be distracted,"* reflecting the potential for competing digital activities to interfere with learning and self-regulation (Fries et al., 2008). Participants described an emotional sense of loss associated with missing important aspects of college life. Koy noted, *"I felt like I missed a part of being a freshman... It is supposedly an exciting phase,"* while Mai described exhaustion from remote learning demands. In response, students cultivated peer networks for resource-sharing and support, consistent with Goodyear and Zenios (2007) on collaborative knowledge work. Peer interaction thus became an informal means of sustaining academic and social connection when familiar campus-based support was less accessible.

Personal Level: Academic Integrity and Digital Self-Regulation. The absence of physical classroom boundaries also changed how students managed their academic responsibilities. Mai reflected, *"I was used to not being prepared... I would even make excuses in class like my signal is unstable... But we have wifi."* She further acknowledged, *"I was prone to cheating... I can search through Google... I am guilty of that."* These accounts illustrate how online learning increased access to immediate digital resources while also creating greater opportunities for avoidance and weakened accountability.

Participants' experiences highlight the importance of self-regulation in navigating these conditions. Limniou et al. (2021) emphasized students' digital capabilities and self-regulated learning during the pandemic, while Tullis and Benjamin (2010) highlighted the importance of managing study time. For these participants, greater control over learning was accompanied by greater responsibility for regulating their own academic behavior.

Positional Level: Socioeconomic Privilege and Academic Autonomy. Participants became more aware of their roles and the unequal conditions experienced by others. They described seeking alternative learning methods and independently sourcing materials, reflecting the resourcefulness and agency observed among distance learners by Andrews and Tynan (2012). Bret noted, *"The students are not the only ones adjusting... but also the professors."*

This adjustment also made socioeconomic differences more visible. Mac observed, *"Classism is evident, and our empathy towards other students who have less privilege... is being tested."* Thus, online learning shaped not only how students managed their own learning but also how they understood their position relative to others within the academic community.

Ideological Level: Digital Delivery as a Mirror of Socioeconomic Disparities. Participants' accounts revealed broader concerns about unequal access to digitally mediated education. Carms emphasized, *"Being able to attend class virtually is not for everyone because it is costly."* This is consistent with research on digital inequality among Filipino students, particularly difficulties associated with limited access to gadgets and internet resources (Giray et al., 2022; Jose et al., 2023).

The online experience therefore challenged the assumption that digital delivery alone could provide equal access to education, as participation remained shaped by students' material conditions.

The Middle Chapter: Shifting to Hybrid Modalities

The transition to hybrid learning combined online and physical academic experiences, bringing renewed social engagement while requiring students to reorganize established routines.

Personal Level: Anticipation and the Restoration of Campus Belonging. The return of partial in-person sessions generated considerable anticipation among participants who had missed the physical campus. Koy shared, *"I was always in the mood to go to school, and the discussions are fun."* The reintroduction of physical spaces provided opportunities for renewed interaction with classmates and participation in campus activities, consistent with Villanueva et al. (2023). For participants, the return was therefore associated not only with physical presence but also with the restoration of forms of interaction disrupted during online learning.

Personal Level: Routine Re-alignment and Resource-Sharing Strategies. Hybrid learning required students to balance asynchronous online requirements with physical campus commitments. For some, this meant changing work and organizational routines. Mac explained, *"I quit my job and became a freelancer instead... then I only had two organizations, from four."* Resource-sharing also continued, with Mai describing the sharing of physical digital devices with classmates who had fewer resources. Hybrid learning thus represented continued adaptation rather than a simple return to pre-pandemic routines.

Positional Level: Students as Active Contributors and Peer Mentors. Participants continued to engage in peer support while taking more active roles in the learning experience. Bret explained, *"Bonding with your classmates gives you the avenue to help them by listening and guiding them."* Peer relationships remained an important means of navigating academic demands, extending collaborative practices that had emerged during online learning. For some, these interactions also influenced future aspirations, as Mac shared, *"That was the time my goal in life shifted into becoming a teacher one day."*

Ideological Level: Hybrid Models as a Hope for Quality Education and Interaction. Participants viewed hybrid learning as an opportunity to combine online flexibility with the social and academic benefits of physical interaction. Mai noted, *"Learning is more fun when you interact physically with your classmates and your professors."* This perspective is consistent with literature suggesting that hybrid learning can support both technology-mediated learning and campus-based interaction (Villanueva et al., 2023).

Rather than positioning online and face-to-face learning as mutually exclusive, the participants appeared to understand hybrid learning as a transitional space where the benefits and limitations of both environments could be experienced together.

The Ending Chapter: Re-adapting to Full Face-to-Face Modalities

The transition to full face-to-face learning restored aspects of campus life but also required students to readjust to expectations and pressures that had become less prominent during online learning.

Personal Level: Reclaiming the Student Identity and Academic Milestones. The return to campus restored aspects of student life that participants had missed. Jake described the difference in student identity between physical and online classes: *"The value is really different when the class is face-to-face because you feel like a student... compared to online, where... your mom doesn't even know that you're attending class."* Mai similarly expressed gratitude for being able to complete an important academic milestone in person: *"I am thankful because [I can graduate face-to-face]."*

These accounts suggest that the physical classroom carried meanings beyond instructional delivery. For participants, being physically present on campus was associated with recognition of themselves as students and with significant milestones in their educational experience.

Personal Level: The Friction of On-Campus Performance and Removal of Virtual Facilities. The return also reintroduced pressures that were less visible online. Jake explained, *"You can no longer use Google right away. Unlike in online classes, if you cannot answer, you may just turn off your camera then search through Google and use ChatGPT."* Mac similarly described the pressure of being evaluated in real time: *"The specific challenge... is your answer will be judged by your classmates and your teacher."* These experiences are consistent with Cardinas-Flamiano (2022), who documented academic challenges associated with the return to complete face-to-face learning.

The contrast with online learning is notable: while the online environment provided easier access to immediate digital resources and reduced some forms of face-to-face evaluation, the physical classroom restored direct accountability and social visibility.

Positional Level: Students as Proactive Communicators. Participants described communicating more directly with faculty members while remaining aware of appropriate interpersonal boundaries. Je and Koy explained, *"We communicate like we used to but still respectfully, and we set up boundaries... We do not message them at night because it is not work hours for them."* Their accounts suggest a growing awareness of communication as a reciprocal relationship, involving both access to academic support and respect for appropriate boundaries.

Ideological Level: Face-to-Face Modality as a Catalyst for Growth and Success. Participants attached broader meanings to the return of physical interaction. Bret reflected, *"I get to realize and value my classmates and also my professors… I now know better how to treasure the lectures, the experiences, in socializing."* Jake similarly stated, *"If you are in the classroom, you are in the university, you can focus on your goals in pursuing your studies."* These perspectives are consistent with Capinding (2023), who reported strong student preference for face-to-face learning following restrictions on physical classes.

Across the narratives, face-to-face learning was associated with social interaction, focus, and renewed appreciation of the educational experience. However, the findings do not establish one modality as universally superior. Rather, moving across modalities changed what students valued and expected from learning.

Taken together, the three narrative chapters show that students' experiences were not simply a progression from one preferred modality to another. Each transition changed the meanings students attached to learning, their roles within the academic community, and their expectations of the institution. Online learning heightened awareness of digital inequality and personal

responsibility; hybrid learning created opportunities for reconnection while requiring continued adjustment; and face-to-face learning restored physical interaction while introducing renewed performance and communication demands.

Viewed through Murray's (2000) framework, adaptation occurred simultaneously at personal, positional, and ideological levels. The findings therefore suggest that educational transitions are experienced not merely as changes in instructional delivery but as changes in how students understand themselves, their relationships, and the conditions shaping participation in higher education. These narratives provide a student-centered perspective that may inform institutional efforts to design learning environments responsive to differences in access, interaction, autonomy, and support.

Conclusion

In this study, the college students demonstrated resilience and adaptability as they navigated online, hybrid, and face-to-face learning modalities during and after the pandemic. Their narratives revealed that these transitions involved changes not only in learning conditions but also in how students understood themselves, their roles within the academic community, and their expectations of learning.

Viewed through Murray's (2000) framework, these changes occurred at the personal, positional, and ideological levels. Personally, students moved from navigating technological and emotional challenges toward greater autonomy, adaptation, and renewed engagement. Positionally, peer relationships and communication practices evolved as students sought support, shared resources, and re-established interaction within the academic community. Ideologically, students became more aware of socioeconomic disparities in digital learning while developing a stronger appreciation for physical interaction and campus-based learning. Taken together, the findings suggest that the significance of these narratives lies not simply in documenting individual learning modalities, but in showing how students' meanings, roles, and expectations were continuously renegotiated as their learning environment changed.

Although the study is limited to seven college students from private higher education institutions in Cagayan de Oro City and is not intended to represent all Filipino college students, their narratives provide a student-centered perspective that may inform institutional responses to changing learning conditions. The findings suggest that digital transformation in higher education should extend beyond technological adoption to include equitable access, meaningful interaction, student autonomy, and appropriate academic support.

References

Alfiras, M., Nagi, M., Bojiah, J., & Sherwani, M. (2021). Students' perceptions of hybrid classes in the context of Gulf University: An analytical study. Journal of Hunan University Natural Sciences, 48(5), 181–188.

Andrews, T., & Tynan, B. (2012). Distance learners: Connected, mobile and resourceful individuals. *Australasian Journal of Educational Technology, 28*(4). https://doi.org/10.14742/ajet.828

Azila-Gbettor, E. M., Agbenyo, L., Fiati, H. M., & Mensah, C. (2023). Student adjustment during COVID-19 pandemic: Exploring the moderating role of university support. *Heliyon, 9*(3). https://doi.org/10.1016/j.heliyon.2023.e13625

Baticulon, R., Sy, J., Alberto, N., Baron, M., Mabulay, R., Rizada, L., Tiu, C., Clarion, C., & Reyes, J. (2021). Barriers to online learning in the time of COVID-19: A national survey of medical students in the Philippines. *Medical Science Educator, 1,* 1-12. https://doi.org/10.1101/2020.07.16.20155747

Capinding, A. T. (2023). Student's readiness on the implementation of face-to-face classes: The aftermath of face-to-face class restriction. *International Journal of Educational Methodology, 9*(2), 309-320. https://doi.org/10.12973/ijem.9.2.309

Cardinas-Flamiano, B. G. A. (2022). Return to complete face to face learning: Level of students' academic excitement and challenges. *Asian Journal of Research in Education and Social Sciences, 4*(1), 317-327.

Commission on Higher Education. (2020). CHED COVID Advisory No.7 – *Guidelines for the Prevention, Control and Mitigation of the Spread of Coronavirus Disease 2019 (COVID-19) in Higher Education Institutions (HEIs).* https://chedro3.ched.gov.ph/wp-content/uploads/2020/10/CHED-COVID-19-Advisory-No.-7.pdf

Fries, S., Dietz, F., & Schmid, S. (2008). Motivational interference in learning: The impact of leisure alternatives on subsequent self-regulation. *Contemporary Educational Psychology, 33*(2), 119-133. https://doi.org/10.1016/j.cedpsych.2007.10.001

Giray, L., Gumalin, D., Jacob, J., & Villacorta, K. (2022). Exploring the online learning experience of Filipino college students during COVID-19 pandemic. *Jurnal Ilmiah Peuradeun, 10*(1), 227-250. https://doi.org/10.26811/peuradeun.v10i1.691

Goodyear, P., & Zenios, M. (2007). Discussion, collaborative knowledge work and epistemic fluency. *British Journal of Educational Studies, 55*(4), 351-368.

Ilias, A., Baidi, N., K. Ghani, E., & Mohd Razali, F. (2020). Issues on the use of online learning: An exploratory study among university students during the COVID-19 pandemic. *Universal Journal of Educational Research. 8.* 5092-5105. 10.13189/ujer.2020.081109.

Jose, J., Juan, K. L. M., Tabiliran, J., Yapo, F., Gatchalian, J., Baluyot, M. K., Torrero, K., Blanco, J., & Tus, J. (2023). Struggle is real: The experiences and challenges faced by Filipino tertiary students on lack of gadgets amidst the online learning. *7,* 174-181. https://doi.org/10.5281/zenodo.7653016

Lewohl, J. M. (2023). Exploring student perceptions and use of face-to-face classes, technology-enhanced active learning, and online resources. *International Journal of Educational Technology in Higher Education, 20(48).* https://doi.org/10.1186/s41239-023-00416-3

Limniou, M., Atkins, T. V., Hands, C., & Elshamaa, M. (2021). Learning, student digital capabilities and academic performance over the COVID-19 pandemic. *Education Sciences, 11(361),* 1-15. https://doi.org/10.3390/educsci11070361

Murray, M. (2000). Levels of narrative analysis in health psychology. *Journal of Health Psychology, 5(3),* 337–347. https://doi.org/10.1177/135910530000500305.

Toquero, C. M., & Maboloc, C. R. (2022). *Risk-based approach for a return to in-person instruction in the Philippines.* Journal of Public Health, 44(4), e654–e655. https://doi.org/10.1093/pubmed/fdab390

Tuguic, L. A., & Bilan, H. P. (2023). College education students' learning experiences on the advent of online distance education in the Philippines: A phenomenological study. *The Qualitative Report, 28(7),* 1869-1879. https://doi.org/10.46743/2160-3715/2023.5644

Tullis, J. G., & Benjamin, A. S. (2010). On the effectiveness of self-paced learning. *Journal of Memory and Language, 64(2),* 109-118. https://doi.org/10.1016/j.jml.2010.11.002

Uzun, B., & LeBlanc, S. (2017). Narrative theoretical framework. *SAGE Encyclopedia of Abnormal and Clinical Psychology*, 9781483365891, 2191 https://doi.org/10.4135/9781483365817.n882

Villanueva, J. A. R., Redmond, P., Galligan, L., & Douglas, E. (2023). Investigating blended learning interactions in Philippine schools through the community of inquiry framework. *Asia Pacific Educ. Rev. Advance online publication.* https://doi.org/10.1007/s12564-023-09826-4

Yechiam, E. (2019). Acceptable losses: The debatable origins of loss aversion. *Psychological Research, 83 (7),* 1327-1339.

Zhang, J. (2022). Analysis of the psychological state of college students in the post-pandemic period and adjustment strategies. In 2022 3rd International Conference on Mental Health, Education and Human Development (MHEHD 2022) (pp. 800-806). Atlantis Press.

Zheng, Y., & Zheng, S. (2023). Exploring educational impacts among pre, during and post COVID-19 lockdowns from students with different personality traits. *International Journal of Educational Technology in Higher Education, 20(1),* 1-20. https://doi.org/10.1186/s41239-023-00388-4

Zhu, Y., Xu, Y., Wang, X., Yan, S., & Zhao, L. (2022). The selectivity and suitability of online learning resources as predictor of the effects of self-efficacy on teacher satisfaction during the COVID-19 lockdown. *Frontiers in Psychology*, *13*, 765832.

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Trapped in the Metric Race: A Psychological Decision-Making Mechanism of Post-Loss Perceptions and Behavioral Outcomes under Higher Education IT-IR Frameworks

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ABSTRACT

Against the backdrop of higher education digital transformation and Institutional Research (IR) governance, Information Technology (IT) adoption often restructures work, redistributes resources, and intensifies indicator-based evaluation, exposing faculty and staff to effort-reward imbalance. The core issue is not workload alone, but the weakening of autonomy, control, and reward under sustained comparison and performance pressure, which generates Workplace Involution Perception. Drawing on equity theory, the effort-reward imbalance model, prospect theory, disappointment theory, and regret theory, this study develops a psychological decision model of Workplace Involution Perception-Negative Perception-Psychological Perception-Behavioral Outcome. A scenario-based questionnaire first measured Forced Competition, then induced Disappointment and Regret, introduced Gain-Frame Perception and Loss-Frame Perception to elicit conservative or risky choices, and assessed subsequent psychological perceptions and outcomes. Data from 322 valid responses showed that Disappointment influenced Overtime Effort Type Involution through Reduced Work Involvement; Regret and Indecisiveness formed a suppression relationship in predicting Quiet Quitting; Risk-Taking Behavior predicted Improvement-Oriented Type Involution; and Re-Engagement in New Opportunities predicted Goal Setting. These findings show that higher education digital transformation is shaped not only by technological systems, but also by how members interpret competition, evaluate loss, and adapt psychologically. By integrating behavioral economics and psychology, this study shows that formal efficiency does not necessarily translate into substantive effectiveness. Effective IT-IR integration should therefore preserve professional discretion, improve workflow fit, and provide credible support to reduce formal compliance and adaptation stagnation.

Keywords: Workplace Involution, AI-Induced Change Anxiety, Framing Effect, Psychological Perceptions, Post-Loss Decision-Making

1. INTRODUCTION

Higher education institutions increasingly integrate Information Technology (IT) with Institutional Research (IR) to improve governance. Yet heavy reliance on quantitative indicators and system-generated judgments may constrain frontline expertise and turn digital governance from decision support into control. When assessment is tied to interdepartmental comparison, resource allocation, and exclusion pressure, members may continue reporting, complying, and adapting despite doubting the value of such effort. This condition produces Forced Competition and reinforces workplace involution.

Forced Competition also heightens uncertainty and digitalisation anxiety by reducing perceived control over competence, professional value, and future resources (Bordia et al., 2004; Pfaffinger et al., 2021). Equity theory and the effort-reward imbalance model suggest that sustained high effort, low reward, and relative disadvantage generate unfairness, strain, and negative work reactions (Adams, 1965; Siegrist, 1996). Workplace involution is therefore a subjective state of imbalance and loss created by forced investment, insufficient rewards, and an inescapable competitive structure.

Existing research often treats workplace involution as stress, burnout, or inefficient effort, but rarely distinguishes its loss perceptions. This study differentiates Disappointment, arising when outcomes fall below expectations, from Regret, arising from comparison with a better unchosen alternative and involving counterfactual reassessment (Bell, 1985; Loomes & Sugden, 1982, 1986; Zeelenberg et al., 1998). Their different reference points may produce distinct psychological and behavioral pathways.

Prospect theory further predicts risk avoidance under gains and risk seeking under losses (Kahneman & Tversky, 1979). Framing is therefore treated not only as cognitive bias, but as a situational rule that changes both choice and the interpretation of loss, amplifying Reduced Work Involvement, Risk-Taking Behavior, Indecisiveness, or Re-Engagement in New Opportunities.

Accordingly, this study examines how Workplace Involution Perception (Forced Competition) generates Disappointment and Regret, how Gain-Frame Perception and Loss-Frame Perception shape subsequent Psychological Perceptions, and how these processes affect Behavioral Outcomes. It thereby explains why IT-IR effectiveness depends not only on infrastructure, but also on how members interpret pressure, loss, and adaptation.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Workplace Involution Perception and Behavioral Outcomes

Workplace involution reflects prolonged high effort with insufficient reward. Under IT-IR integration, metric-based evaluation, resource competition, and exclusion pressure may compel

faculty and staff to sustain substantial effort even when returns are limited. The central dilemma is that continued investment causes depletion, while reduced participation creates evaluation and resource risks, trapping members in ineffective effort.

Such Forced Competition may produce different outcomes. Continued compliance may lead to Overtime Effort Type Involution, while persistent ineffectiveness and reduced discretion may lead to Quiet Quitting. When change is viewed as an opportunity for growth or repositioning, members may instead exhibit Improvement-Oriented Type Involution or Goal Setting.

(1) Forced Competition refers to compelled effort without control over whether it yields commensurate rewards (Cheng, 2022). It comprises Resource Threat, reflecting involuntary competition and limited autonomy, and Fruitless Competition, reflecting excessive effort without corresponding returns.

(2) Overtime Effort Type Involution refers to compelled, depleting effort under forced investment (Siegrist, 1996; Cheng, 2022). It comprises Overtime Effort Type and Self-Esteem Impairment Type, reflecting excessive investment and damage to self-worth.

(3) Improvement-Oriented Type Involution refers to additional learning and work effort driven by growth and future development (Cheng, 2022). It comprises Social Value Pursuit Type and Self-Actualization Pursuit Type; without support or reward, however, such effort may become self-imposed pressure and depletion (Hobfoll, 1989; Bakker & Demerouti, 2014).

(4) Quiet Quitting refers to limiting effort to minimum role requirements and withholding additional behavioral or emotional involvement (Formica & Sfodera, 2022). It is associated with effort-reward imbalance, burnout, lower job satisfaction, and turnover intention (Galanis et al., 2023; Anand et al., 2024).

(5) Goal Setting refers to constructing and pursuing meaningful goals that direct attention, sustain effort, and guide resource allocation (Locke & Latham, 1990, 2002, 2007; Morisano et al., 2010). It comprises Goal Construction and Goal Selection.

Forced Competition therefore explains both continued investment under relative evaluation and differentiated behavioral outcomes. The following hypotheses are proposed:

H1-1: Workplace Involution Perception (Forced Competition) has a positive effect on Overtime Effort Type Involution.

H1-2: Workplace Involution Perception (Forced Competition) has a positive effect on Quiet Quitting.

2.2 Multiple Pathways from Negative Perceptions to Psychological Perceptions

2.2.1 Transformation Loss: Disappointment and Regret

During transformation, employees expect system learning and compliance to improve efficiency. Once this expectation becomes a reference point, usability and rewards are evaluated as gains or losses (Kahneman & Tversky, 1979). When technological effort fails to

produce comparable benefits, employees may perceive a Transformation Loss.

Transformation Loss may take the form of Disappointment or Regret depending on its reference point. Disappointment arises when actual outcomes fall below prior expectations, whereas Regret arises when the chosen outcome is perceived as worse than an unchosen alternative through counterfactual comparison (Bell, 1982, 1985; Loomes & Sugden, 1982, 1986; Zeelenberg et al., 1998). Losses linked to system design, policy, or organizational control are therefore more likely to evoke Disappointment, while those linked to prior adaptation or investment choices are more likely to evoke Regret.

Both may shift decisions from utility maximization to loss minimization, leading to avoidance, defensive compliance, or paralysis. Disappointment may promote Reduced Work Involvement and conservative action, whereas Regret may motivate corrective action or avoidance of repeated mistakes (Gul, 1991; Zeelenberg & Pieters, 2007).

2.2.2 Framing Effects and Psychological Perceptions

Cognitive bias is commonly viewed in psychology as a systematic deviation arising from heuristic judgment, whereas behavioral economics treats it not merely as judgment error but as a stable choice tendency shaped by decision framing (Tversky & Kahneman, 1974). Prospect theory predicts risk avoidance under gains and risk seeking under losses (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981). Following the Asian Disease Problem, this study uses structurally equivalent gain- and loss-framed scenarios to examine not only conservative and risky choices, but also how framing stabilizes these tendencies and amplifies their underlying Psychological Perceptions (Levin et al., 1998).

2.2.3 Psychological and Behavioral Pathways under Framing

Framing is treated as an amplifying and stabilizing mechanism that converts Negative Perceptions into more directional Psychological Perceptions. Under Forced Competition, perceived loss first differentiates into Disappointment and Regret as early negative appraisals. Individuals then assess control, action possibilities, and whether improvement remains feasible (Lazarus, 1991). Through subjective value evaluation, framing reshapes the perceived value of available actions, stabilizing diffuse negative reactions into distinct psychological pathways and subsequent work behaviors (Berkman, 2018).

(1) Reduced Work Involvement refers to declining psychological commitment and behavioral investment when work no longer satisfies value expectations (Kanungo, 1982). It comprises Withdrawal and Reallocation, reflecting detachment and the redirection of effort or resources.

(2) Risk-Taking Behavior refers to greater tolerance for uncertainty and failure when individuals perceive loss or disadvantage. It comprises Uncertainty Tolerance and High-Risk Willingness and is consistent with risk seeking under losses (Kahneman & Tversky, 1979).

(3) Indecisiveness refers to delayed action, choice avoidance, or low confidence in decisions

(Frost & Shows, 1993). It comprises Decision-Making Difficulty and Post-Decision Worry; under high uncertainty, nondecision may also reduce anticipated regret (Anderson, 2003).

(4) Re-Engagement in New Opportunities refers to redirecting psychological resources and motivation after an original goal becomes difficult to achieve. It comprises Goal Reconstruction and Redirection and Persistent Engagement in New Opportunities and supports adjustment and restored control (Wrosch et al., 2003).

Based on these definitions, four pathways are proposed:

Disappointment × Gain Frame: Reduced Work Involvement and Overtime Effort Type Involution

Under Gain-Frame Perception, Disappointment strengthens certainty seeking and may lead to Reduced Work Involvement. Members may withdraw psychologically while maintaining visible compliance to protect evaluations, producing Overtime Effort Type Involution and a resource-loss spiral (Hobfoll, 1989; Kahneman & Tversky, 1979).

Disappointment × Loss Frame: Risk-Taking Behavior and Improvement-Oriented Type Involution

Under Loss-Frame Perception, Disappointment may heighten Risk-Taking Behavior as a last attempt to avoid further loss. Difficult projects, risky assignments, or intensive training may then produce Improvement-Oriented Type Involution (Kahneman & Tversky, 1979).

Regret × Loss Frame: Indecisiveness and Quiet Quitting

Under Loss-Frame Perception, Regret-driven caution conflicts with pressure to take risks, producing Indecisiveness, delay, and repeated reassessment. As adaptive motivation declines, members may withdraw emotionally and engage in Quiet Quitting (Bell, 1982; Loomes & Sugden, 1982; Zeelenberg et al., 1998).

Regret × Gain Frame: Re-Engagement in New Opportunities and Goal Setting

Under Gain-Frame Perception, Regret may support correction rather than paralysis. By disengaging from ineffective paths, revising expectations, and pursuing feasible alternatives, members may develop Re-Engagement in New Opportunities and ultimately Goal Setting (Kahneman & Tversky, 1979).

H2-1: Workplace Involution Perception (Forced Competition) first affects Disappointment, which subsequently influences Overtime Effort Type Involution through Reduced Work Involvement.

H2-2: Workplace Involution Perception (Forced Competition) first affects Regret, which subsequently influences Quiet Quitting through Indecisiveness.

H3-1: The effect of Disappointment on Reduced Work Involvement is moderated by Gain-Frame Perception.

H3-2: The effect of Regret on Indecisiveness is moderated by Loss-Frame Perception.

H4-1: Reduced Work Involvement has a positive effect on Overtime Effort Type Involution.

H4-2: Indecisiveness has a positive effect on Quiet Quitting.

3. METHODOLOGY

3.1 Research Framework and Procedure

This study used a scenario-based questionnaire to examine how Workplace Involution Perception (Forced Competition) generates Disappointment or Regret, which develop into Psychological Perceptions under Gain-Frame Perception and Loss-Frame Perception and subsequently affect Behavioral Outcomes. Scenario activation provided a common decision context (Aguinis & Bradley, 2014; Atzmüller & Steiner, 2010). Respondents first completed Forced Competition measures, followed by Disappointment and Regret stimuli, manipulation checks, binary framed choices, and measures of psychological perceptions and outcomes.

3.2 Measures and Factor Structure

All variables were measured on five-point Likert scales. Controls included gender, age, education, cumulative work experience, school background, and industry. Item counts, reliability, and exploratory factor results are reported in Table 1.

Bartlett's tests were significant for all constructs ($p < .05$); KMO values ranged from .50 to .90, eigenvalues from 1.24 to 4.39, and explained variance from 40.39% to 63.97%. Each construct yielded one common factor.

Table 1 Reliability and Factor Analysis Results

Variable Category	Variable	Items	Cronbach's α	KMO	Bartlett's
Workplace Involution Perception	Forced Competition	2	.75	.50	16.54*
Negative Perception	Disappointment	3	.61	.60	59.66*
	Regret	4	.76	.66	186.87*
Psychological Perception	Reduced Work Involvement	7	.74	.70	624.32*
	Risk-Taking Behavior	7	.86	.87	706.33*
	Indecisiveness	7	.90	.90	1,020.17*
	Re-Engagement in New Opportunities	7	.86	.85	738.39*
Workplace Involution Outcome	Overtime Effort Type Involution	4	.77	.76	280.90*
	Improvement-Oriented Type Involution	4	.81	.80	330.63*
	Quiet Quitting	4	.60	.68	96.23*
	Goal Setting	4	.75	.71	253.31*

3.3 Sample and Data Analysis

Participants were workers with experience of competition or unequal resource allocation; 322 valid responses were obtained. Descriptive, factor, and reliability analyses assessed the data and measures. Independent- and paired-samples t tests examined perceptual differences; Cochran's Q and McNemar tests compared conservative and risky choices; subgroup regression, mediation, and moderation analyses tested the proposed relationships.

4. RESULTS

4.1 Choice and Perceptual Differences

Experience-based stimuli elicited stronger Negative Perceptions than vignette-based stimuli. Disappointment was higher in the experience group (M = 3.64) than in the vignette group (M = 3.32), t = 2.46, p = .02; the same pattern emerged for Regret (M = 3.67 vs. 3.01), t = 4.02, p < .001.

Manipulation checks showed that the Disappointment stimulus produced higher Disappointment than Regret (M = 3.43 vs. 2.83), t = 8.99, p < .001. Under the Regret stimulus, however, Disappointment and Regret did not differ significantly (M = 3.32 vs. 3.17), t = 1.86, p = .06, indicating that the Disappointment condition was more focused, whereas the Regret condition activated both outcome disappointment and counterfactual comparison.

Choice distributions differed across the four conditions, Cochran's Q = 65.97, p < .001. Risky choices predominated under Disappointment × Loss-Frame Perception (63.04%) and Regret × Loss-Frame Perception (59.94%), whereas conservative choices predominated under Disappointment × Gain-Frame Perception (57.14%) and Regret × Gain-Frame Perception (59.63%). McNemar tests confirmed significant framing differences within both negative-perception conditions (both p < .001), consistent with greater risk seeking under losses and caution under gains.

Psychological perceptions also varied by frame and choice. Under Disappointment × Gain-Frame Perception, conservative choosers reported higher Reduced Work Involvement than risky choosers (M = 3.47 vs. 3.29), and within the conservative group it exceeded Risk-Taking Behavior, t = 2.63, p = .01. Under Disappointment × Loss-Frame Perception, risky choosers reported slightly higher Risk-Taking Behavior than conservative choosers (M = 3.26 vs. 3.14), and within the risky group it slightly exceeded Reduced Work Involvement (M = 3.20). Under Regret × Loss-Frame Perception, risky choosers reported higher Indecisiveness than conservative choosers (M = 3.65 vs. 3.45), and within the risky group it exceeded Re-Engagement in New Opportunities, t = 3.72, p < .01. Under Regret × Gain-Frame Perception, conservative choosers reported higher Re-Engagement in New Opportunities than risky choosers (M = 3.82 vs. 3.49), t = -2.80, p = .01, and within the conservative group it exceeded Indecisiveness, t = 2.10, p = .04.

4.2 Correlations

Disappointment and Regret were moderately correlated (r = .43, p < .01). Correlations among the four Psychological Perceptions ranged from -.12 to .68, and those among the four behavioral outcomes ranged from -.14 to .62. Forced Competition correlated with Negative Perceptions from .21 to .29 and with Psychological Perceptions from .03 to .31. Correlations

between Negative and Psychological Perceptions ranged from .00 to .51, and those between Psychological Perceptions and behavioral outcomes ranged from -.10 to .59.

4.3 Main and Mediation Effects

Hierarchical regressions entered gender and age, followed by Forced Competition, Negative Perception, and Psychological Perception. The Overtime Effort Type Involution model explained 37% of the variance (adjusted $R^2 = .36$, $F = 36.36$, $p < .001$), while the Quiet Quitting model explained 18% (adjusted $R^2 = .16$, $F = 13.51$, $p < .001$). VIF values were below 3.84. Younger respondents reported greater Overtime Effort Type Involution, and gender was significant in the Quiet Quitting model; both controls were retained.

4.3.1 Overtime Effort Type Involution

In the conservative-choice subgroup, Forced Competition positively predicted Overtime Effort Type Involution ($\beta = .28$, $p < .001$; $\Delta R^2 = .08$). Disappointment was also significant ($\beta = .16$, $p < .05$), reducing the Forced Competition coefficient from .28 to .25. After Reduced Work Involvement was entered, it strongly predicted Overtime Effort Type Involution ($\beta = .51$, $p < .001$), while Forced Competition declined to .11 and Disappointment to .08, both becoming nonsignificant or marginal. Thus, Reduced Work Involvement was the key mechanism linking Forced Competition and Disappointment to Overtime Effort Type Involution, reflecting psychological withdrawal alongside continued formal effort. H1-1, H2-1, and H4-1 were supported.

4.3.2 Quiet Quitting

In the risky-choice subgroup, Forced Competition positively predicted Quiet Quitting ($\beta = .27$, $p < .001$; $\Delta R^2 = .07$), whereas Regret had no direct effect ($\beta = -.05$). After Indecisiveness was entered, it positively predicted Quiet Quitting ($\beta = .36$, $p < .001$), Forced Competition declined to .22, and Regret became significantly negative ($\beta = -.16$, $p < .05$). This indicates a suppression relationship: Regret may motivate reflection and correction, but when converted into Indecisiveness, repeated comparison and action delay promote withdrawal and minimum-role performance. H1-2 and H4-2 were supported, whereas H2-2 was not.

4.4 Moderation Effects

The Reduced Work Involvement model explained 13% of the variance (adjusted $R^2 = .12$, $F = 11.68$, $p < .001$), and the Indecisiveness model explained 16% (adjusted $R^2 = .15$, $F = 15.31$, $p < .001$).

For Reduced Work Involvement, Forced Competition was significant in the conservative group ($\beta = .30$, $p < .001$). After Disappointment was entered, both Disappointment ($\beta = .15$, $p < .05$) and Forced Competition ($\beta = .27$) remained significant. However, Disappointment also

predicted Reduced Work Involvement in the risky group (β = .19, p < .05). Because the effect was not specific to the Gain-Frame Perception condition, H3-1 was not supported.

For Indecisiveness, Forced Competition was significant in the risky group (β = .16, p < .05). After Regret was entered, Regret showed a stronger positive effect (β = .32, p < .001), while Forced Competition declined to .14. In the conservative group, Regret was only marginally related to Indecisiveness (β = .17). Thus, Regret was more strongly amplified into Indecisiveness under the Loss-Frame Perception/risky-choice condition, supporting H3-2.

4.5 Additional Analyses

In the Disappointment-Risk-Taking Behavior-Improvement-Oriented Type Involution pathway, Risk-Taking Behavior positively predicted Improvement-Oriented Type Involution, suggesting that it reflects an active compensatory or threshold-breaking response to loss rather than a direct effect of Forced Competition or Disappointment.

In the Regret-Re-Engagement in New Opportunities-Goal Setting pathway, Re-Engagement in New Opportunities consistently predicted Goal Setting. When new directions are perceived as feasible, developmental, and worthwhile, individuals are more likely to redirect psychological resources toward new goals. Consistent with value-based decision-making, Re-Engagement in New Opportunities should therefore be viewed as a key antecedent of Goal Setting rather than merely a positive attitude (Berkman, 2018).

5. DISCUSSION

5.1 Main Findings

5.1.1 Disappointment, Reduced Work Involvement, and Overtime Effort Type Involution

Reduced Work Involvement emerged as the key mechanism linking Disappointment to Overtime Effort Type Involution. Under indicator-driven IT-IR systems, faculty and staff may remain in high-effort, low-reward conditions, generating Disappointment and resource-conserving withdrawal (Siegrist, 1996; Hobfoll, 1989). Yet external evaluation and exclusion pressures prevent actual exit, sustaining overtime and visible effort. Overtime Effort Type Involution therefore reflects pseudo-compliance—psychological withdrawal alongside continued labor—rather than proactive commitment. Because this pattern extended beyond the gain-frame condition, Reduced Work Involvement appears to be a relatively stable defensive response to technological outcome gaps.

5.1.2 Regret, Indecisiveness, and Quiet Quitting

Indecisiveness, rather than Regret itself, emerged as the key mechanism leading to Quiet Quitting. Regret may initially support reflection and corrective action, but when members lack

coping resources or viable alternatives, it can develop into Indecisiveness, decision paralysis, and minimum-role performance (Lazarus, 1991; Zeelenberg et al., 1998). In high-pressure digital transformation contexts, algorithmic accountability shifting and elimination threats may intensify this conflict by making employees recognize failed adaptation while fearing further mistakes. The resulting suppression pattern indicates that Regret retains corrective potential, but its conversion into Indecisiveness depletes that potential and promotes withdrawal. This process was stronger under Loss-Frame Perception, suggesting that loss framing amplifies counterfactual comparison and hesitation.

5.2 Theoretical Implications

5.2.1 Contextualized Measurement Integrating Psychological Perceptions and Decision Rules

The scenario-based design integrates behavioral economics' measurement of choice with psychology's analysis of post-choice perception. It shows that identical conservative or risky choices may conceal different processes: Disappointment may generate either Reduced Work Involvement or Risk-Taking Behavior, while Regret and Indecisiveness jointly reveal the suppression mechanism underlying Quiet Quitting. Psychological Perceptions should therefore be understood as situational appraisals, not stable traits or simple biases.

5.2.2 From Linear Paths to a Psychological Decision Structure: An Inverted-U Integrative Perspective

Linear paths may obscure the shared structure of the four mechanisms. This study therefore proposes an inverted-U perspective that positions Reduced Work Involvement, Indecisiveness, Risk-Taking Behavior, and Re-Engagement in New Opportunities by loss intensity and psychological tolerance.

The model does not imply a fixed sequence. At lower loss levels, individuals conserve resources through Reduced Work Involvement; at moderate levels, the conflict between ineffective investment and risky withdrawal produces Indecisiveness (Imas, 2016).

Near the tolerance threshold, responses may shift from detailed appraisal to loss-frame risk seeking, producing Risk-Taking Behavior and, potentially, Improvement-Oriented Type Involution. This may explain why the Disappointment × Loss-Frame Perception pathway was not fully supported as linear mediation.

Beyond the threshold, individuals may redirect rather than escalate risk. Re-Engagement in New Opportunities depends on identifiable, accessible, and transferable opportunities such as job redesign, cross-unit mobility, and system support. Under these conditions, Regret may lead to Goal Setting rather than chronic depletion.

5.2.3 Psychological Differentiation behind Overt Choices

This study advances framing research from explaining how individuals choose to revealing what psychological perceptions underlie those choices. Although framing effects confirmed risk avoidance under gains and risk seeking under losses, identical choices carried different psychological meanings. Risky choice reflected Indecisiveness under Regret × Loss-Frame Perception, but Risk-Taking Behavior under Disappointment × Loss-Frame Perception. By distinguishing the psychological processes behind overt choices, this study extends choice-based classification beyond behavioral preference alone.

5.2.4 Psychological Perceptions as Situational Cognitive Appraisals

The four Psychological Perceptions are situational cognitive appraisals that vary with work context, framing, and perceived gain or loss. They reflect judgments about resources, control, and action consequences rather than stable personality traits or irrational bias (Allport, 1937; Costa & McCrae, 1992).

5.3 Practical Implications for Higher Education IT-IR Integration

The findings extend to higher education's integration of AI, IT, and IR. Digital transformation depends not only on systems and data, but also on how members interpret change pressure, assess effort-reward balance, and respond psychologically. Management should therefore move beyond usage and compliance metrics to diagnose psychological decision states and adjust performance systems, support, and communication.

First, managers should identify formal compliance and restore credible effort-performance-reward links. Disappointment may lead to Overtime Effort Type Involution through Reduced Work Involvement, producing psychological withdrawal alongside continued effort. Faculty and staff may keep reporting, using systems, and working overtime under evaluation pressure even when they doubt the system's value. Managers should therefore assess whether digital tools reduce duplication, improve workflows, and support decisions rather than equating usage with effectiveness. Simplified reporting, transparent data use, traceable feedback, and frontline participation can improve the value of digital effort.

Regret should be redirected toward correction rather than stagnation. When Regret develops into Indecisiveness, reflection becomes delay and withdrawal. Low-risk, reversible, and error-tolerant arrangements, such as pilots, phased implementation, parallel systems, and dedicated IT support, can preserve corrective motivation. When depletion is severe, job redesign, cross-unit collaboration, role adjustment, and rotation can support Re-Engagement in New Opportunities, Goal Setting, and work reconstruction.

Second, change communication should diagnose psychological meaning rather than behavior alone. Caution may reflect Disappointment and resource conservation, hesitation may reflect

Regret and Indecisiveness, and intense effort may reflect threshold-level Risk-Taking Behavior—a compensatory attempt to reverse loss rather than genuine commitment. Managers should therefore identify members' reference points, sources of loss, and tolerance positions.

Loss-framed messages may trigger short-term action but also intensify anxiety and hesitation. Gain-framed communication should instead show how systems support teaching, preserve professional value, reduce administrative burden, and create development opportunities. Such messages must be backed by visible institutional improvements and resources; otherwise, they may deepen Disappointment.

6. CONCLUSION

6.1 Conclusion

Overall, effective digital transformation requires more than technological adoption. It depends on whether institutions can prevent forced competition from turning digital participation into psychological withdrawal, indecisiveness, or compensatory risk taking. By restoring credible effort-reward links, providing safe adjustment and redirection opportunities, and aligning communication with members' psychological states, IT-IR integration can move beyond formal compliance toward genuine process improvement, organizational learning, and educational effectiveness.

6.2 Limitations and Future Research

The one-time questionnaire may have introduced learning effects, fatigue, and cognitive interference, while the younger sample limits generalizability. Future studies should use multi-stage designs and broader samples, test external opportunities as a moderator, and further examine compensatory risk taking and repair motivation.

REFERENCES

Adams, J. S. (1965). Inequity in social exchange. *Advances in Experimental Social Psychology, 2*, 267-299. https://doi.org/10.1016/S0065-2601(08)60108-2

Aguinis, H., & Bradley, K. J. (2014). Best practice recommendations for designing and implementing experimental vignette methodology studies. *Organizational Research Methods, 17*(4), 351-371. https://doi.org/10.1177/1094428114547952

Allport, G. W. (1937). *Personality: A psychological interpretation*. Holt.

Anand, A., Doll, J., & Ray, P. (2024). Drowning in silence: A scale development and validation of quiet quitting and quiet firing. *International Journal of Organizational Analysis, 32*(4), 721-743. https://doi.org/10.1108/IJOA-01-2023-3600

Anderson, C. J. (2003). The psychology of doing nothing: Forms of decision avoidance result

from reason and emotion. *Psychological Bulletin, 129*(1), 139-166. https://doi.org/10.1037/0033-2909.129.1.139

Atzmüller, C., & Steiner, P. M. (2010). Experimental vignette studies in survey research. *Methodology, 6*(3), 128-138. https://doi.org/10.1027/1614-2241/a000014

Bakker, A. B., & Demerouti, E. (2014). Job demands-resources theory. In P. Y. Chen & C. L. Cooper (Eds.), *Wellbeing: A complete reference guide, Volume III: Work and wellbeing* (pp. 37-64). Wiley-Blackwell. https://doi.org/10.1002/9781118539415.wbwell019

Bell, D. E. (1982). Regret in decision making under uncertainty. *Operations Research, 30*(5), 961-981. https://doi.org/10.1287/opre.30.5.961

Bell, D. E. (1985). Disappointment in decision making under uncertainty. *Operations Research, 33*(1), 1-27. https://doi.org/10.1287/opre.33.1.1

Berkman, E. T. (2018). Value-based choice: An integrative, neuroscience-informed model of health goals. *Psychology & Health, 33*(1), 40-57. https://doi.org/10.1080/08870446.2017.1316847

Bordia, P., Hobman, E., Jones, E., Gallois, C., & Callan, V. J. (2004). Uncertainty during organizational change: Types, consequences, and management strategies. *Journal of Business and Psychology, 18*(4), 507-532. https://doi.org/10.1023/B:JOBU.0000028449.99127.f7

Cheng, S. (2022). Employee involution: Conceptualization and scale development] [Doctoral dissertation, National Chengchi University. https://doi.org/10.6814/NCCU202200711

Costa, P. T., Jr., & McCrae, R. R. (1992). Four ways five factors are basic. *Personality and Individual Differences, 13*(6), 653-665. https://doi.org/10.1016/0191-8869(92)90236-I

Formica, S., & Sfodera, F. (2022). The great resignation and quiet quitting paradigm shifts: An overview of current situation and future research directions. *Journal of Hospitality Marketing & Management, 31*(8), 899-907. https://doi.org/10.1080/19368623.2022.2136601

Frost, R. O., & Shows, D. L. (1993). The nature and measurement of compulsive indecisiveness. *Behaviour Research and Therapy, 31*(7), 683-692. https://doi.org/10.1016/0005-7967(93)90121-A

Galanis, P., Katsiroumpa, A., Vraka, I., Siskou, O., Konstantakopoulou, O., Moisoglou, I., Gallos, P., & Kaitelidou, D. (2023). The quiet quitting scale: Development and initial validation. *AIMS Public Health, 10*(4), 828-848. https://doi.org/10.3934/publichealth.2023055

Gul, F. (1991). A theory of disappointment aversion. *Econometrica, 59*(3), 667-686. https://doi.org/10.2307/2938223

Hobfoll, S. E. (1989). Conservation of resources: A new attempt at conceptualizing stress. *American Psychologist, 44*(3), 513-524. https://doi.org/10.1037/0003-066X.44.3.513

Imas, A. (2016). The realization effect: Risk-taking after realized versus paper losses. *American Economic Review, 106*(8), 2086-2109. https://doi.org/10.1257/aer.20140386

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47*(2), 263-291. https://doi.org/10.2307/1914185

Kanungo, R. N. (1982). *Work alienation: An integrative approach*. Praeger.

Lazarus, R. S. (1991). *Emotion and adaptation*. Oxford University Press.

Levin, I. P., Schneider, S. L., & Gaeth, G. J. (1998). All frames are not created equal: A typology and critical analysis of framing effects. *Organizational Behavior and Human Decision Processes, 76*(2), 149-188. https://doi.org/10.1006/obhd.1998.2804

Locke, E. A., & Latham, G. P. (1990). *A theory of goal setting and task performance*. Prentice Hall.

Locke, E. A., & Latham, G. P. (2002). Building a practically useful theory of goal setting and task motivation: A 35-year odyssey. *American Psychologist, 57*(9), 705-717. https://doi.org/10.1037/0003-066X.57.9.705

Locke, E. A., & Latham, G. P. (2007). New developments in and directions for goal-setting research. *European Psychologist, 12*(4), 290-300. https://doi.org/10.1027/1016-9040.12.4.290

Loomes, G., & Sugden, R. (1982). Regret theory: An alternative theory of rational choice under uncertainty. *The Economic Journal, 92*(368), 805-824. https://doi.org/10.2307/2232669

Loomes, G., & Sugden, R. (1986). Disappointment and dynamic consistency in choice under uncertainty. *The Review of Economic Studies, 53*(2), 271-282. https://doi.org/10.2307/2297651

Morisano, D., Hirsh, J. B., Peterson, J. B., Pihl, R. O., & Shore, B. M. (2010). Setting, elaborating, and reflecting on personal goals improves academic performance. *Journal of Applied Psychology, 95*(2), 255-264. https://doi.org/10.1037/a0018478

Pfaffinger, K. F., Reif, J. A. M., Huber, A. K., Eger, V. M., Dengler, M. K., Czakert, J. P., Spieß, E., & Berger, R. (2021). Digitalisation anxiety: Development and validation of a new scale. *Discover Mental Health, 1*, Article 3. https://doi.org/10.1007/s44192-021-00003-w

Siegrist, J. (1996). Adverse health effects of high-effort/low-reward conditions. *Journal of Occupational Health Psychology, 1*(1), 27-41. https://doi.org/10.1037/1076-8998.1.1.27

Siegrist, J. (2002). Effort-reward imbalance at work and health. In P. L. Perrewé & D. C. Ganster (Eds.), *Research in occupational stress and well-being* (Vol. 2, pp. 261-291). Emerald. https://doi.org/10.1016/S1479-3555(02)02007-3

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science, 185*(4157), 1124-1131. https://doi.org/10.1126/science.185.4157.1124

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science, 211*(4481), 453-458. https://doi.org/10.1126/science.7455683

Wrosch, C., Scheier, M. F., Miller, G. E., Schulz, R., & Carver, C. S. (2003). Adaptive self-regulation of unattainable goals: Goal disengagement, goal reengagement, and subjective well-being. *Personality and Social Psychology Bulletin, 29*(12), 1496-1508. https://doi.org/10.1177/0146167203256921

Zeelenberg, M., & Pieters, R. (2007). A theory of regret regulation 1.0. *Journal of Consumer Psychology, 17*(1), 3-18. https://doi.org/10.1207/s15327663jcp1701_3

Zeelenberg, M., van Dijk, W. W., Manstead, A. S. R., & van der Pligt, J. (1998). The experience of regret and disappointment. *Cognition & Emotion, 12*(2), 221-230. https://doi.org/10.1080/026999398379727

Zeelenberg, M., van Dijk, W. W., van der Pligt, J., Manstead, A. S. R., van Empelen, P., & Reinderman, D. (1998). Emotional reactions to the outcomes of decisions: The role of counterfactual thought in the experience of regret and disappointment. *Organizational Behavior and Human Decision Processes, 75*(2), 117-141. https://doi.org/10.1006/obhd.1998.2784

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Beyond AI-Generated Insight: Human-Mediated Critical Reflection Through the Expansion of a GCED Program in Cambodia

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ABSTRACT

Global Citizenship Education (GCED) is a UNESCO-endorsed educational priority, yet GCED research remains concentrated in predominantly English-speaking developed countries, and studies of its implementation in resource-constrained developing countries remain rare. This longitudinal embedded case study traces one GCED program across three institutional sites: a three-year (2022–2024) program (Phase 1) that the author ran as a KOICA-NGO volunteer at Phare Ponleu Selpak (PPS), an NGO-affiliated arts school in Battambang, Cambodia, and its expansion (Phase 2), since August 2026, into two accredited institutions, the National University of Battambang (NUBB) and the Battambang Teacher Education College (BTEC). Phase 1 drew on program reports, reflection journals, and post-program surveys from 31 participants to analyze the curriculum's theoretical rationale, three-stage evolution, and sustaining factors; participants demonstrated evidence across all three of UNESCO's (2015) domains (cognitive, socio-emotional, behavioral), with the learner-as-instructor approach providing particularly visible behavioral evidence. Phase 2 delivered in-person GCED instruction to 29 NUBB/BTEC students in August 2026, with four online follow-up sessions and a practicum planned through January 2027; this paper reports interim findings from the six in-person sessions and a comprehensive survey (n = 25). Preliminary data showed participants rated thoughts developed through experiential activities more highly than those generated by AI (4.50 versus 3.74 on a 5-point scale), and post-activity reflections were selected far more often than AI-generated answers when asked what would stay with them longest. This study introduces and preliminarily examines a Human-Mediated Critical Reflection (**HMCR**) framework embedded in the Phase 2 design, distinguishing AI-generated insight from critical reflection (learners' capacity to question their position within unjust structures and act with others), which the findings associate more strongly with sustained human dialogue and experiential activity. An NGO pilot's transfer into formal higher education in a resource-constrained country suggests that GCED design should distinguish AI-suited informational functions from experiential, dialogue-based critical reflection.

Keywords: Global Citizenship Education, Critical GCED, Human-Mediated Critical Reflection, International Development Cooperation, Cambodia, Higher Education Expansion

Introduction

UNESCO has identified Global Citizenship Education (GCED) as a major educational priority relevant across education sectors, including higher education (UNESCO, 2015); yet the discourse remains overwhelmingly dominated by institutions in the Global North, leaving the realities of resource-constrained developing contexts largely unexamined (Massaro, 2022). At its core, GCED asks learners to critically reflect on global inequality and injustice and to participate in building a fairer, more sustainable society, yet studies of how GCED is implemented and expanded in developing countries, especially within formal higher education institutions, remain rare.

This question is sharpened by today's trend of schools adopting artificial intelligence (AI) and data-driven tools. AI excels at synthesizing information into insight; Freire (1970) and Andreotti (2006), however, locate GCED's core elsewhere, in critical reflection: learners' capacity to question their position within unjust structures and act with others. Taking this distinction as its starting point, this study tracks two phases of one Cambodian GCED program: (1) its origin at an NGO-affiliated, non-higher-education institution, and (2) its expansion into formally accredited higher education institutions, to examine the role of human interaction in GCED's reflective core.

Developing countries face real financial and institutional barriers to traditional exchange programs, making locally grounded alternatives for building global competencies important. Korea's ODA system dispatches NGO volunteers to run such programs, and stronger ties to global civil society are associated with greater institutionalization of GCED in national education policy (Kim, 2020). Such NGO-led pilots, however, often remain isolated from the formal education system they are meant to influence, so their value depends on whether they can move from a single site into institutions with authority to sustain and scale them. The author designed and ran a GCED program as a KOICA-NGO World Friends Korea volunteer at PPS (2022–2024; KCOC, 2023; Lee, 2023) and has since August 2026 partnered formally with NUBB and BTEC to expand it, testing whether PPS's success is reproducible under different institutional conditions and whether introducing GCED at BTEC, a teacher-training college whose graduates become Cambodian teachers, can open a channel into the wider school system.

The purpose of this study is to examine, in the age of AI, this Cambodian GCED program through the following three research questions:

- RQ1. On what theoretical and contextual grounds were this program's curriculum and pedagogy designed to elicit learners' critical reflection?
- RQ2. What human-mediated mechanisms sustained the program in Phase 1, and how are

these mechanisms being transferred into Phase 2?

• RQ3. How do learners distinguish AI-provided informational input from reflection developed through experiential and dialogic activities, and what implications does this distinction have for the **HMCR** model?

Literature Review / Background Information

Distinguishing Insight from Reflection

AI is a useful educational tool because it can synthesize vast information into insight quickly. Here, insight refers to the structured synthesis of existing information, as distinct from critical reflection, a situated, value-laden process of reinterpreting that information in dialogue with others. Yet as information access improves, cognitive offloading (a decline in individuals' own effort to process information) has been consistently reported (Risko & Gilbert, 2016; Sparrow, Liu, & Wegner, 2011). Research on reflective learning shows that reflection arises not at the moment information is acquired, but through a social process of reinterpreting it in dialogue with others and against one's own values (Mälkki & Green, 2016); recent theory on AI-era educational technology echoes this, casting AI as a partner that expands the space for dialogue rather than a substitute for human thinking (Wegerif & Casebourne, 2026). This study takes as its theoretical axis that GCED's ultimate goal lies in forming this reflective capacity, rather than simply accumulating insight (Andreotti, 2006; Freire, 1970).

The Human-Mediated Critical Reflection (HMCR) Model

This study introduces and preliminarily examines the Human-Mediated Critical Reflection (**HMCR**) framework, developed theoretically before Phase 2 and prospectively embedded in its instructional and data-collection design. As an original framework proposed by this study rather than an established theory, HMCR draws directly on Mälkki and Green's (2016) account of reflection as a dialogic, relational process, and operationalizes Freire's (1970) conscientization and Andreotti's (2006) critical GCED into a codable, session-level model. **HMCR** comprises three components: (1) prior personal reflection: learners articulate a personal thought before exposure to external information (including AI), guarding against uncritical acceptance of externally generated information; (2) dialogic reconstruction: learners reconstruct acquired information through in-person dialogue with peers, instructors, and the local community, the core function of the learner-as-instructor strategy and bilingual materials; and (3) consolidating reflection through comparison: comparing initial and post-dialogue thinking makes learners aware of how their reflection changed. These components are already embodied in Phase 2's four-part within-session sequence ('prior personal reflection → AI query → core activity → comparative reflection'), showing **HMCR** was built into the design rather than conceptualized after the fact. **HMCR** extends the structural reflection called for by Andreotti's (2006) 'critical GCED' and Freire's (1970) conscientization by operationalizing the

conditions under which critical reflection remains human-mediated in an AI-supported information environment.

Institutional Context: PPS, NUBB, and BTEC

Phare Ponleu Selpak (PPS), where the program began, grew from a 1994 arts program for refugee-camp children into a composite institution combining basic education, professional arts training (VAAS), and a self-funded performing-arts troupe; it is not a degree-granting university (Phare Ponleu Selpak, n.d.). The resulting Battambang Global Citizen Education project partnered with Beyond Interest NGO (BINGO), a civil-society volunteer cooperative, to train PPS staff and students in global citizenship education, who then taught the curriculum to local elementary school pupils (Lee, 2023), consistent with Kim's (2020) civil-society institutionalization finding noted above.

Phase 2 moved this model into two formally accredited institutions in the same region. The National University of Battambang (NUBB), a public university established in 2007 under Cambodia's Ministry of Education, Youth and Sport, is the largest state university in northwestern Cambodia and houses a Peace and Sustainable Development major aligned with this study's GCED agenda (NUBB, n.d.). The Battambang Teacher Education College (BTEC), formed by merging former teacher-training centers (BTEC, n.d.; Tep, 2024), runs a '12+4' Bachelor of Education program whose graduates become Cambodian teachers; introducing GCED into BTEC's pre-service curriculum therefore opens a channel into the wider school system. Because PPS is a non-degree-granting arts institution while NUBB and BTEC are accredited higher education institutions, Phase 1 and Phase 2 present a clear institutional contrast, making Phase 2 a genuine test of whether the same GCED model holds across different institutional conditions.

UNESCO (2015) defines GCED as competency-based education spanning cognitive, socio-emotional, and behavioral domains, which this program addressed through SDG education, reflection on human rights and inequality, and elementary-school teaching practicum, respectively. Prior studies of Korean university students report a persistent gap between global-citizenship knowledge and practice, calling for more action-oriented GCED (Kim, Kim, & Yoon, 2021; Park, 2024; Kwon, 2024); Kwon (2024) further found that a GCED course incorporating project-based and team activities was associated with significant pre–post increases in students' collaborative self-efficacy and global citizenship awareness, supporting this program's team-based instructor-training approach.

Taken together, this literature leaves two gaps this study addresses. First, existing GCED scholarship documents outcomes chiefly at single institutions and rarely follows a program as it moves across institutional types, so evidence on whether a given design actually transfers (rather than simply being redescribed in a new setting) remains scarce (Massaro, 2022). Second, the cognitive-offloading literature has shown that convenient access to externally generated

information can reduce learners' own effortful processing (Risko & Gilbert, 2016; Sparrow, Liu, & Wegner, 2011), and more recent work finds that frequent reliance on AI tools specifically is associated with weaker critical-thinking performance (Gerlich, 2025); separately, dialogic AI-in-education theory argues that generative AI should function as a dialogic partner that expands opportunities for reflective exchange rather than substituting for it (Tang, Cooper, Rappa, Cooper, Sims, & Nonis, 2024; Wegerif & Casebourne, 2026). These two strands, however, have developed largely independently — one measuring whether AI reliance weakens thinking, the other proposing how AI-mediated dialogue should be designed — and few studies have combined them into a session-level coding framework that distinguishes AI-provided informational input from human-mediated reflection as it unfolds within a live instructional program. By tracking one program's transfer from PPS to NUBB/BTEC and by building the **HMCR** codebook directly into program design and data collection, this study aims to fill both gaps rather than simply add another single-site GCED case.

Methodology

Research Design and Participants

A longitudinal embedded case study design (Yin, 2018) was chosen because the research questions ask not only what changed for participants but how and why one GCED program's underlying design held as it transferred across three institutional sites, a question that a purely quantitative or single-site design could not answer. Concretely, the case is the GCED program itself, not any one site: it unfolded in two phases — Phase 1 (completed) at PPS, an NGO-affiliated arts school in Battambang, Cambodia (2022–2024), and Phase 2 (ongoing), its transfer since August 2026 to NUBB and BTEC, government-accredited institutions in the same region — so that PPS, NUBB, and BTEC together form three embedded units nested within this one longitudinal case rather than three separate case studies. The two phases share the same researcher, region, and curricular principles but differ in institutional type and participant characteristics, making them a suitable basis for examining the model's transferability across the three sites.

Phase 1 participants were 31 VAAS students at PPS (15 in 2022, 16 in 2023) who volunteered for the program. Phase 2 participants were 29 NUBB/BTEC students in the August 2026 in-person program (15 BTEC; 14 NUBB), recruited through each institution's cooperation office with voluntary application; all signed consent forms. Phase 2's sample reflects purposive, volunteer-based sampling of everyone the partner offices could recruit at this stage rather than a priori sample-size calculation, a limitation discussed below.

Data Collection and Analysis

Phase 1 drew on program reports, reflection journals, learner essays, activity outputs, and a mixed-format post-program survey. For Phase 2, data collection utilized per-session reflection

questionnaires designed to capture personal thoughts prior to external information exposure (Q1) alongside subsequent responses to an AI query (Q2), during which students used their own mobile devices to freely query a generative-AI tool of their own choosing (whichever they normally used) with a common, instructor-provided question on that session's topic, thereby embedding **HMCR**'s 'prior personal reflection' into the research instrument from the outset. For clarity, AI-generated responses were treated throughout as external informational input rather than as participants' own reflective responses. In addition, a comprehensive post-program survey (comprising 28 Likert items and 9 open-ended items) yielded 25 responses out of 29 participants. Descriptive statistics were calculated for the Likert items, including two composite mean item scores: the seven-item human-dialogue/experiential-activity composite (Items 8–14, Cronbach's $\alpha = .84$) and the AI-information composite. Item 7, originally reverse-keyed, was analyzed separately ($M = 3.25$) rather than included in the composite, since it appeared to capture cognitive anchoring rather than perceived usefulness. The AI-information composite therefore comprised the remaining six positively keyed items (Items 1–6, Cronbach's $\alpha = .89$), reported as a mean item score. Given the exploratory pilot design and small sample, no inferential statistical tests were conducted. Initial qualitative coding was conducted by the researcher based on the codebook presented in Table 1, applying UNESCO's (2015) three-domain framework to Phase 1 data and integrating the **HMCR**-extension codes for Phase 2. To date, the six August 2026 in-person sessions have undergone preliminary coding; remaining datasets (online sessions, practicum, interviews) will be coded, with independent inter-coder cross-coding by the author's advisor, once collection is complete. To address RQ2, program reports, monitoring records, and institutional coordination records were additionally analyzed for recurring mechanisms related to program continuity and transfer; this analysis focused on local capacity building, relational continuity, institutional coordination, and local ownership.

Table 1: Codebook for Cognitive, Socio-Emotional, Behavioral, and **HMCR** Domains

Category	Sub-code	Operational Definition	Data Type
Cognitive	01 Concept Linking	Connects concepts (SDGs, rights, environment, inequality) to everyday experience or community issues	Reflection essays
	02 Structural Awareness	Frames global problems as rooted in structures, not individual misfortune	Essays, interviews
Socio-emotional	01 Solidarity	Expresses connection or belonging with others/community/world	Reflection essays
	02 Respect for Diversity	Notes respect for different values/cultures or a shift in perspective	Essays, interviews
Behavioral	01 Intention to Act	States intent or plans for future action	Essays, surveys
	02 Behavior Performed	Records action actually taken (practicum, campaigns, materials)	Outputs, records
Prior Personal Reflection (**HMCR**)	01 Prior Thinking	First response, based on own experience, before AI query/external input	Session Q1

Dialogic Reconstruction (**HMCR**)	02 Reinterpretation	Reconstructs information in own words via dialogue with peers/instructors/community	Lesson plans, discussion
	03 Perspective Conflict/Adjustment	Describes a clash with others' views during dialogue and the resulting change	In-depth interviews
Consolidating Reflection through Comparison (**HMCR**)	04 Awareness of Change	Compares prior personal reflection with post-activity reflection and identifies changes in thinking	Pre-/post-activity reflection questionnaires, survey

Note. Compiled by the author, based on UNESCO's (2015) three-domain framework and this study's Human-Mediated Critical Reflection (**HMCR**) model.

Trustworthiness and Research Ethics

Phase 1 triangulated official documents, learner materials, and NGO monitoring records; the researcher's dual role as program designer and analyst remains a limitation not fully removed by triangulation. To mitigate this, participants' original statements and the researcher's interpretive memos are recorded separately, planned inter-coder cross-coding will be used to check consistency, and Phase 2 adds member-checking not conducted in Phase 1. All participants gave written consent; the August 2026 instruction proceeded with institutional consent, while post-practicum interviews still require Sungkyunkwan University's R-BAY IRB approval, not yet obtained. Both surveys rely on self-report, and English-medium items translated into Khmer and Korean without back-translation may carry subtle loss.

Program Design and Curriculum

Table 2 traces the program's three-stage development at PPS and its expansion into Phase 2, showing how externally introduced knowledge became grounded local capacity and was ultimately transferred into formal higher education.

Table 2: Three-Stage Development of Phase 1 (PPS) and Expansion into Phase 2 (NUBB and BTEC)

Stage	Period	Participants	Main Activities	Support
1. Introduction	Oct–Nov 2022	15 VAAS students	Basic English lectures on 6 GCED themes	WFK KOICA-NGO dispatch
2. Deepening	Jul–Dec 2023	16 VAAS students	In-depth lectures, Khmer materials, 16-hour practicum, instructor training	Government ODA funding
3. Sustainability	Feb–Aug 2024	Local PPS instructors/students	Remote digital instruction (3 Zoom sessions) led by local instructors	Civil-society (BINGO) funding
Phase 2: Expansion	Aug 2026–Jan 2027	29 NUBB/BTEC students	6 in-person (Aug 2026) + 4 online (Sep–Dec 2026) + practicum/interviews (Jan 2027, planned)	NUBB/BTEC cooperation offices

Note. Compiled by the author from program reports and monitoring records for Phase 1 (PPS) and Phase 2 (NUBB/BTEC).

The program used the UN SDGs as its core reference, running a 10-topic curriculum of six in-

person and four online sessions (Table 3), built around a bilingual design: English-language instruction followed by an elementary-school teaching practicum in Khmer. The bilingual principle developed in Phase 1 was retained in Phase 2, while the curriculum was expanded to include ten topics and an explicit **HMCR**-based reflection sequence.

Table 3: Ten-Topic GCED Curriculum

No.	Format	Topic	Key Activity
1	In-person	Understanding Global Citizens	My Global Citizen Declaration (individual then group)
2	In-person	SDGs / Youth and SDGs	Problem-solving project on a global issue
3	In-person	Environment and Sustainable Living	Mannequin Challenge video on planetary challenges
4	In-person	Poverty and Inequality	Building an Ideal Village game (unequal resources)
5	In-person	Our Rights, Human Rights	Supply Card / Find the Right game; Universal Declaration of Human Rights
6	In-person	Sustainable Economy	Fair Trade Chocolate Game (producer–distributor–consumer)
7	Online	Diversity and Interconnectedness	Map That Connects the World
8	Online	Peace	Peace, Speak With Your Senses / Making a Peace Book
9	Online	International Development Cooperation	Film “The Boy Who Harnessed the Wind”; 4-stakeholder discussion
10	Online	Voices for Change	Case studies of changemakers across fields

Note. Compiled by the author from the program's curriculum materials and lesson plans.

Findings and Discussion

Phase 1 (PPS): Evidence Across UNESCO's Three Domains

Four design principles stood out in implementation: local relevance (connecting GCED's global values to community realities), experiential learning (games, discussion, and projects over lectures), capability expansion through learner-as-instructor (students taught elementary pupils directly), and local-language materials (Khmer lesson plans reconstructed, not merely translated, for local context). These principles reinforced one another: local-language materials made activities accessible to students with limited English, while the learner-as-instructor role gave them a concrete reason to master the materials. Across the cognitive, socio-emotional, and behavioral domains, students began linking global issues such as the SDGs, environment, and human rights to daily life (S3, 2022), formed solidarity and cross-cultural respect through cooperation (S7, 2022; S18, 2023), and translated knowledge into action, such as a plogging campaign after the environment lesson (S11, 2022). Evidence bearing on RQ2 also emerged: across Phase 1's three stages, local capacity building (Stage 2's practicum and instructor training) and a gradual handover of delivery, culminating in Stage 3's remote sessions being led entirely by local instructors, suggest that continuity depended on these relational and capacity-building mechanisms rather than the researcher's ongoing presence.

Phase 2 (NUBB and BTEC): Preliminary Results

The following interim results draw on two Phase 2 sources: 127 cumulative per-session responses from the six August 2026 in-person sessions (~21 submissions per session, out of 29 participants), and the comprehensive post-program survey (25 respondents). These are a comparison point with Phase 1 rather than final Phase 2 findings, since online, practicum, and interview data are not yet collected. Cognitively, students connected topics such as climate change, poverty, and fair trade to both personal experience and structural causes (e.g., NUBB-02 on needing to change "the whole system and social behavior"). Socio-emotionally, solidarity and respect for diversity recurred throughout (survey item, 4.23/5). Behaviorally, the intention-to-act item averaged 4.38/5, with concrete intentions (reducing single-use plastics, buying fair-trade goods, teaching peers) reported in open-ended responses; actual behavior can only be confirmed after the January 2027 practicum.

On the **HMCR** items, post-activity reflections were selected more often than AI-generated answers across the 127 session-level responses: about half chose post-activity thoughts versus 15.0% choosing the AI's answer (65 [51.2%] vs. 19 [15.0%] of 127) when asked what stayed with them most, widening to 69.3% versus 5.5% (88 vs. 7) when asked what would be remembered longer. Many noted AI answers lacked "emotional connection," "personal context," and "cultural nuance." The comprehensive survey showed the same pattern: the human dialogue/experiential-activity composite averaged 4.50/5 versus 3.74/5 for the AI-information composite, and "human dialogue was more useful" (Item 19, 4.42) outscored "AI was more useful" (Item 18, 3.54); both are distinct from Item 7, reported separately below. Notably, Item 7 (difficulty generating alternative perspectives after an AI response) showed a positive but not statistically significant association with the AI-information composite (r = .36, p = .08), tentatively consistent with an anchoring pattern; given the small sample (n = 25) and exploratory design, this should be read as suggestive rather than conclusive. Institutionally, Phase 2 includes four online follow-up sessions (Sep–Dec 2026) and a January 2027 practicum and interview phase confirmed with both partner offices, though this remains at the planning stage. This transfer was facilitated through local coordination rather than researcher-led delivery alone: NUBB and BTEC cooperation offices supported recruitment and scheduling and have agreed to continue the program through the sessions and practicum described above, suggesting that Phase 1's relational continuity and local ownership are being reproduced and complemented by institutional coordination.

Integrated Discussion and Limitations

This study highlights not merely that the program continued, but the conditions that let critical reflection form as AI makes acquiring information easier; this emerged more precisely in Phase 2, where the four-part within-session sequence was designed in from the start, letting learners compare their thinking before the AI query, after the AI's answer, and after the activity

(**HMCR**-04). The consistent gap between activity-based and AI-based responses across both session questionnaires and the comprehensive survey preliminarily supports, even in a formal higher-education context, **HMCR**'s core claim: critical reflection was most visibly associated with human-mediated processes (collaborative experiential activities, locally contextualized materials, and in-person dialogue) that ran alongside, rather than were replaced by, whatever insight AI supplied. This pattern is broadly consistent with cognitive-offloading research showing that convenient access to externally generated information can substitute for learners' own effortful engagement (Risko & Gilbert, 2016; Sparrow, Liu, & Wegner, 2011; Gerlich, 2025), and it extends dialogic accounts of AI in education (Tang et al., 2024; Wegerif & Casebourne, 2026) by showing, at the session level, when learners actually favored human dialogue over an AI response rather than only theorizing that AI should be designed as a dialogic partner. The reappearance at NUBB and BTEC of the transfer mechanisms first identified at PPS (RQ2) — local capacity building, relational continuity, and local ownership — also echoes Kim's (2020) finding that closer ties to civil-society partners are associated with greater institutionalization of GCED, suggesting this pattern may generalize beyond a single NGO-to-university transfer. Read against the three research questions, these results suggest that the curriculum's design principles (RQ1) were associated with evidence of reflection in both phases; that Phase 1's human-mediated mechanisms (RQ2) — local capacity building, relational continuity, and local ownership — are, so far, visible in Phase 2's in-person sessions and are beginning to be complemented by institutional coordination, though transfer to the remote and practicum stages remains to be confirmed; and that, for RQ3, learners consistently distinguished AI-provided informational input from reflection developed through experiential and dialogic activities. These learner-level findings, however, rest on qualitative interpretation without a pre-post or control-group design, so they describe an observed pattern rather than prove causal effectiveness.

This longitudinal embedded case design partially mitigates, but does not eliminate, the generalizability limits of a single-case study. Phase 1 and Phase 2 had similar participant numbers (31 vs. 29) but differ in institutional type and participants' prior English proficiency, and Phase 2's sustainability cannot be confirmed until the January 2027 practicum is complete. The findings should therefore be read as suggesting theoretical transferability rather than statistical generalization. Because this is ongoing research, all Phase 2 findings reported here remain tentative, with final conclusions to appear in the author's doctoral dissertation.

Conclusion

This study examined the theoretical and contextual basis of a Cambodian GCED program, the human-mediated mechanisms involved in its transfer from PPS to NUBB and BTEC, and learners' distinctions between AI-provided informational input and reflection developed through experiential and dialogic activities. The findings suggest that, even as AI can

efficiently generate insight, sustained human-to-human dialogue plays a central role in learners' critical reflection. The conclusions, corresponding to the three research questions, are as follows.

Regarding RQ1, the program's curriculum and pedagogy were grounded in Freire's (1970) conscientization, Andreotti's (2006) critical GCED, and UNESCO's (2015) three-domain framework, operationalized through four design principles (local relevance, experiential learning, learner-as-instructor, local-language materials) associated with evidence of critical reflection across its developmental stages. Regarding RQ2, across Phase 1's three-stage arc, human-mediated mechanisms — local capacity building, relational continuity, and local ownership — were central to sustaining the program, particularly through the Stage 3 shift to remote, locally led instruction; in Phase 2, these mechanisms are visible in the in-person sessions and beginning to be complemented by institutional coordination through NUBB and BTEC, with transfer to the remote and practicum components to be confirmed once that data is collected. Regarding RQ3, examined specifically in Phase 2, learners consistently distinguished AI-provided informational input from reflection developed through experiential and dialogic activities, perceiving AI-generated responses as carrying less personal stake and cultural grounding — supporting **HMCR**'s central claim in the Phase 2 context as well.

This study contributes a real-world developing-country case to GCED research concentrated mainly in wealthy countries, addresses a limitation in prior single-site, non-higher-education designs by tracing an actual NGO-to-university transfer, and offers **HMCR** as an integrative framework linking GCED, cognitive-science research on reflection, and AI-era education theory. As a qualitative case study with a modest, non-random sample and no comparison group, its conclusions remain provisional; the author's doctoral research will address these limits through more systematic methods, full analysis of Phase 2's remaining data, and connection to recent dialogic theories of AI-era educational technology (Wegerif & Casebourne, 2026).

For institutions integrating GCED into teacher training, this program offers concrete design principles: bilingual instruction, learner-as-instructor, and local-language materials, suggesting a pathway through which NGO-based educational initiatives may transfer into formal higher education in Cambodia and comparable resource-constrained contexts.

In conclusion, this Cambodian program suggests that critical GCED can take root in a resource-constrained developing country, supported not by any single technological solution but by sustained human-to-human reflection and relationship-building that goes beyond AI-generated insight: AI-suited functions such as synthesizing information can be automated, while the dialogue that turns information into critical, situated reflection appears to depend on sustained human interaction.

References

Andreotti, V. (2006). Soft versus critical global citizenship education. *Policy and Practice: A Development Education Review*, *3*, 40-51. https://www.developmenteducationreview.com/issue/issue-3/soft-versus-critical-global-citizenship-education

Battambang Teacher Education College [BTEC]. (n.d.). *About us*. https://www.btec.edu.kh/about-us

Freire, P. (1970). *Pedagogy of the oppressed*. Herder and Herder.

Gerlich, M. (2025). AI tools in society: Impacts on cognitive offloading and the future of critical thinking. *Societies*, *15*(1), 6. https://doi.org/10.3390/soc15010006

Kim, J. E., Kim, K. A., & Yoon, H. J. (2021). University students' global citizenship: Types and determinants [in Korean]. *Global Education Research*, *13*(4), 83-111. https://doi.org/10.19037/agse.13.4.04

Kim, J. H. (2020). A study on the institutionalization of global citizenship education [in Korean]. *Korean Journal of International Understanding Education*, *15*(2), 47-95. https://doi.org/10.35179/jeiu.2020.15.2.47

Korea NGO Council for Overseas Cooperation [KCOC]. (2023, May 15). 2022 World Friends Korea KOICA-NGO Volunteers Project support program notice [Announcement, in Korean]. http://www.ngokcoc.or.kr/bbs/board.php?bo_table=news01&wr_id=1705

Kwon, M. E. (2024). The effects of global citizenship education on university students' global citizenship awareness, global citizenship competency, and collaborative self-efficacy [in Korean]. *Journal of International Culture*, *17*(1), 129-155. https://doi.org/10.34223/jic.2024.17.1.129

Lee, J. (2023, December 13). *How global citizenship education is shaping the next generation of leaders at Phare Ponleu Selpak*. Phare Ponleu Selpak. https://phareps.org/2023/12/13/global-citizenship-education/

Mälkki, K., & Green, L. (2016). Ground, warmth, and light: Facilitating conditions for reflection and transformative dialogue. *Journal of Educational Issues*, *2*(2), 169-183. https://doi.org/10.5296/jei.v2i2.9947

Massaro, V. R. (2022). Global citizenship development in higher education institutions: A systematic review of the literature. *Journal of Global Education and Research*, *6*(1), 98-114. https://doi.org/10.5038/2577-509X.6.1.1124

National University of Battambang [NUBB]. (n.d.). *Home*. https://nubb.edu.kh/en/

Park, S. Y. (2024). A study on the formation of global citizenship through global citizenship education among university students [in Korean]. *Journal of Education & Culture*, *30*(3), 397-415. https://doi.org/10.24159/joec.2024.30.3.397

Phare Ponleu Selpak. (n.d.). *Visual and Applied Arts School (VAAS)*. https://phareps.org/visual-applied-arts-school/

Risko, E. F., & Gilbert, S. J. (2016). Cognitive offloading. *Trends in Cognitive Sciences*, *20*(9), 676-688. https://doi.org/10.1016/j.tics.2016.07.002

Sparrow, B., Liu, J., & Wegner, D. M. (2011). Google effects on memory: Cognitive consequences of having information at our fingertips. *Science*, *333*(6043), 776-778. https://doi.org/10.1126/science.1207745

Tang, K. S., Cooper, G., Rappa, N., Cooper, M., Sims, C., & Nonis, K. (2024). A dialogic approach to transform teaching, learning & assessment with generative AI in secondary education: A proof of concept. *Pedagogies: An International Journal*, *19*(3), 493-503. https://doi.org/10.1080/1554480X.2024.2379774

Tep, V. (2024). Teacher educators as curriculum developers: A case study of teacher education colleges in Cambodia. *Frontiers in Education*, *9*, 1328023. https://doi.org/10.3389/feduc.2024.1328023

UNESCO. (2015). *Global citizenship education: Topics and learning objectives*. UNESCO Publishing.

Wegerif, R., & Casebourne, I. (2026). A dialogic theoretical foundation for integrating generative AI into pedagogical design. *British Journal of Educational Technology*, *57*(3), 639-654. https://doi.org/10.1111/bjet.70026

Yin, R. K. (2018). *Case study research and applications: Design and methods* (6th ed.). SAGE.

P26050

SentiNet: An AI-Powered Sentiment Analysis and Heat Mapping of Internet Connectivity at Divine Word College of Legazpi

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ABSTRACT

Reliable internet connectivity is essential for supporting teaching, learning, research, and administrative services in higher education. However, conventional campus connectivity assessments often rely on quantitative satisfaction measures and provide limited insight into users' experiences and the spatial distribution of perceived connectivity problems. This study presents SentiNet, an AI-powered institutional research framework that integrates descriptive statistical analysis, AI-assisted qualitative analysis, and facility-based heat mapping to assess internet connectivity at Divine Word College of Legazpi (DWCL). A mixed-methods descriptive design was employed through an institution-wide cross-sectional survey involving 422 students, teaching personnel, and non-teaching personnel from two campuses. Quantitative responses were analyzed using frequency, percentage, and weighted mean, while facility-level satisfaction ratings were visualized through connectivity heat maps. Responses to five open-ended questions were analyzed using OpenAI GPT-5.4 for sentiment classification and thematic analysis, with generated outputs reviewed by the researchers. Findings showed that campus connectivity was generally rated Average, with the College Library receiving the highest rating at 3.47 (Good). Slow internet speed (40.52%), frequent disconnection (18.72%), weak Wi-Fi signal (14.22%), and limited coverage (10.19%) were the most frequently reported connectivity challenges. Respondents also reported slower connectivity during the afternoon (29.86%), indicating perceived temporal variation in service quality. The findings demonstrate that combining facility-level satisfaction, AI-assisted user-experience analysis, and spatial visualization provides a more contextual assessment than satisfaction ratings alone. SentiNet can support institutional decision-making by identifying locations and recurring concerns that warrant further technical assessment and infrastructure planning. Because the study is based

on user perceptions from a single institution and does not include objective network performance measurements, the framework should be further validated using multi-institutional and technical network data.

Keywords: Artificial Intelligence, Campus Connectivity, Heat Mapping, Higher Education, Sentiment Analysis

Introduction

Reliable internet connectivity is essential to higher education, supporting teaching, learning, research, and administrative services through digital learning platforms, cloud applications, and online collaboration tools. As institutions continue their digital transformation, reliable campus connectivity has become an important component of an effective and equitable digital learning environment (Timotheou et al., 2023).

Despite investments in network infrastructure, connectivity may remain inconsistent across campus facilities because of differences in wireless coverage, bandwidth allocation, network congestion, and user density. Such variations can affect access to online resources and produce location-dependent user experiences (Akmad & Abatayo, 2024; Gloria et al., 2025; Fernandez et al., 2025). Conventional satisfaction surveys can quantify these experiences through Likert-scale ratings, but numerical results alone provide limited explanation of users' concerns and where connectivity problems are perceived to occur.

Recent developments in Large Language Models (LLMs) have expanded the use of artificial intelligence in analyzing textual feedback, including sentiment classification and thematic analysis (Gilardi et al., 2023; Törnberg, 2024). At the same time, facility-based heat mapping can visualize differences in perceived connectivity across campus locations. However, these approaches are commonly treated as separate analytical activities. A more useful institutional research approach is to combine them so that quantitative ratings identify the level of satisfaction, qualitative feedback explains users' experiences, and facility-level visualization identifies locations requiring attention.

To address this gap, this study presents SentiNet, an AI-powered institutional research framework for campus internet connectivity assessment at Divine Word College of Legazpi (DWCL). SentiNet integrates three complementary evidence streams: descriptive satisfaction analysis to measure perceived connectivity, GPT-based sentiment and thematic analysis to interpret users' qualitative experiences, and facility-based heat mapping to visualize variations across campus locations. The integration transforms user feedback into structured evidence that can support institutional planning and information technology decision-making. Specifically, the study evaluates internet connectivity satisfaction across campus facilities, analyzes users' reported experiences through AI-assisted qualitative analysis, visualizes facility-level connectivity ratings, and identifies implications for improving campus digital infrastructure.

Literature Review

The literature establishes internet connectivity as an important component of digital transformation in higher education. Reliable digital infrastructure supports access to learning platforms, online resources, cloud applications, collaboration tools, and administrative services, making connectivity an important institutional concern (Timotheou et al., 2023). Studies of campus connectivity likewise indicate that unstable internet access can affect academic activities and user satisfaction (Akmad & Abatayo, 2024; Fernandez et al., 2025).

User-experience research has increasingly incorporated sentiment analysis to examine qualitative educational feedback. Traditional sentiment analysis has been applied to student feedback to identify patterns that may not be evident from numerical ratings alone (Altrabsheh et al., 2014; Dake & Gyimah, 2023). More recent studies demonstrate the potential of large language models for text annotation and qualitative analysis, including sentiment classification and thematic interpretation (Gilardi et al., 2023; Törnberg, 2024). These developments suggest that LLM-assisted analysis can complement conventional survey-based approaches when qualitative responses are systematically reviewed.

However, existing approaches to campus connectivity assessment generally emphasize either user satisfaction or technical network measurements. This study addresses this gap by integrating quantitative satisfaction ratings, AI-assisted analysis of user narratives, and facility-based heat mapping. SentiNet therefore links what users experience, how they perceive

connectivity, and where differences occur, providing an institutional research perspective on campus connectivity assessment.

Conceptual Framework

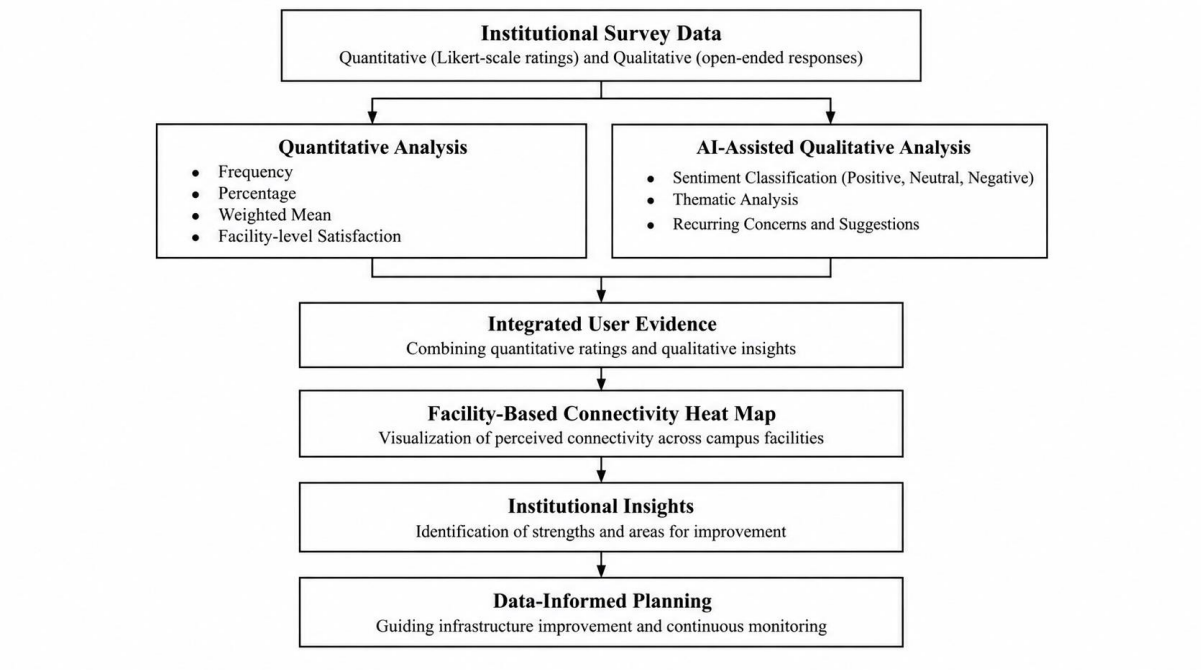


Figure 1. Conceptual workflow of the SentiNet framework for institutional campus connectivity assessment.

SentiNet integrates quantitative satisfaction analysis, GPT-5.4-assisted qualitative analysis, and facility-based connectivity heat mapping. These evidence streams combine user ratings and experiences with facility-level visualization to identify perceived connectivity differences and inform institutional planning. SentiNet functions as an institutional research decision-support framework rather than an automated technical diagnostic system.

Methodology

Research Design

This study employed a mixed-methods descriptive research design using a cross-sectional survey to assess perceived internet connectivity at Divine Word College of Legazpi (DWCL). Quantitative data measured satisfaction across campus facilities using a five-point Likert scale, while qualitative data examined users' experiences through five open-ended questions analyzed

using GPT-5.4. The findings were integrated with facility-based heat mapping to provide an institutional assessment of campus connectivity.

Research Setting and Participants

The study was conducted at Divine Word College of Legazpi (DWCL), a private Catholic educational institution in Legazpi City, Albay, Philippines. The institution operates two campuses under a shared internet infrastructure: the St. Arnold Janssen Campus, serving undergraduate and graduate programs, and the St. Josef Freinademetz Campus, serving Junior and Senior High School departments. The campuses are connected through a dedicated fiber-optic link and supported by primary and secondary internet services.

The target population comprised 5,081 eligible internet users, including students, teaching personnel, and non-teaching personnel. An institution-wide online survey yielded 422 valid responses, exceeding the minimum sample of 357 calculated using Cochran's formula at a 95% confidence level and 5% margin of error. Of the respondents, 280 were from the St. Arnold Janssen Campus and 142 were from the St. Josef Freinademetz Campus.

Survey Instrument

Data were collected using a structured questionnaire administered through Google Forms. The instrument contained three sections: respondent information, facility-based internet connectivity assessment using a five-point Likert scale, and five open-ended questions concerning users' experiences and perceptions. Facility-level ratings covered academic, administrative, and common-use locations and served as the basis for the connectivity assessment and heat maps. The questionnaire was content-validated by experts in information technology and educational research for clarity, relevance, and appropriateness.

Data Collection and Analysis

Following institutional approval, the questionnaire was distributed through official institutional channels. Participation was voluntary, informed consent was obtained, and only complete and valid responses were included. Responses were exported to Microsoft Excel, anonymized, and

prepared for analysis. Quantitative data were summarized using frequency, percentage, and weighted mean, with scores interpreted as Excellent (4.21–5.00), Good (3.41–4.20), Average (2.61–3.40), Poor (1.81–2.60), and Very Poor (1.00–1.80).

Qualitative responses were analyzed using OpenAI GPT-5.4 through a zero-shot structured prompt. The analysis identified sentiment, connectivity issues, positive observations, time-of-day patterns, and infrastructure priorities. Outputs were reviewed against the original anonymized responses before aggregation and interpretation. GPT-5.4 served as an analytical support tool, while the researchers retained responsibility for validation and interpretation. No independent human-coder agreement procedure was conducted; therefore, the classifications are treated as researcher-reviewed AI-assisted outputs rather than independently validated ground-truth labels.

Facility-Based Connectivity Heat Mapping

Facility-based heat maps were generated from the weighted mean ratings of campus facilities using the predefined five-point interpretation scale. The maps represent user-perceived facility-level connectivity, not measured signal strength, GPS data, or geographic interpolation. They were used to visualize relatively higher and lower satisfaction across campus locations and identify areas that may warrant further institutional assessment.

The heat-map findings were interpreted together with the quantitative and qualitative results to examine whether locations with lower satisfaction were also associated with recurring user-reported connectivity concerns.

Ethical Considerations

Permission to conduct the study was obtained from the administration of DWCL. Participation was voluntary, informed consent was obtained, and responses were anonymized and reported only in aggregate. GPT-5.4 was used solely for analysis of anonymized qualitative responses, while the researchers retained responsibility for validating, interpreting, and reporting the findings.

Results and Discussion

Internet Connectivity Satisfaction Across Campus Facilities

Table 1. Highest- and Lowest-Rated Campus Facilities

Campus	Highest-Rated Facility (WM)	Lowest-Rated Facility (WM)
St. Arnold Janssen	College Library (3.47)	AV Hall (2.70)
St. Josef Freinademetz	SHS Computer Laboratory (3.07)	Gymnasium (2.73)

The facility-based assessment shows variation in perceived internet connectivity across campus locations. At the St. Arnold Janssen Campus, the College Library received the highest rating (WM = 3.47, Good), while the AV Hall received the lowest (WM = 2.70, Average). At the St. Josef Freinademetz Campus, the SHS Computer Laboratory had the highest rating (WM = 3.07, Average), while the Gymnasium had the lowest (WM = 2.73, Average). Overall, academic and computer-oriented facilities received relatively higher ratings than multipurpose spaces, although the observed differences represent user perceptions and do not establish specific technical causes.

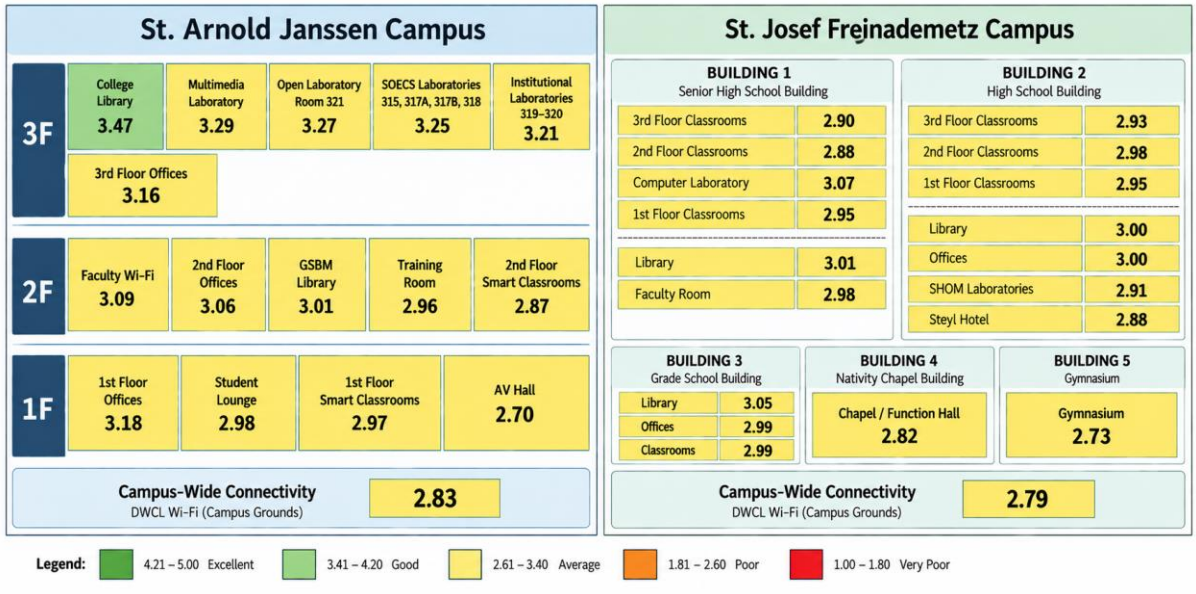


Figure 2. Facility-level perceived internet connectivity heat maps for both campuses

The heat maps illustrate the spatial distribution of perceived connectivity and identify facilities that may warrant further assessment. These spatial findings are consistent with qualitative reports of slower speeds, unstable connections, and weaker signals in selected locations, showing how SentiNet links facility-level perceptions with users' reported experiences.

AI-Assisted Sentiment Analysis of Users' Internet Experience

Table 2. Overall Sentiment Distribution of Respondents' Internet Experience

Positive	Neutral	Negative
98 (23.22%)	204 (48.34%)	120 (28.44%)

The AI-assisted analysis showed that neutral sentiment was predominant (48.34%), followed by negative (28.44%) and positive sentiment (23.22%). The predominance of neutral responses indicates that many respondents considered campus internet generally functional but not consistently satisfactory. The negative responses further indicate persistent connectivity concerns, while positive responses show that reliable service was experienced in some situations.

These findings provide qualitative context for the predominantly Average facility ratings. Respondents commonly described unstable connectivity, varying signal strength, and location-dependent performance, suggesting that perceived service quality was influenced by consistency and reliability. Thus, the sentiment analysis complements the quantitative assessment by explaining users' experiences behind the numerical ratings. Within SentiNet, these AI-assisted, researcher-reviewed findings provide additional evidence for identifying recurring concerns associated with perceived connectivity differences.

Connectivity Challenges and Their Impact on Academic and Work Activities

Table 3. Primary Connectivity Challenges Reported by Respondents

Connectivity Challenge	Frequency	Percentage (%)
Slow Internet Speed	171	40.52
Frequent Disconnection	79	18.72
Weak Wi-Fi Signal	60	14.22
Limited Coverage	43	10.19
Authentication/Login Issues	25	5.92
Network Congestion	18	4.27
No Major Issue Reported	20	4.74
Other	6	1.42
Total	**422**	**100.00**

Slow internet speed was the most frequently reported challenge (40.52%), followed by frequent disconnection (18.72%), weak Wi-Fi signal (14.22%), and limited coverage (10.19%). Only 4.74% reported no major issue. These results indicate that users' concerns were primarily related to speed, stability, and coverage, rather than internet availability alone.

Respondents reported impacts on online classes, learning resources, research, virtual meetings, and academic or work-related activities, with some relying on mobile data when connectivity was unreliable. The findings highlight the need to improve network stability, wireless coverage, and service reliability, while recognizing that these are user-reported experiences rather than direct technical measurements.

Positive Experiences with Campus Internet Services

The AI-assisted analysis showed that 24.64% of respondents reported no positive experience, while reliable internet in specific facilities was the most frequently identified positive experience (22.75%), followed by support for online learning (16.11%) and fast internet performance (14.22%). These findings indicate that satisfactory connectivity was experienced in selected locations and was particularly valuable for academic activities.

The concentration of positive experiences in specific facilities, together with the substantial proportion reporting no positive experience, suggests that favorable connectivity was not consistently experienced across the campuses. This finding complements the facility-level ratings and heat maps, which showed variations in perceived connectivity by location. Overall, the results indicate that improving the consistency of connectivity across facilities is as important as maintaining areas where users already experience reliable service.

Table 4. Positive Experiences Reported by Respondents

Positive Experience	Frequency	Percentage (%)
No Positive Experience Reported	104	24.64
Reliable Internet in Specific Facilities	96	22.75
Supports Online Learning	68	16.11
Fast Internet Performance	60	14.22
Accessible Internet Services	45	10.66
Stable Internet Connection	30	7.11
Wide Wi-Fi Coverage	12	2.84
Convenient for Academic and Work Activities	5	1.18
Other	2	0.48
Total	**422**	**100.00**

Temporal Connectivity Patterns

Table 5. Reported Time-of-Day Connectivity Patterns

Connectivity Pattern	Frequency	Percentage (%)
Slower in the Afternoon	126	29.86
No Noticeable Pattern	119	28.20
Better in the Morning	74	17.54
Consistently Slow Throughout the Day	48	11.37
Other reported patterns	55	13.03
Total	**422**	**100.00**

The reported patterns show that 29.86% of respondents experienced slower connectivity in the afternoon, while 28.20% observed no noticeable pattern. Meanwhile, 17.54% reported better connectivity in the morning and 11.37% perceived connectivity as consistently slow throughout the day. These findings indicate that perceived connectivity varied by time for some users, although no single time-of-day pattern was experienced across all respondents.

Qualitative responses commonly associated slower performance with afternoon class hours and periods of higher user activity, while better connectivity was reported during lower-traffic periods. However, these observations are based on user experiences and do not constitute direct measurements of bandwidth utilization or network congestion. The findings therefore identify afternoon periods as potential priorities for further technical monitoring, while the heat maps provide the complementary spatial perspective on facility-level connectivity.

Overall Perception of Internet Connectivity at Divine Word College of Legazpi

Respondents generally viewed the institutional internet as adequate for teaching, learning, research, and administrative activities in facilities with more reliable connectivity. However, slow speed, unstable connections, limited wireless coverage, and location- and time-dependent performance remained major concerns. Overall, the integrated facility ratings, AI-assisted qualitative findings, and heat maps indicate that DWCL connectivity is generally functional but uneven, identifying locations and user concerns that may warrant further technical assessment and planning.

Conclusion

This study assessed internet connectivity at Divine Word College of Legazpi using SentiNet, which integrates facility-based satisfaction ratings, GPT-5.4-assisted qualitative analysis, and

connectivity heat mapping. Connectivity was generally perceived as Average, with variations across facilities and recurring concerns involving speed, stability, coverage, and time-dependent performance.

The integrated approach provides a broader view than satisfaction ratings alone by connecting facility-level perceptions with users' reported experiences. SentiNet can therefore support evidence-informed identification of areas for further network assessment and improvement. However, the study reflects user perceptions from a single institution and does not directly measure technical network performance. Future research may strengthen the framework through objective network measurements, multi-institutional validation, and comparative evaluation of AI models.

References

Akmad, A., & Abatayo, A. V. (2024). Caught In The Slow Lane: Effects Of Unstable Internet Connectivity On Accessing Academic Resources And Collaborative Learning. Journal of Interdisciplinary Perspectives, 2(9), 278–286. https://doi.org/10.69569/jip.2024.0370

Altrabsheh, N., Cocea, M., & Fallahkhair, S. (2014). Sentiment Analysis: Towards A Tool For Analysing Real-Time Students' Feedback. In Proceedings of the 2014 IEEE 26th International Conference on Tools with Artificial Intelligence (pp. 419–423). IEEE. https://doi.org/10.1109/ICTAI.2014.70

Dake, D.K., & Gyimah, E. (2022). Using Sentiment Analysis to Evaluate Qualitative Students' Responses. Education And Information Technology 28, 4629–4647 (2023). https://doi.org/10.1007/s10639-022-11349-1

Fernandez, J. R. E., Morales, I. A., & Edradan, L. V. E. (2025). Assessing the Relationship Between Campus Wi-Fi Reliability and Student Academic Success. International Journal of Advanced Research in Science, Communication and Technology, 5(9), 97–106. https://doi.org/10.48175/IJARSCT-28246

Gilardi, F., Alizadeh, M., & Kubli, M. (2023). ChatGPT outperforms crowd workers for text-annotation tasks. Proceedings of the National Academy of Sciences, 120(30), e2305016120. https://doi.org/10.1073/pnas.2305016120

Gloria, D. S., Pelayo, E. T. C., & Castro, R. D. (2025). The Role of Infrastructure and Student Satisfaction in Higher Education: Inputs for Campus Development Plan. Problems of Education in the 21st Century, 83(4), 502–519. https://doi.org/10.33225/pec/25.83.501

Timotheou, S., Miliou, O., Dimitriadis, Y., Sánchez, J., Gagatsis, A., & Gómez-Soberón, J. M. (2023). Impacts of Digital Technologies on Education and Factors Influencing Schools' Digital Capacity and Transformation: A Literature Review. Education and Information Technologies, 28, 6695–6726. https://doi.org/10.1007/s10639-022-11431-8

Törnberg, P. (2024). Best practices for text annotation with large language models. https://arxiv.org/abs/2307.13106

Sub-Theme V

Ethics and Pragmatics of AI in Education and IR

P26033

Comparing LDA and NMF for Thematic Analysis of Bilingual Higher-Education Discourse on Reddit

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ABSTRACT

Institutional research increasingly mines free-text student feedback, yet the methodological choices behind this work are rarely examined and almost never treated as ethical ones. This study compares Latent Dirichlet Allocation (LDA) and Non-negative Matrix Factorization (NMF) on 24,110 comments from four Philippine university subreddits (Ateneo, UP, De La Salle, and Benilde). Because the discourse is heavily code-switched between Filipino and English (Taglish), we also ask how well English-centric pipelines represent bilingual student speech. Holding topic count at k = 15, we test three placements of Rapid Automatic Keyword Extraction (RAKE) and evaluate models on coherence, diversity, codebook alignment, and cross-method agreement. NMF produced more coherent and interpretable topics ($C_v \approx 0.70$ vs. ≈ 0.55 for LDA) and mapped more cleanly onto the codebook. RAKE helped only as a post hoc labeler: it slightly reduced NMF coherence (0.698 vs. 0.705) and collapsed LDA into a single dominant domain. The models disagreed sharply on individual topics (mean Jaccard ≈ 0.11) but converged on each institution's domain profile (cosine 0.87–0.98), so institution-level conclusions held regardless of model. We interpret method choice as itself a representational-ethics decision, not merely a technical one. For institutional researchers, the significance is that these communities offer a low-cost early signal of student concerns, provided findings are read at the aggregate, domain level and treated as a listening instrment rather than a performance metric. The paper's ethical contribution centers on representational fairness: whether an analysis portrays a community accurately, not only whether it satisfies privacy or consent.

Keywords: topic modeling, code-switching, student voice, institutional research, research ethics

1. Introduction

Universities now treat student voice as a core input to quality assurance and planning, yet in practice they lean on the numeric parts of course evaluations and leave written comments largely unread, because reading them at scale is expensive (Sun & Yan, 2023). Natural

language processing (NLP), and topic modeling in particular, has made it practical to extract recurring themes from thousands of comments (Gencoglu et al., 2023; Hayat et al., 2024). Meanwhile, much of the most candid student commentary has migrated off official surveys onto social media. Reddit is a clear example: its university-specific forums let students speak frankly under pseudonyms, making them a useful, if messy, source for institutional research (Nwaoha et al., 2024).

Turning that discourse into something an institution can act on is not a neutral technical step. The two most common topic models—LDA (Blei et al., 2003) and NMF (Lee & Seung, 1999)—start from different assumptions and can describe the same corpus quite differently, especially for text as short and noisy as social-media posts (Chen et al., 2019; Egger & Yu, 2022). Smaller choices matter too, such as where keyword extraction sits in the pipeline or how topic quality is scored. None of these stays purely technical once the text is student speech (some possibly written by minors or disclosing distress) and once results may feed institutional decisions (boyd & Crawford, 2012; Mittelstadt et al., 2016). In plain terms, both methods group frequently co-occurring words into a handful of themes ("topics"), differing mainly in their statistical assumptions; RAKE (Rose et al., 2010) is a complementary tool that extracts multi-word key phrases and is used here to help name topics.

The Philippine context adds a further complication. Students in these communities routinely switch between Filipino and English (Taglish), often within a sentence, and computational resources for this code-switched register remain thin (Cruz & Cheng, 2019; Cosme & De Leon, 2024; Montalan et al., 2025). Tools built mainly for English can misread culturally specific phrasing: an accuracy problem that becomes a fairness problem once communities are compared. Yet despite busy institution-specific subreddits, almost no one has systematically modeled this bilingual discourse or tested how different modeling approaches handle it.

Three gaps motivate this study. Empirically, head-to-head comparisons of LDA and NMF, and of where RAKE belongs, are scarce for bilingual code-switched higher-education text. Conceptually, studies weighing these options rarely connect them to the ethics of analyzing student discourse, though method choice partly decides whether a community is portrayed fairly. And on granularity, per-school comparison against an a priori codebook (and whether rival models agree about analytical constructs rather than individual topics) has had little attention. We address all three by comparing LDA and NMF at a fixed $k = 15$ across three RAKE configurations, on comments from four Philippine university subreddits, reading the methodological results together with their ethical implications. Four research questions follow:

RQ1. How do LDA and NMF compare in topic coherence, topic diversity, and alignment to an a priori codebook when applied to bilingual (Filipino–English) higher-education discourse at k = 15?
RQ2. How does the placement of RAKE (as a pre-processing feature step, omitted entirely, or as a post-processing topic-labeling step) affect topic quality and interpretability for each model?
RQ3. To what extent do LDA and NMF agree at the level of individual topics versus at the level of codebook domains, and how does this cross-method agreement vary across institutions?
RQ4. What ethical considerations arise when applying these methods to student-generated discourse for institutional research, and in what sense do the methodological choices function as representational-ethics choices?

This study makes four contributions. Empirically, it assembles and analyses a rarely modelled bilingual (Filipino–English) higher-education corpus from institution-specific Reddit communities. Methodologically, it compares LDA and NMF and, distinctively, evaluates their agreement not only topic-by-topic but at the level of codebook domains, isolating the effect of RAKE placement. Conceptually, it develops a representational-ethics argument: how an analysis portrays a community is itself an ethical matter, so a modelling choice that distorts or erases part of a community's discourse is not merely inaccurate but unfair. Practically, it translates these findings into guidance for institutional research. The primary contribution is methodological and ethical; the institutional-research implications follow from that core.

2. Review of Related Literature

We organize the review in three widening tiers, from global, Asian, and Southeast Asian so that general methods and theory lead into the regional and linguistic setting of this study.

2.1 Global perspectives

LDA treats each document as a probabilistic mixture of latent topics (Blei et al., 2003), while NMF factorizes a term–document matrix into non-negative, parts-based components (Lee & Seung, 1999). On short texts, comparisons tend to favor NMF: Chen et al. (2019) found higher-quality topics than LDA under matched settings across several short-text corpora, and Egger and Yu (2022) reported the same for social-media posts, where LDA struggles with short, unstructured input. Judging topic quality takes more than inspection—the c_v measure (Röder et al., 2015) tracks human interpretability ratings, and topic diversity (Dieng et al., 2020) flags redundancy. Keyword extractors such as RAKE (Rose et al., 2010) are increasingly bolted onto topic models for labelling, though where they best fit is seldom tested. On the applied side, topic modeling is now common on institutional feedback: Sun and Yan (2023) applied LDA to teaching evaluations and noted it does less well on short comments; Gencoglu et al. (2023) showed topic modeling can add value beyond expert coding; and Hayat et al. (2024) benchmarked competing approaches on student feedback directly. Student voice also surfaces

outside surveys with Nwaoha et al. (2024) running longitudinal topic modeling on four Canadian universities' subreddits, showing what pseudonymous institution-specific communities reveal, including rising mental-health talk. Because these data come from people, a sizeable literature warns that public does not mean consented (Zimmer, 2010; boyd & Crawford, 2012) and that lifting peer-directed posts into research can breach the norms they were shared under (Nissenbaum, 2010); AoIR guidance (Markham & Buchanan, 2012; Franzke et al., 2020) and applied frameworks (Townsend & Wallace, 2016) converge on aggregating, avoiding verbatim quotation, and protecting vulnerable participants. Mittelstadt et al. (2016) add that algorithmic choices carry normative weight—precisely when a modeling decision shapes how a community is portrayed. Our corpus also tags each comment by tie strength (weak/strong) in Granovetter's (1973) sense.

2.2 Asian perspectives

Across Asia, educational research has adopted topic modeling enthusiastically, mostly via LDA and its structural variants on short review-style text. Chen, Zou, Cheng, and Xie (2020) used structural topic modeling in Hong Kong to map four decades of educational-technology research; Li et al. (2024) mined Chinese MOOC reviews with LDA at k = 15 (the count we adopt) to derive course-quality strategies. Two patterns stand out: LDA dominates, and tooling is built for high-resource languages—both reasons for caution once text is bilingual or code-switched.

2.3 Southeast Asian and Philippine perspectives

Southeast Asia shows the same pattern; in Indonesia, Lubis et al. (2019) applied helpfulness-weighted LDA to course reviews. What sets the region apart is language. Philippine discourse mixes Filipino and English heavily, and NLP resources are only catching up: Cruz and Cheng (2019) set early low-resource finetuning benchmarks; Cosme and De Leon (2024) built FiReCS, the first sentiment-annotated Filipino–English code-switched review corpus, adapting transformers to Taglish; and Montalan et al. (2025) released Batayan, a Filipino benchmark that deliberately keeps naturally occurring code-switching. Across this work, topic modeling is well established for educational feedback, but Philippine NLP still clusters around sentiment classification and benchmark building rather than thematic discovery, and the bilingual register leaves accuracy and fairness questions open. Very few studies compare LDA and NMF on Philippine higher-education discourse, ask where RAKE fits, check construct-level agreement across institutions, or treat the ethics of analyzing student speech as part of the method. This study takes on that combined gap.

3. Methodology

3.1 Corpus and data source

The corpus comprises 24,110 user comments from four Philippine higher-education institution (HEI) communities on Reddit: *r/Ateneo* (AdMU; n = 10,049), *r/peyups* (University of the Philippines; n = 6,759), *r/dlsu* (De La Salle University; n = 4,108), and *r/Benilde* (De La Salle–College of Saint Benilde; n = 3,194). Evaluation-centric comments were retrieved from publicly accessible subreddits over a five-year window using a custom Python script interfacing with Reddit's API via the Python Reddit API Wrapper (PRAW; Boe, 2012). To avoid missing organic faculty-evaluation discourse that avoids formal vocabulary, the script used a two-tier keyword strategy: Tier 1 for formal evaluation terms (e.g., "faculty evaluation") and Tier 2 for colloquial Filipino/English student language (e.g., "prof terror," "yung prof") followed by a secondary relevance filter. Usernames and direct identifiers were removed; only comment text and non-identifying metadata were retained. Each comment also carries a tie-strength attribute (weak/strong) following Granovetter (1973); tie-strength effects are reserved for separate analysis. An eight-token minimum was applied at load time, so the 24,110 figure already reflects that filter and constitutes the corpus used to fit the models; coherence, diversity, and alignment are computed on it in a shared reduced vocabulary (Section 3.6), and the per-school analysis spans all 24,110 comments via dominant-topic assignments. All scripts and data are available in the project repository (https://github.com/matborbon/SEAAIR2026).

3.2 Preprocessing

Text was lowercased and stripped of URLs, markup, and non-alphabetic noise. We removed a bilingual stopword set (standard English plus a curated Filipino list) along with platform artefacts and bot content, lemmatised remaining tokens, and excluded comments with fewer than eight content tokens. The vocabulary was capped at 5,000 terms. NMF used TF–IDF weighting (*unigrams and bigrams; minimum document frequency = 5, maximum document frequency = 0.85*); LDA used a bag-of-words gensim dictionary with the same bounds (*no_below = 5, no_above = 0.85, keep_n = 5,000).*

3.3 A priori codebook and topic–codebook alignment

Topic interpretation was anchored to a deductive codebook of four domains: A—Faculty Performance Evaluation; B—Institutional and Course Evaluation; C—Evaluative Rhetoric and Epistemic Framing; and D—Community Norms and Relational Dynamics, each operationalized by seed-term sets. A discovered topic was aligned post hoc by matching its top twelve terms against the seeds: aligned when seed overlap met a threshold (≥ 2 matched terms) and exceeded the next-best domain by ≥ 1; ambiguous when it matched multiple domains without a clear winner; and an inductive candidate ("?") when no seed matched. This three-way status supports a combined deductive–inductive reading that retains emergent structure rather than forcing it into the codebook. The codebook was derived from prior literature on

student evaluation of teaching and institutional assessment (e.g., Seldin, 2006; Berk, 2013; Uttl et al., 2017; Fan et al., 2019). Its four domains and fifteen subthemes, with exact seed terms, appear in Table 1. Three of domain C's four subthemes and one of domain D's were defined conceptually but left without lexical seeds, which constrains what seed-based alignment can detect (Section 5.1).

Table 1. *A priori codebook: domains, subthemes, and seed terms used for post-hoc topic–codebook alignment.*

Domain	Subtheme	Seed terms
A	A1 Teaching effectiveness	teach, teaching, explain(s/ed), lecture, lessons, clear, understand, magaling, galing, knowledgeable, engaging, boring, prepared, learn(ed), discussion, approachable
A	A2 Grading and assessment	grade(s), grading, exam(s), quiz, recitation, rubric, score, fail(ed), passing, output, requirements, curve, bell, lenient, deadline, points
A	A3 Professional conduct	late, absent, cancel, respond, reply, email, bias(ed), favoritism, pabor, terror, strict, rude, respectful, unfair, fair, unprofessional, ghosting, accommodating, attitude
A	A4 Recommendation / avoidance	avoid, recommend, beware, warning, warn, suggest, advice, choose, pick, iwasan, kunin, drop, enroll
B	B1 Course evaluation	course, subject(s), syllabus, units, load, elective, curriculum, workload, materials, modules, trimester, semester, prerequisite
B	B2 Institutional policies	tuition, fee(s), enrollment, registrar, admin(istration), policy/policies, registration, system, office, scholarship, financial
B	B3 Comparative institutional evaluation	dlsu, ateneo, admu, benilde, peyups, lasalle, salle, ust, mapua, compared, comparison, versus, kesa, better
C	C1 Evidence type	— (conceptual subtheme; no lexical seeds)
C	C2 Rhetorical strategy	— (conceptual subtheme; no lexical seeds)
C	C3 Evaluation specificity	— (conceptual subtheme; no lexical seeds)
C	C4 Platform reflexivity	reddit, subreddit, sub, thread(s), upvote, downvote, karma, repost, mod(s)
D	D1 Evaluation credibility norms	— (conceptual subtheme; no lexical seeds)
D	D2 Solidarity and support	support, agree, same, true, valid, sorry, kaya, kakayanin, laban, congrats, ingat, fellow, classmate, batchmate, sana, goodluck
D	D3 Gatekeeping and exclusion	gatekeep, elitist, deserve, entitled, exclusive, poser
D	D4 Filipino cultural evaluation frames	terror, pabor, bahala, kulit, diskarte, sir, maam, ate, kuya, suki, hiya, utang, padrino, lusot, palakasan, iskolar, mentor

Subthemes marked "— (conceptual; no lexical seeds)" were defined but not lexically operationalized, so seed-based alignment could not detect them, which is the principal reason domain C did not surface (Section 5.1).

3.4 Topic models

Two models were compared at a fixed k = 15 (selected from candidate counts of 10, 15, and 20). In pilot runs, k = 10 under-differentiated the four domains while k = 20 fragmented topics and raised the inductive share without a matching coherence gain, so k = 15 gave the cleanest codebook alignment while keeping coherence competitive that is consistent with coherence-

guided topic-count selection (Röder et al., 2015) and with Li et al. (2024), who likewise set k = 15 on MOOC reviews. LDA (Blei et al., 2003) was estimated in gensim (15 passes, 400 iterations, automatically learned document–topic α and topic–word η priors); NMF (Lee & Seung, 1999) in scikit-learn on the TF–IDF matrix (nndsvda initialization, up to 500 iterations). A fixed random seed (42) ensured reproducibility.

3.5 RAKE configurations

RAKE (Rose et al., 2010) was evaluated in three positions at k = 15. (1) Pre-processing: corpus-level multi-word RAKE phrases (≥ 2 words) were merged into atomic underscore tokens (e.g., "high tuition fees" → "high_tuition_fees") and injected into both feature spaces, so each phrase was modelled as a single feature alongside unigrams. (2) No RAKE (baseline): standard TF–IDF/NMF and bag-of-words/LDA, the reference for the other two. (3) Post-processing (labeling): the baseline models were retained and RAKE applied to each topic's comments to generate a human-readable label, without influencing discovery.

3.6 Evaluation metrics

Four families of measures were computed. Coherence was the c_v measure (Röder et al., 2015), computed with a single reference dictionary and text set per configuration so LDA and NMF were scored on identical material—the 24,110 retained comments in a shared reduced vocabulary defined by the document-frequency thresholds (minimum 5 documents, maximum 85% of documents, 5,000-term cap). Topic diversity (Dieng et al., 2020) was the proportion of unique terms across all topics' top words. Cross-method agreement was quantified by greedily matching topics on top-word Jaccard similarity (RAKE phrase tokens expanded to their component words) and averaging best-match scores. Codebook alignment was summarized by counts of aligned, ambiguous, and inductive topics. In accessible terms: coherence reflects how often a topic's highest-weighted words co-occur in real comments (higher = more interpretable); Jaccard is the share of top words two topics have in common (0–1); and cosine measures how closely two profiles point in the same direction (1 = identical proportions). For the per-school analysis, every comment was assigned its dominant topic (for NMF, the argmax of the document–topic activation, excluding zero-signal documents; for LDA, the mode of the document–topic posterior) and mapped to its codebook domain. Because raw topic indices are not comparable across models, per-school comparison was conducted at the domain level, measuring cross-method agreement as the cosine similarity between the LDA and NMF domain-proportion vectors. Analyses used gensim (Řehůřek & Sojka, 2010) and scikit-learn (Pedregosa et al., 2011).

3.7 Ethical considerations and data governance

We analyzed only publicly accessible content and followed established internet-research ethics guidance (Markham & Buchanan, 2012; Franzke et al., 2020; Townsend & Wallace, 2016). Since public availability is not consent (Zimmer, 2010), we adopted a contextual-integrity

stance (Nissenbaum, 2010) with safeguards against re-identification: usernames and identifiers were stripped; results are reported only in aggregate (topic-level term lists and institution-level domain proportions); no comments are quoted verbatim, with illustrative terms shown as decontextualized keywords; and no attempt was made to link posts to individuals or profile users. Sensitive disclosures (well-being, financial hardship) were handled only at the aggregate level. Formal ethics review was not sought, as the study involves only secondary analysis of publicly available, de-identified user-generated content with no interaction with participants; nonetheless the work followed AoIR guidance (Franzke et al., 2020; Markham & Buchanan, 2012) and the principles of the Philippine Data Privacy Act (RA 10173), recognizing that public availability does not constitute consent and that the corpus may contain sensitive disclosures and posts by minors. Section 6 develops this reasoning.

3.8 Human validation

Because topic modeling is interpretive, fit statistics alone cannot establish whether the recovered structure reflects students' meanings, particularly in Taglish (Chang et al., 2009; Newman et al., 2010; Grimmer & Stewart, 2013). We therefore conducted a blinded bilingual validation of the no-RAKE baseline. Two independent Filipino–English coders rated all 30 baseline topics (15 LDA, 15 NMF) as a complete census, each shown only its twelve highest-weighted terms and its RAKE label, with model identity withheld and topics presented in a fixed randomized order. Coding used Taguette (Rampin & Rampin, 2021), each coder working in a separate project. Four criteria were operationalized as mutually exclusive ordinal tags: coherence (Low/Medium/High), domain correctness (best-fitting codebook domain A–D or Inductive, assigned independently of the model), label quality (Poor/Acceptable/Good), and cultural fidelity (Artifact/Mixed/Authentic—whether the topic reflects genuine Taglish discourse rather than a tokenization artefact). Both coders completed all 30 topics with no missing judgments, yielding 60 topic ratings and 240 individual judgments.

Three measures were computed. Inter-coder reliability used Cohen's κ (Cohen, 1960), interpreted against Landis and Koch (1977) benchmarks (≤ 0.20 slight; 0.21–0.40 fair; 0.41–0.60 moderate; 0.61–0.80 substantial), with the caveat that these labels are lenient for applied work (McHugh, 2012); percent agreement is reported alongside. Coder–model concordance used accuracy and macro-averaged F1 (robust to class imbalance) for each coder against the model, overall and by model type (Sokolova & Lapalme, 2009). Finally, ordinal ratings were scored 1–3 and LDA vs. NMF compared on each criterion with the one-sided Mann–Whitney U test (Mann & Whitney, 1947), appropriate for ordinal data and small samples. Results appear in Section 4.5.

4. Results and Findings

4.1 Model quality: coherence, diversity, and codebook alignment

In every configuration, NMF produced more coherent and more codebook-interpretable topics than LDA on this corpus. Coherence sat at $c_v \approx 0.70$ versus ≈ 0.55 for LDA with an absolute gap of about 0.16 ($\approx 29\%$ relative) that held across all three configurations. NMF also matched the a priori codebook far more readily, aligning 5–6 of its 15 topics and leaving only 2 inductive, versus 2 aligned and 5–6 inductive for LDA. LDA led on one measure only, topic diversity (≈ 0.98 vs. ≈ 0.79–0.84), but given its weaker coherence and alignment, that diversity reflects top-word lists spread thin rather than genuinely distinct topics (Table 2).

Table 2. *Topic-model quality at k = 15 by RAKE configuration.*

Configuration	Model	C_v	Diversity	Aligned	Ambiguous	Inductive	Topic Jaccard
RAKE pre-process	LDA	0.555	0.989	2	8	5	0.143
RAKE pre-process	NMF	0.698	0.794	6	7	2	0.143
No RAKE (baseline)	LDA	0.545	0.983	2	7	6	0.112
No RAKE (baseline)	NMF	0.705	0.839	5	8	2	0.112

RAKE post-processing reuses the No-RAKE (baseline) models, so its coherence, diversity, and alignment remained unchanged. Its contribution was limited to topic labeling, successfully labeling 100% of topics for both models, with cleaner labels for NMF than for LDA.

4.2 Effect of RAKE configuration

Injecting RAKE phrases as features (pre-processing) yielded no coherence benefit (NMF c_v was 0.698 versus a baseline 0.705, and LDA 0.555 versus 0.545, both within noise) and destabilized LDA's thematic structure. Under pre-processing, LDA concentrated 88.6–94.4% of every school's comments into domain B, with Faculty Performance (A) at or below 0.7% and Community/Relational (D) at 0%, whereas NMF remained distributed across domains. By contrast, RAKE as post-processing labelled 100% of topics for both models, but label quality tracked coherence: NMF yielded clean, nameable phrases (e.g., course, financial aid, degree program, first year, appeal, reservation fee), while LDA produced several uninterpretable strings (e.g., "saken sinabi ean magcacause," "deep part nung bag"). RAKE therefore added value as a labeler—particularly over the more coherent NMF topics—but not as a feature-engineering step.

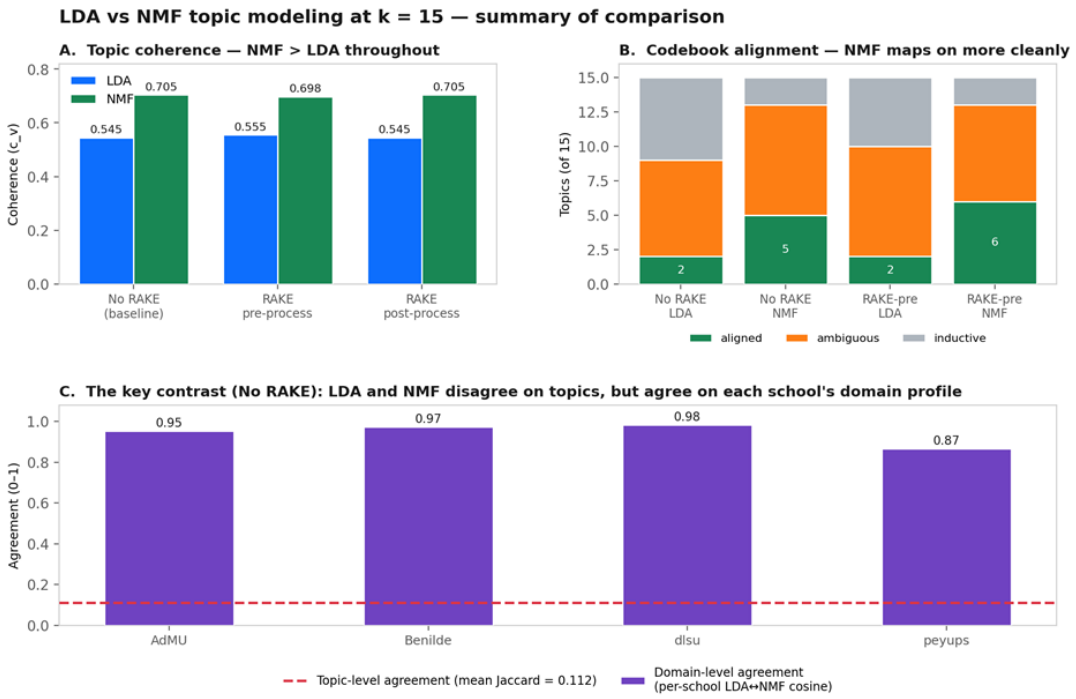


Figure 1. *LDA vs. NMF at k = 15: (A) NMF leads on coherence in every configuration; (B) NMF maps more cleanly onto the codebook; (C) the two models disagree on individual topics (mean Jaccard ≈ 0.11, dashed line) yet agree closely on each school's domain profile (per-school cosine 0.87–0.98).*

4.3 Cross-method agreement: topic level versus domain level

At the topic level the two models barely agreed: mean best-match top-word Jaccard was 0.112 without RAKE and 0.143 with RAKE pre-processing, and many topic pairs shared no top terms at all. Rolled up to codebook domains, the picture flips: within each institution the methods agreed closely (per-school domain-mix cosine 0.87–0.98, no RAKE), and both independently made domain B dominant everywhere. Figure 1 reconciles the two views that model choice changes which specific topics surface but leaves each institution's domain profile largely unchanged.

4.4 Per-school findings

Under both models, all four institutions were dominated by Institutional and Course Evaluation (domain B); what distinguished them was the secondary domain (Table 3). The University of the Philippines community (r/peyups) was the steady outlier—the most Community/Relational (D) content under NMF (38%), the largest inductive or uncoded share under LDA (19%), and the weakest cross-method agreement of any school (cosine 0.866 without RAKE, 0.793 with pre-processing). De La Salle University (r/dlsu) and Benilde (r/Benilde) agreed most closely (0.97–0.98). Across the board, NMF picked up more relational content than LDA.

Table 3. *Per-school codebook-domain mix and representative keywords (no-RAKE baseline).*

Reddit Handle	Model	Domain mix (no RAKE)	Representative keywords
AdMU	LDA	B 74%, A 17%, D 6%, ? 3%, C 0%	B: class, ateneo, prof, fee, experience · A: exam, grade, result
AdMU	NMF	B 54%, A 29%, D 6%, ? 11%, C 0%	B: professor, fee, online, first year · A: appeal, result, rejected
Benilde	LDA	B 71%, D 13%, A 6%, ? 10%, C 0%	B: class, prof, fee, experience · D: health, campus, sorry
Benilde	NMF	B 61%, D 26%, A 8%, ? 5%, C 0%	B: professor, fee, online · D: yan, hahaha, sana, sir
dlsu	LDA	B 74%, D 12%, A 8%, ? 6%, C 0%	B: class, prof, fee, experience · D: health, campus, sorry
dlsu	NMF	B 59%, D 17%, A 14%, ? 10%, C 0%	B: professor, fee, online · D: yan, hahaha, sir, term
peyups	LDA	B 65%, ? 19%, D 12%, A 4%, C 0%	B: class, prof, ust, experience · high inductive share
peyups	NMF	B 48%, D 38%, A 8%, ? 6%, C 0%	B: professor, fee, online · D: yan, sana, hahaha, tapos, mag

Percentages are the share of each school's comments assigned to each domain via dominant-topic assignment; "?" denotes inductive/uncoded. Domain C did not appear in any school (0%).

4.5 Human validation results

4.5.1 Inter-coder reliability

Agreement between the two coders was fair to moderate (Table 4): highest for label quality (κ = 0.41, 60.0% agreement), reaching the "moderate" band, and lower for domain correctness (κ = 0.29, 53.3%), cultural fidelity (κ = 0.22, 50.0%), and coherence (κ = 0.20, 50.0%), which fall in the "fair"-to-"slight" range. This is consistent with the well-documented difficulty of interpreting topics, where human judgments are noisy (Chang et al., 2009); lower agreement on domain and fidelity is expected, since both demand a more abstract, theory-laden judgment than reading a label, and the short, code-switched corpus makes any single reading less certain.

Table 4. *Inter-coder reliability (Main vs. Secondary coder), 30 no-RAKE topics.*

Criterion	% agreement	Cohen's κ	Landis–Koch band
Coherence	50.0	0.20	Slight–Fair
Domain correctness	53.3	0.29	Fair
Label quality	60.0	0.41	Moderate
Cultural fidelity	50.0	0.22	Fair

4.5.2 NMF versus LDA on human-rated quality

The decisive result is comparative and robust (Table 5). Pooling both coders, the NMF topics were rated higher than the LDA topics on every quality criterion: coherence (mean 2.50 vs.

1.90), label quality (2.20 vs. 1.40), and cultural fidelity (2.77 vs. 2.20), each difference significant by the one-sided Mann–Whitney U test (coherence U = 664, p < .001; label U = 690, p < .001; fidelity U = 659, p < .001). The direction held for each coder analyzed separately, with all six per-coder tests significant (p < .02). That two analysts, blind to model identity and coding independently, both judged NMF topics to be more coherent, more aptly labelled, and more culturally faithful directly corroborates the computational finding that NMF produced higher-coherence topics than LDA on this corpus ($c_v \approx 0.71$ vs. 0.55).

Table 5. *NMF vs. LDA on human-rated quality (both coders pooled; ratings scored 1–3; one-sided Mann–Whitney U).*

Criterion	LDA mean	NMF mean	U	p
Coherence	1.90	2.50	664	< .001
Label quality	1.40	2.20	690	< .001
Cultural fidelity	2.20	2.77	659	< .001

4.5.3 Concordance with the model's domain assignment

The coders' independent domain judgments matched the model's seed-based assignment only modestly (Table 6). The main coder agreed with the model on 53.3% of topics overall (macro-F1 = 0.31) and the secondary coder on 43.3% (macro-F1 = 0.28); the two coders agreed with each other on domain for 53.3% of topics. For both coders, concordance was higher on LDA topics (60.0% and 46.7%) than on NMF topics (46.7% and 40.0%). Rather than undercutting the study, this modest concordance is itself informative: it shows empirically that assigning a single codebook domain to a topic is genuinely uncertain, which supports the paper's argument that agreement and reporting should be pitched at the level of the domain profile rather than the individual topic, with the inductive/uncoded share made explicit (Sections 4.3–4.4, 5.1).

Table 6. *Concordance of each coder's independent domain judgment with the model's assignment.*

Coder	Overall accuracy	LDA accuracy	NMF accuracy	Macro-F1
Main coder	53.3%	60.0%	46.7%	0.31
Secondary coder	43.3%	46.7%	40.0%	0.28

Ordinal scales: coherence Low/Medium/High = 1/2/3; label Poor/Acceptable/Good = 1/2/3; fidelity Artifact/Mixed/Authentic = 1/2/3. Cohen's κ per Cohen (1960); bands per Landis & Koch (1977).

4.5.4 Synthesis of human validation

The validation yields two complementary conclusions. Absolute inter-coder agreement was only fair to moderate, which, consistent with the interpretive nature of topic modelling (Chang et al., 2009; Grimmer & Stewart, 2013), cautions against treating any single topic's domain label as ground truth and reinforces the paper's emphasis on construct-level reporting and disclosed uncertainty. At the same time, the study's central comparative claim survived the

most demanding test available to it: independent, blinded human judgment reproduced the NMF-over-LDA ordering on coherence, labelling, and cultural fidelity, with statistical significance at both the pooled and the per-coder level. Human validation therefore does not merely accompany the computational results; it independently confirms their principal finding while empirically justifying the paper's caution about fine-grained interpretation.

5. Discussion

The main methodological takeaway is that NMF fits this corpus of short, bilingual comments better than LDA. Factorizing a TF–IDF matrix into parts-based components gives NMF sharper, more lexically focused topics on short documents, whereas LDA's generative mixture assumptions are token-hungry and falter when each document offers only a handful. That is what we observed: NMF led on coherence and codebook alignment; LDA led on raw diversity but trailed on coherence and alignment, its diversity resembling dispersion more than interpretability.

The RAKE results show where keyword extraction earns its place. Injected as features, RAKE phrases did nothing for coherence and actively collapsed LDA onto one dominant domain, likely because the high-weight phrase tokens swamped the bag-of-words likelihood and pulled the posterior toward a narrow band of institutional-evaluation topics. Used afterward as a labeler, RAKE was genuinely helpful, turning coherent NMF components into readable labels. The practical lesson is to use RAKE for naming and interpretation, not to learn the representation.

The weak agreement on topics but strong agreement on domains split matters for construct validity. A researcher comparing solutions only topic-by-topic might conclude that LDA and NMF are incompatible, yet the same two models, scored against a theoretically grounded codebook, reach the same institution-level conclusions. We therefore suggest reporting agreement at the level of the analytical construct, not just the individual topic, which separates surface-level algorithmic disagreement from real disagreement about what the data says. On substance, every community puts institutional and course evaluation first, suggesting these forums mostly help students navigate enrolment, fees, scheduling, and the logistics of studying. The *r/peyups* community is the exception, with more relational and community-norm content and a larger uncoded share: a difference both models pick up and that NMF makes most visible through domain D.

5.1 Limitations

Several limitations qualify these findings. First, domain C (Evaluative Rhetoric and Epistemic Framing) never appeared in either model. Because it is a rhetorical rather than topical construct, it is lexically diffuse and hard to catch with top-word seed matching; concretely, three of its

four subthemes (evidence type, rhetorical strategy, evaluation specificity) were defined conceptually but never operationalised with lexical seeds (only platform reflexivity carried seeds), so its absence is a property of the codebook's lexical coverage rather than of the discourse itself. Second, the per-school rollup uses hard dominant-topic (argmax) assignment, which discards LDA's mixed-membership structure, likely understating its performance and inflating its inductive share; a mixed-membership analysis retaining per-comment distributions (or NMF's soft activations) could reveal comments that span several domains and shift the profiles—a needed complementary view, not a mere refinement. Third, codebook alignment depends on the chosen seed sets, so "NMF aligns better" means its top words hit these particular seeds more often, not that it is better in any absolute sense; the codebook, its seed lists, and the interpretive labelling also embed researcher judgement, a source of analyst bias the bilingual-coder validation (Section 3.8) is intended to reduce. Fourth, we fixed k = 15 and did not exhaustively test sensitivity to k, to other coherence measures, or to the preprocessing thresholds (eight-token minimum, 5,000-term cap); confirming robustness is left to future work. Finally, the corpus covers four institutions on a single platform, and both platform self-selection and the bilingual register may limit generalization—the model ranking, the RAKE findings, and the domain profiles are specific to this preprocessing-and-evaluation pipeline, to English-centric tooling, and to k = 15, and should be read as pipeline-conditional rather than as general properties of LDA and NMF. Reddit contributors are, moreover, self-selected, so the corpus indicates what is discussed, not how common a concern is across the student body.

5.2 Institutional research implications

These results carry directly to institutional research (IR) practice, but only if read at the right level. The dependable signal is the domain profile (i.e., the mix of faculty-evaluation, institutional/course, and relational content) which was stable across two very different models; individual topics were not, and should not be reported as findings. In a quality-assurance or planning workflow, the domain profile is best used as a low-cost listening and agenda-setting instrument: a shift, or a cross-institution difference, in (say) institutional-and-course concern is a prompt to look (or to ask where enrolment, fees, or scheduling friction is arising) and then corroborate through authoritative, representative channels such as surveys, registrar data, or focus groups. Just as important is what leaders should not infer. Because contributors are self-selected and unrepresentative, the profiles indicate what is discussed, not how prevalent a concern is or how the wider student body feels; they are hypothesis-generating, not measurements of quality, and must not be used to rank faculty, courses, or units, or to evaluate individuals. A responsible IR report would present aggregate domain proportions and their trends together with their uncertainty (the inductive or uncoded share and the degree of cross-method agreement), describe them as "topics students raise" rather than "the student view," name no individuals and quote no posts, and state plainly that the source is a self-selected

online community. Used this way, the method informs where to look without becoming an instrument of surveillance.

6. Ethical Pragmatics of AI in Institutional Research

This work rests on one claim: in AI-assisted institutional research, the practical and the ethical cannot be pulled apart. The pipeline decisions we test as questions of accuracy (e.g., which model to use, where to put keyword extraction, how to assign comments to topics, and how to judge agreement) also decide whether a student community reaches its institution's decision-makers faithfully or in distorted form. That makes methodological care more than good practice; it is an ethical obligation. The subsections below turn the argument into specific safeguards.

6.1 Method choice as a representational-ethics decision

Pipeline choices visibly change the portrait of a community. RAKE pre-processing pushed 88.6–94.4% of every school's comments into domain B and drove Faculty Performance to ≤ 0.7% and Community/Relational content to 0%, a configuration that, taken at face value, would have told every institution its students discuss almost nothing but logistics, erasing concerns the baseline and NMF clearly detect. Likewise, because the two models agreed only weakly at the topic level and hard dominant-topic assignment discards LDA's mixed-membership structure, any single model's "dominant-topic" summary can misrepresent what a community is actually discussing. The remedy is procedural: report how sensitive the results are to method rather than presenting one solution, trust construct-level (domain) agreement over fragile topic-to-topic claims, and treat uncertainty (the inductive share and per-school agreement) as a headline result rather than a footnote. Being honest about what a method cannot see is part of representing a community fairly.

6.2 Privacy, consent, and contextual integrity

The data is public, but the students who wrote these comments did not agree to be analyzed by their universities, and treating availability as consent is widely seen as inadequate (Zimmer, 2010; boyd & Crawford, 2012). Through a contextual-integrity lens (Nissenbaum, 2010), posts written within a peer community for peer purposes are moved out of that context when turned into institutional intelligence, which can break the norms they were shared under. We limit the harm by working only at the aggregate level and refusing to quote verbatim, since a distinctive phrase in a short post can be traced back to its author even after usernames are removed. Downstream IR work should take the same stance: paraphrase rather than quote, limit the purpose, and avoid any individual-level linkage.

6.3 Vulnerable participants and sensitive content

Student forums may include minors as well as disclosures involving mental health, financial hardship, and academic distress. Indeed, the relational domain surfaced terms such as "health" and "sorry," illustrating the possibility of sensitive content within the dataset. Although

aggregation reduces the risk of harm, it does not eliminate it. Responsible practice therefore requires avoiding features designed to isolate individual distress, refraining from surfacing sensitive individual-level content, and prohibiting the use of analytical outputs to identify or act against specific students. When a corpus may include minors, additional safeguards should be applied and, where feasible, institutional ethics review should be sought before analysis.

6.4 Fairness for bilingual and low-resource discourse

English-centric tooling, lemmatisation, and the stopword and seed lists may all under-represent Filipino and code-switched (Taglish) meaning; the absence of domain C and the larger uncoded share for the more Filipino-inflected *r/peyups* community may owe as much to lexical and seed bias as to anything genuinely missing. Systematically misreading culturally specific or code-switched expression is a fairness problem, because it can make some communities look less coherent or codable than others purely as a tool artefact. Concretely, code-switching stresses every stage of the pipeline: tokenisation and lemmatisation assume English morphology and can fragment or mis-lemmatise affixed Filipino forms (e.g., *magaling, kakayanin, iniisip*); English stopword lists leave high-frequency Filipino function words (e.g., *yung, naman, talaga, ang*) in place, where they can dominate topics; seed matching depends on anticipating Filipino spellings, slang, and code-switched variants, so unlisted forms go uncoded; and coherence estimated over a partly mis-tokenised vocabulary may under- or over-state topic quality unevenly across communities. These effects most plausibly disadvantage the most Filipino-inflected community and are a likely contributor to /r/*peyups*'s larger uncoded share. Useful correctives include bilingual validation, native-speaker review of topics and labels, broader seed sets for rhetorical and culturally specific constructs, and a plain acknowledgement of coverage limits in any institutional report.

6.5 Responsible institutional use and governance

The very capability that lets institutions listen can drift into function creep: surveillance of student speech, chilling effects, punitive use against individuals or units, or decisions based on a self-selected, non-representative sample (Mittelstadt et al., 2016). We therefore see legitimate use as agenda-setting and listening, not evaluating or disciplining individuals. That means keeping a human in the loop for interpretation, limiting both purpose and access, setting retention limits, being open with the community where possible, and saying plainly that forum discourse is not a representative measure of institutional quality. In politically active communities the dual-use risk is sharper still, and outputs should never be turned toward monitoring or silencing legitimate dissent.

6.6 A responsible-use checklist for institutional research

We condense these principles into a practical set of reporting standards, prohibited uses, and a minimal ethics workflow for IR offices analyzing social-media discourse in Table 7.

Table 7. *A responsible-use checklist for institutional research on social-media discourse.*

Category	Practice
Reporting standards	• Report aggregate, domain-level results only; never individual posts or identifiable quotes. • Report uncertainty with every figure: the inductive (uncoded) share and the cross-method (domain) agreement. • State the model, k, preprocessing thresholds, and their known sensitivity, so readers can judge robustness. • State the bilingual-validation status and any coverage gaps (e.g., unseeded constructs).
Prohibited uses	• No individual profiling or re-identification of users. • No disciplinary action against students, faculty, or staff based on forum discourse. • No monitoring or targeting of activists or of legitimate dissent. • No ranking or evaluation of departments, courses, or individuals from Reddit content.
Ethics workflow (in order)	• 1. Define a specific purpose and obtain ethics review or a documented exemption before collection. • 2. Collect the minimum necessary; de-identify and aggregate before analysis. • 3. Validate interpretations with bilingual human coders. • 4. Report with uncertainty and the caveats above. • 5. Limit access and retention, review periodically, and be transparent with the community where feasible.

7. Conclusion

This study compared LDA and NMF for thematic analysis of bilingual higher-education discourse on Reddit, tested three positions for RAKE, and introduced a per-school comparison anchored to a codebook. Three conclusions follow. First, for the short, code-switched Reddit comments studied here, NMF performed better under the tested preprocessing and evaluation pipeline: at k = 15 it gave more coherent, more codebook-alignable, and more easily labelled topics than LDA. Second, RAKE belongs in the pipeline as a post-processing labeler, not a feature-injection step, which bought no coherence and destabilized LDA. Third, cross-method agreement should be checked at both the topic and the construct (domain) level: the two models diverged sharply on individual topics but converged on each institution's domain profile, so the institution-level findings hold up regardless of model. On substance, Philippine HEI subreddits are dominated by institutional and course evaluation, with the University of the Philippines community standing out for its more relational, community-oriented discourse.

For RQ4, four ethical considerations proved inseparable from the method. On privacy and consent, although the comments are public, students never shared them for institutional analysis, making a contextual-integrity approach essential: aggregate-only findings, no verbatim quotation, and no individual linkage. On vulnerability, forums may include minors or expressions of distress that must never be surfaced or acted on individually. On fairness, English-centric tools can misread Filipino and code-switched expression, so coverage gaps like the unrealized domain C may be measurement artifacts rather than genuine findings. On use, these outputs suit listening and agenda-setting, not surveillance, individual evaluation, or discipline, and they require human interpretation and governance throughout. Because the

model, the placement of RAKE, and the document-assignment rule each visibly reshape a community's portrait, choosing a method is itself an act of representational ethics: which is why reporting method sensitivity, favoring construct-level over topic-level agreement, and disclosing uncertainty are obligations, not niceties.

Future work could bring in the tie-strength (weak/strong) dimension already recorded in the corpus, adopt per-school comparisons that respect LDA's mixed-membership assignments instead of collapsing them, widen the codebook seeds for rhetorical constructs like domain C, and extend the comparison to more institutions, platforms, and topic counts. Specifically, we plan bilingual human validation involving student advisory groups and independent Filipino–English coders, mixed-membership per-school analysis that preserves probabilistic assignments, Filipino-adapted tokenisation and stopword resources, a coherence sweep across k values, and replication on other platforms and languages. In AI-assisted IR, the choices that make a thematic analysis accurate (i.e., validating across methods, reporting uncertainty, respecting the context and privacy of the people analyzed, and accounting for bilingual expression) are the very choices that make it responsible.

References

Berk, R. A. (2013). Top 10 flashpoints in student ratings and the validity of their use as proxies for teaching effectiveness. Journal of the Professoriate, 5(1), 1--45.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. Journal of Machine Learning Research, 3, 993--1022.

Boe, B. (2012). PRAW: The Python Reddit API Wrapper (Version 7.7.1) [Software]. GitHub. https://github.com/praw-dev/praw

boyd, d., & Crawford, K. (2012). Critical questions for big data. Information, Communication & Society, 15(5), 662--679. https://doi.org/10.1080/1369118X.2012.678878

Chang, J., Gerrish, S., Wang, C., Boyd-Graber, J. L., & Blei, D. M. (2009). Reading tea leaves: How humans interpret topic models. Advances in Neural Information Processing Systems, 22, 288--296. https://papers.nips.cc/paper/3700-reading-tea-leaves-how-humans-interpret-topic-models

Chen, X., Zou, D., Cheng, G., & Xie, H. (2020). Detecting latent topics and trends in educational technologies over four decades using structural topic modeling: A retrospective of all volumes of Computers & Education. Computers & Education, 151, Article 103855. https://doi.org/10.1016/j.compedu.2020.103855

Chen, Y., Zhang, H., Liu, R., Ye, Z., & Lin, J. (2019). Experimental explorations on short text topic mining between LDA and NMF based schemes. Knowledge-Based Systems, 163, 1--13. https://doi.org/10.1016/j.knosys.2018.08.011

Cohen, J. (1960). A coefficient of agreement for nominal scales. Educational and Psychological Measurement, 20(1), 37--46. https://doi.org/10.1177/001316446002000104

Cosme, C. J., & De Leon, M. M. (2024). Sentiment analysis of code-switched Filipino--English product and service reviews using Transformers-based large language models. In A. Iglesias, J. Shin, B. Patel, & A. Joshi (Eds.), Proceedings of the World Conference on Information Systems for Business Management (ISBM 2023) (Lecture Notes in Networks and Systems, Vol. 834, pp. 123--135). Springer. https://doi.org/10.1007/978-981-99-8349-0_11

Cruz, J. C. B., & Cheng, C. (2019). Evaluating language model finetuning techniques for low-resource languages. arXiv. https://doi.org/10.48550/arXiv.1907.00409

Dieng, A. B., Ruiz, F. J. R., & Blei, D. M. (2020). Topic modeling in embedding spaces. Transactions of the Association for Computational Linguistics, 8, 439--453. https://doi.org/10.1162/tacl_a_00325

Grimmer, J., & Stewart, B. M. (2013). Text as data: The promise and pitfalls of automatic content analysis methods for political texts. Political Analysis, 21(3), 267--297. https://doi.org/10.1093/pan/mps028

Fan, Y., Shepherd, L. J., Slavich, E., Waters, D., Stone, M., Abel, R., & Johnston, E. L. (2019). Gender and cultural bias in student evaluations: Why representation matters. PLoS ONE, 14(2), Article e0209749. https://doi.org/10.1371/journal.pone.0209749

Franzke, A. S., Bechmann, A., Zimmer, M., Ess, C., & the Association of Internet Researchers. (2020). Internet research: Ethical guidelines 3.0. Association of Internet Researchers. https://aoir.org/reports/ethics3.pdf

Gencoglu, B., Helms-Lorenz, M., Maulana, R., Jansen, E. P. W. A., & Gencoglu, O. (2023). Machine and expert judgments of student perceptions of teaching behavior in secondary education: Added value of topic modeling with big data. Computers & Education, 193, Article 104682. https://doi.org/10.1016/j.compedu.2022.104682

Granovetter, M. S. (1973). The strength of weak ties. American Journal of Sociology, 78(6), 1360--1380. https://doi.org/10.1086/225469

Hayat, F., Shatnawi, S., & Haig, E. (2024). Comparative analysis of topic modelling approaches on student feedback. In Proceedings of the 16th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management (KDIR 2024) (pp. 226--233). SciTePress. https://doi.org/10.5220/0012890400003838

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. Biometrics, 33(1), 159--174. https://doi.org/10.2307/2529310

Lee, D. D., & Seung, H. S. (1999). Learning the parts of objects by non-negative matrix factorization. Nature, 401(6755), 788--791. https://doi.org/10.1038/44565

Li, H., Gu, H., Hao, X., Yan, X., & Zhu, Q. (2024). Data-driven analytics for student reviews in China's higher vocational education MOOCs: A quality improvement perspective. PLOS ONE, 19(3), e0298675. https://doi.org/10.1371/journal.pone.0298675

Lubis, F. F., Rosmansyah, Y., & Supangkat, S. H. (2019). Topic discovery of online course reviews using LDA with leveraging reviews helpfulness. International Journal of Electrical and Computer Engineering (IJECE), 9(1), 426--438. https://doi.org/10.11591/ijece.v9i1.pp426-438

Mann, H. B., & Whitney, D. R. (1947). On a test of whether one of two random variables is stochastically larger than the other. The Annals of Mathematical Statistics, 18(1), 50--60. https://doi.org/10.1214/aoms/1177730491

Markham, A., & Buchanan, E. (2012). Ethical decision-making and internet research: Recommendations from the AoIR Ethics Working Committee (Version 2.0). Association of Internet Researchers. https://aoir.org/reports/ethics2.pdf

McHugh, M. L. (2012). Interrater reliability: The kappa statistic. Biochemia Medica, 22(3), 276--282. https://doi.org/10.11613/BM.2012.031

Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L. (2016). The ethics of algorithms: Mapping the debate. Big Data & Society, 3(2), 1--21. https://doi.org/10.1177/2053951716679679

Montalan, J. R., Layacan, J. P., Africa, D. D., Flores, R. I. S., Lopez II, M. T., Magsajo, T. D., Cayabyab, A., & Tjhi, W. C. (2025). Batayan: A Filipino NLP benchmark for evaluating large language models. In Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Vol. 1: Long Papers) (pp. 31239--31273). Association for Computational Linguistics. https://aclanthology.org/2025.acl-long.1509/

Newman, D., Lau, J. H., Grieser, K., & Baldwin, T. (2010). Automatic evaluation of topic coherence. In Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the ACL (pp. 100--108). Association for Computational Linguistics. https://aclanthology.org/N10-1012

Nissenbaum, H. (2010). Privacy in context: Technology, policy, and the integrity of social life. Stanford University Press.

Nwaoha, F., Gaffar, Z., Chun, H. J., & Sokolova, M. (2024). Longitudinal sentiment topic modelling of Reddit posts. arXiv. https://doi.org/10.48550/arXiv.2401.13805

O'Connor, C., & Joffe, H. (2020). Intercoder reliability in qualitative research: Debates and practical guidelines. International Journal of Qualitative Methods, 19, 1--13. https://doi.org/10.1177/1609406919899220

Pedregosa, F., et al. (2011). Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12, 2825--2830.

Rampin, R., & Rampin, V. (2021). Taguette: Open-source qualitative data analysis. Journal of Open Source Software, 6(68), 3522. https://doi.org/10.21105/joss.03522

Řehůřek, R., & Sojka, P. (2010). Software framework for topic modelling with large corpora. In Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks (pp. 45--50). ELRA.

Röder, M., Both, A., & Hinneburg, A. (2015). Exploring the space of topic coherence measures. In Proceedings of the Eighth ACM International Conference on Web Search and Data Mining (WSDM '15) (pp. 399--408). ACM. https://doi.org/10.1145/2684822.2685324

Rose, S., Engel, D., Cramer, N., & Cowley, W. (2010). Automatic keyword extraction from individual documents. In M. W. Berry & J. Kogan (Eds.), Text mining: Applications and theory (pp. 1--20). Wiley. https://doi.org/10.1002/9780470689646.ch1

Seldin, P. (2006). Evaluating faculty performance: A practical guide to assessing teaching, research, and service. Anker.

Sokolova, M., & Lapalme, G. (2009). A systematic analysis of performance measures for classification tasks. Information Processing & Management, 45(4), 427--437. https://doi.org/10.1016/j.ipm.2009.03.002

Sun, J. & Yan, L. (2023). Using topic modeling to understand comments in student evaluations of teaching. Discover Education, 2. https://doi.org/10.1007/s44217-023-00051-0

Townsend, L., & Wallace, C. (2016). Social media research: A guide to ethics. University of Aberdeen. https://www.gla.ac.uk/media/Media_487729_smxx.pdf

Uttl, B., White, C. A., & Gonzalez, D. W. (2017). Meta-analysis of faculty's teaching effectiveness: Student evaluation of teaching ratings and student learning are not related. Studies in Educational Evaluation, 54, 22--42. https://doi.org/10.1016/j.stueduc.2016.08.007

Zimmer, M. (2010). "But the data is already public": On the ethics of research in Facebook. Ethics and Information Technology, 12(4), 313--325. https://doi.org/10.1007/s10676-010-9227-5

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How Critical Are Students of Technology? Development and Validation of the Critical Technoskepticism Inventory

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Abstract

Many believe that new technology is essential for improving society and solving key problems. However, experts highlight the complex and often contradictory relationship between technology and society, noting the political and ideological issues it entails. Recent discussions also emphasize the importance of critical technology education in schools. Technoskepticism holds that, rather than reacting negatively to technology, one should carefully consider whether it is the right solution to a given problem. Despite growing discussion of technoskepticism, research into how individuals assess the societal and ethical impacts of technology is limited by a lack of empirical tools. To address this gap, this study developed and validated the Critical Technoskepticism Inventory (CTI) using standard psychometric validation protocols. Grounded in digital ethics and critical AI literacy, the CTI was refined through content validation by 16 experts using Lawshe's Content Validity Ratio. With a sample of 402, Exploratory Factor Analysis and Principal Axis Factoring with oblimin rotation revealed a robust four-domain structure of 17 items. A Confirmatory Factor Analysis with 403 college students confirmed the inventory's structural validity, indicating a stable measurement structure. CTI provides higher education institutions with a theoretically grounded diagnostic tool for understanding how students' dispositions toward engaging with digital and AI-driven technologies, offering valuable insights to inform curriculum design that fosters ethical reasoning and reflexive agency alongside technical competence.

Keywords: Technoskepticism, digital ethics, instrument validation, critical AI literacy, higher education, reflexive agency

Introduction

In an era of rapid advances in information and technology, the belief that technological innovation drives social progress is widespread. Proponents of techno-optimism argue that technological advancements can alleviate human problems and address pressing social and environmental

challenges (Danaher, 2022; Nordhaus & Shellenberger, 2003). This optimistic view positions technology as essential in resolving complex societal issues, reinforcing the notion that engineering and innovation are pivotal to human development (Andreessen, 2023; Johnston, 2018; Kelly, 2010; Weinberg, 1967).

However, critical perspectives on this techno-optimistic narrative are also gaining momentum. Researchers are increasingly scrutinizing the assumption that technology is inherently beneficial or socially neutral. Initial critiques of techno-solutionism (Morozov, 2013). Likewise, Zuboff (2019) illustrates how digital technologies can reshape power dynamics, raising concerns about surveillance, autonomy, and democratic accountability. In educational contexts, post-digital scholars emphasize the importance of understanding technology more deeply, recognizing that its interactions with society can be complex and contradictory (Jandrić et al., 2018); Selwyn (2019) stresses that educational technology must underline the importance of examining the underlying political and ideological constructs embedded within technological advancements. Recent discussions underline the need to incorporate critical technology education into curricula. This integration empowers students to effectively navigate and question the technical, social, and political aspects of technology (Pleasant et al., 2023).

The shift from uncritical acceptance of technology to a more reflective and cautious approach marks the so-called "waning of techno-futurism" (Potkalitsky, 2026). This evolving mindset encourages technoskepticism, a critical lens for evaluating technological claims and considering their ethical and social implications (Livingstone et al., 2025; Markham, 2020; Selwyn, 2019). One should question the rapid shift to digital learning in higher education and the increased use of online teaching methods since COVID. Techno-skeptical views offer useful ideas for discussing these topics (Zaimakis et al., 2022).

According to Trieste & Turchetti (2024), researchers often view technoskepticism as a negative reaction to stress from new technologies, and they go on to say that this stress can stem from difficulty adapting to these technologies in a healthy way (Brod, 1984; Salanova, 2003; Salanova et al., 2013). It can also arise from fears about technology, such as job loss (Mellor et al., 2015).

On the other hand, critiques of technology challenge overly positive views but do not call for its complete rejection, fostering a mindset that supports technoskepticism. This mindset encourages critical thinking about technology's capabilities, values, and ethics (Livingstone et al., 2025; Markham, 2020; Selwyn, 2019). Technoskepticism does not oppose technology but questions whether technology is always the right solution and considers its social impacts before accepting new ideas.

In this study, technoskepticism suggests that, rather than completely reacting negatively to technology, one should carefully consider whether it is the right solution to different problems. Technoskepticism involves understanding how technologies work, their impact on society, and the political choices

around their use. It also involves thinking critically about technologies and taking fair actions (Pleasants, Krutka & Nichols, 2024).

Despite growing discourse on technoskepticism, a significant gap remains in empirically measuring this construct as a personal trait. Previous research has explored technoskepticism within contexts such as educational methodologies (Heath et al., 2024; Pleasants et al., 2023; Pleasants et al., 2025) and critiques of optimistic technological narratives (Morozov, 2013; Selwyn, 2019), yet few studies have sought to create a reliable tool for assessing individual levels of technoskepticism. This deficiency limits research on how people evaluate technology, analyze its social and ethical impacts, and consider alternatives to technology-centric solutions.

To address these challenges, this study developed and validated the Critical Technoskepticism Inventory (CTI). By establishing evidence of content validity, construct validity, reliability, and convergent validity, the CTI aims to provide a systematic instrument for assessing technoskepticism. By providing a means to measure this construct, the study contributes to a deeper understanding of how individuals engage critically with technology in a digital, AI-driven landscape. Ultimately, this research advances the idea that technoskepticism fosters a disposition towards ethical, reflective, and critical engagement with technology, providing a necessary counterbalance to unchecked technological enthusiasm.

Literature Review

This study introduces the Critical Technoskepticism Inventory (CTI), a tool for measuring how university students critically evaluate technology. The CTI draws from critical technology studies, educational technology, digital ethics, futures literacy, and pedagogy. Following Pleasants et al. (2023, 2025), critical technoskepticism is understood as a reflective and ethical stance toward technology. Rather than asking, "How can we use this?" it asks, "What relationship do we want with it?" CTI includes four domains: awareness of non-neutrality, ethical and societal impact, personal agency, and imaginative alternatives.

The CTI differs from several related constructs and measures. It is distinct from Nagpal et al.'s (2025) Techno-solutionism Scale. It measures the extent to which individuals regard technological solutions as better suited to organizational and societal problems, with near-term and long-term dimensions, while CTI evaluates technology through non-neutrality, ethical reflection, reflexive agency, and alternatives rather than prioritizing technological solutions. CTI differs from technophobia (Brosnan, 1998), which refers to affective, fear-based avoidance of technology, because CTI emphasizes careful evaluation rather than avoidance. It also differs from technostress (Ragu-Nathan et al., 2008), which focuses on overload, invasion, and strain associated with technology use, whereas CTI represents a deliberative orientation that does not assume distress. Likewise, CTI is not equivalent to simple technology resistance.

CTI also differs fundamentally from technology acceptance models such as TAM (Davis, 1989), which predict adoption based on perceived usefulness and ease of use. In contrast, CTI focuses on the reasoning that informs both adoption and non-adoption. It builds on, but extends beyond, critical digital literacy (Hinrichsen & Coombs, 2013; Markham, 2020), which is primarily epistemic and concerned with interpreting and navigating digital information. CTI adds ethical evaluation, self-directed agency, and the capacity to imagine alternatives. Finally, although it overlaps with Critical AI Literacy (Roe et al., 2025), CTI is broader because it addresses technology in general, not artificial intelligence alone. Table 1 compares CTI with selected measures.

Table 1.

Comparison of the CTI with Selected Related Measures

Instrument	Primarily measures	Key distinction from CTI
Techno-Solutionism Scale Nagpal et. al. (2025)	Belief in technology's privileged capacity to solve societal/ organizational problems	CTI evaluates technology through non-neutrality awareness, ethical reflection, reflexive agency, and consideration of alternatives rather than privileging technological solutions
Technology Acceptance Model (TAM) scales Davis (1989)	Perceived usefulness, ease of use, and acceptance	Concerned with acceptance/adoption, not critical evaluation of technological systems
Attitudes toward Digital Educational Technologies Novikova et al. (2023)	Cognitive, affective, and behavioral attitudes toward educational technology	CTI measures critical-reflective disposition rather than favorability toward technology
Technostress Creators Ragu-Nathan et al. (2008)	Technology-related overload, invasion, complexity, insecurity, and uncertainty	CTI is not a stress/distress construct and does not presume a negative technology experience
AI Literacy Hornberger et al. (2025).	Knowledge and understanding of AI	CTI is technology-general and disposition-oriented rather than primarily knowledge/competence-oriented

After distinguishing critical technoskepticism from neighboring constructs, the development of the CTI also involved refining its internal conceptual structure. An earlier conceptualization included a fifth domain, Caution Toward Adoption and Hype, representing skepticism toward exaggerated technological claims and premature adoption. During exploratory factor analysis, however, the domain did not retain enough factorially distinct indicators to justify its retention as an independent dimension. Its removal prompted reconsideration of its conceptual relationship with the remaining domains. Caution toward technological claims may be expressed partly through Critical Awareness of Non-Neutrality, which entails questioning the assumptions and interests surrounding technological development, and through Ethical and Societal Impact Reflection, which involves deliberating potential consequences before adoption. Thus, the empirical refinement from five to four domains does not imply that caution is irrelevant to technoskepticism; rather, the present findings suggest that it may not constitute a sufficiently distinct dimension within the CTI as currently operationalized.

Critical Awareness of Non-Neutrality. Winner's (1980) Theory of Technological Politics asserts that "artifacts have politics," emphasizing that technological designs encode values, reinforce social hierarchies, and make design itself a political act. Selwyn's (2013) *Distrusting Educational Technology* and Krutka et al. (2020) extend this critique to education, arguing that educational technologies often reproduce neoliberal values and weaken education as a public good. Pleasants et al. (2023, 2025) further develop this perspective through the "Technoskepticism Iceberg" in the *Harvard Educational Review*, highlighting how visible technological features tend to receive attention while deeper ideological assumptions remain overlooked. Recognizing that technology is not neutral encourages critical evaluation of digital tools instead of blind acceptance. The next domain, *The Ethical and Societal Impact,* recommends evaluating technology not just on whether to adopt it, but also on whether its use is fair, justified, and respects human rights and community well-being.

Ethical and Societal Impact. UNESCO's 2021 framework on AI ethics emphasizes responsible use of technology, advocating for justice and human rights while cautioning against harmful technologies. The DISCO Network's 2025 work highlights the dangers of digital platforms perpetuating inequality and calls for critical engagement with technology. Roe, Perkins, and Furze (2025) introduce Critical AI Literacy (CAIL) and urge learners to explore AI's societal implications beyond technical functionality. Experts like Markham et al. (2018) and Sonia Livingstone (2023) stress the importance of moral reflection and a rights-based approach to digital design. D. Graham Burnett examines how AI challenges concepts of authorship, prompting deeper reflection on human values. Overall, technology's ethical implications demand critical engagement, raising questions about personal responsibility and informed choices in online spaces. The next focus area, Agency and Reflexivity, explores how ethics can enhance self-control and thoughtful participation online.

Agency and Reflexivity. Michel Foucault's concept of "technologies of the self" focuses on identity formation as an active process shaped by power structures. Agency is developed through self-reflection and ethical engagement, particularly in the digital realm. Ravi Agarwal (2003) emphasizes reclaiming identity from technology through critical examination of its use, while Hinrichsen and Coombs highlight the importance of self-awareness in digital literacy. Markham advocates for critical pedagogy to enhance understanding of data's impact on personal lives. These perspectives frame technoskepticism as an active practice of questioning technology to facilitate ethical decision-making and focus amidst digital distractions. The Critical Technoskepticism Index (CTI) measures individuals' sense of control over technology use, reinforcing that agency and reflection are key to building identity despite technology's influence. Ultimately, the text encourages envisioning technology in a more humane and socially just way.

Imaginative Alternatives. Escobar (2018) introduces autonomous design, merging local cultures and environmental awareness to reflect community values in technology, which aligns with CTI's push for ethical, sustainable design through community control. Costanza-Chock (2020) emphasizes Design

Justice and advocates for marginalized voices in tech, while de Sousa Santos (2015) promotes diverse knowledge to challenge Western tech dominance. Both highlight the importance of imagination in politics and ethics for envisioning better futures. Heath et al. (2024) argue that technoskepticism should inspire community-driven pedagogies, and Miller (2018) points to UNESCO's Futures Literacy Framework as essential for critical thinking about the future. Imaginative Alternatives, a core aspect of CTI, encourages creative and inclusive approaches to technology that respect human dignity.

Together, these domains provide a coherent account of technoskepticism as a multidimensional disposition. This account extends from Winner's (1980) claim that artifacts encode political values, through the ethical frameworks of UNESCO (2021) and the DISCO Network (2025), to Foucault's (1988) technologies of the self and Agarwal's (2003) principled resistance, and toward the imaginative futures described by Escobar (2018) and Costanza-Chock (2020). As conceptualized in this study, technoskepticism is distinct from technophobia, technostress, resistance, acceptance, and general knowledge of AI. Rather, it represents an ethically grounded and imaginative orientation toward technology, organized into four domains rather than five. To further clarify the conceptual and theoretical grounding, Table 2 presents the CTI domains, their construct definitions, theoretical foundations, illustrative items, and the expected relationships among CTI's four domains and related constructs.

Table 2.

Domain Definitions, Theoretical Foundations, Sample Items, and Expected Relationships for CTI

CTI Domain	Construct Definition	Principal Theoretical Foundations	Illustrative Item	Expected Relationship with Related Constructs
Critical Awareness of Non-Neutrality	Awareness that technologies are not inherently neutral but embody design choices, values, assumptions, interests, and power relations that may shape individuals and society.	Winner (1980); Selwyn (2013); Krutka et al. (2021);	*"Technologies often reflect the values and assumptions of those who designed them."*	Expected to relate positively to critical digital/AI literacy and ethical technology attitudes, while remaining distinct from technology acceptance or simple positive/negative attitudes toward technology.
Ethical & Societal Impact Reflection	Disposition to think carefully about the ethical, social, equity, inclusion, accountability, and long-term effects of technology, including who benefits and who may be harmed.	Markham et al. (2018). Livingstone (2023); Roe et al. (2025); UNESCO (2021)	*"I think about who benefits and who is disadvantaged by technology."*	Expected to relate positively to responsible/ethical technology attitudes and critical digital literacy, but not necessarily to technology acceptance or frequency of use.
Agency & Reflexivity	The ability to think about one's relationship with technology, understand	Foucault (1988); Hinrichsen & Coombs	*"I believe it is important to critically examine my*	Expected to relate positively to reflective/critical digital engagement and

	how technology shapes choices and behavior, and use technology in an informed, intentional, and ethical way.	(2013); Krutka et al. (2021); Agarwal (2003)	*own reliance on technology"*	responsible technology use, while remaining conceptually distinct from technological self-efficacy or behavioral intention to use technology.
Imaginative Alternatives	Disposition to consider multiple, human-centered, socially just, and non-technological or alternative technological solutions instead of assuming that technological innovation is always the best answer.	Escobar (2018); Costanza-Chock (2020); de Sousa Santos (2014); Miller (2018)	*"I can imagine alternative ways of solving problems without relying on new technologies."*	Expected to relate positively to futures literacy, critical digital agency, and ethical reflection, and potentially inversely to strong techno-solutionist orientations.

Among the existing measures reviewed, no validated instrument integrates these four dimensions into a single measure of critical engagement with technology. This measurement gap provides the principal rationale for developing the CTI.

Methodological Procedures in the Development and Validation of the CTI

The development and validation of the Critical Technoskepticism Inventory (CTI) followed a sequential, multi-stage process involving construct conceptualization, item generation, expert content validation, pilot testing, reliability assessment, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and assessment of convergent and discriminant validity.

The construct of technoskepticism was conceptualized through an extensive review of literature in technology studies, educational technology, digital ethics, critical AI literacy, agency, reflexivity, and futures-oriented design. This theoretical synthesis initially identified five domains: *Critical Awareness of Non-Neutrality, Caution Toward Adoption and Hype, Ethical and Societal Impact Reflection, Agency and Reflexivity, and Imaginative Alternatives.* These domains provided the conceptual basis for generating the initial item pool.

The team developed items from the theoretical literature and contextualized them for university students, reflecting a critical yet non-rejectionist orientation toward technology. Sixteen experts evaluated the items using a three-point essentiality scale (1 = *not essential*, 2 = *useful but not essential*, and 3 = *essential*). The team evaluated content validity using Lawshe's (1975) Content Validity Ratio (CVR), the Item-Level Content Validity Index (I-CVI), and the Average Scale-Level Content Validity Index (S-CVI/Ave). The team used a minimum CVR of .529 and an I-CVI of .82 as criteria for item retention. The refined instrument subsequently underwent two pilot tests to examine item performance and internal consistency. The team conducted an initial developmental EFA with 211 university students using a broader item pool to examine the emerging dimensional structure and inform item refinement. Based on empirical performance and theoretical coherence, the research team

reviewed overlapping and poorly performing indicators, resulting in a reduced set of candidate items for subsequent validation.

For the main validation stage, the team collected data from 805 university students. To provide independent exploratory and confirmatory evidence and minimize chance-related inflation, the team randomly divided the sample into an EFA subsample (n = 402) and an independent CFA holdout subsample (n = 403). EFA on the exploratory subsample employed Principal Axis Factoring (PAF) with Direct Oblimin rotation, consistent with the theoretical expectation that the dimensions of technoskepticism would be correlated. Sampling adequacy and factorability were evaluated using the Kaiser-Meyer-Olkin measure and Bartlett's test of sphericity. Factor loadings below .40 were suppressed, while item-retention decisions were based on statistical performance alongside theoretical coherence.

During factor refinement, researchers removed one item from the Ethical and Societal Impact Reflection (TES5) because it showed a stronger empirical association with Agency and Reflexivity than with its theoretically specified domain. The resulting 17-item solution was then analyzed for factor retention using parallel analysis, which clearly supported four factors and provided marginal evidence for a potential fifth dimension. Consequently, the team examined a diagnostic five-factor principal axis factoring (PAF) solution; however, the additional factor did not yield a substantively coherent or adequately represented dimension. Therefore, the theoretically specified four-factor structure was retained for independent confirmation.

CFA was then conducted on an independent holdout sample of 403 participants to evaluate the fit of the 17-item, four-factor measurement model. The four latent dimensions were specified as correlated first-order factors. Model adequacy was evaluated using multiple fit indices, including the chi-square statistic and chi-square/degrees-of-freedom ratio, Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA) with its 90% confidence interval, as well as other absolute and incremental fit indices. The standardized factor loadings and latent-factor correlations were also examined.

Internal consistency of the final 17-item CTI was evaluated in the independent CFA validation sample (n = 403) using Cronbach’s alpha (α) and McDonald’s omega (ω). Construct reliability and convergent validity at the latent-construct level were further evaluated using Composite Reliability (CR) and Average Variance Extracted (AVE), respectively. Discriminant validity among the four latent domains was assessed using the heterotrait–monotrait ratio of correlations (HTMT). External convergent evidence was examined by correlating CTI scores with Attitudes toward Digital Educational Technologies and Interest in AI.

Ethical Considerations. Before data collection, the Liceo de Cagayan University Research Ethics Board (LREB) granted ethical approval through expedited review. The study was granted Approval for Implementation on January 29, 2026, under Study Document No. 2026-01-2579-FFR. Following

ethical approval, eligible university students were invited to participate through online recruitment. The questionnaire was administered electronically using Google Forms. Before accessing the survey items, participants received information about the study's purpose, voluntary participation, confidentiality, and their right to withdraw. Participants were also provided contact information through which they could ask questions, report research-related concerns, withdraw from the study, or clarify their rights as research participants. They were informed that data will be retained securely and destroyed three years after publication of the study results.

Results

Participant Characteristics. Table 3 presents the demographic characteristics of the independent EFA (n = 402) and CFA (n = 403) subsamples. Participants represented three higher education institutions and varied by year level, gender, and academic program. The demographic profiles are described separately for the exploratory and confirmatory samples used in the validation analyses.

Table 3.

Participants' Demographic Profile for EFA and CFA

Characteristic	Category	EFA (n = 402), n (%)	CFA (n = 403), n (%)
Institution	Non-Sectarian	245 (60.9)	244 (60.5)
	Sectarian A	77 (19.2)	79 (19.6)
	Sectarian B	80 (19.9)	80 (19.9)
Year Level	First Year	100 (24.9)	106 (26.3)
	Second Year	168 (41.8)	116 (28.8)
	Third Year	87 (21.6)	70 (17.4)
	Fourth Year	47 (11.7)	111 (27.5)
Gender	Male	126 (31.3)	102 (25.3)
	Female	255 (63.4)	273 (67.7)
	Prefer not to say	21 (5.2)	28 (6.9)
Course	Social Science	344 (85.6)	131 (32.5)
	Health	56 (13.9)	269 (66.7)
	Information Technology	2 (0.5)	3 (0.7)

The CVR analysis found that 19 of 26 items (73.1%) met the minimum standard of 0.529, which is deemed important for measuring technoskepticism. The remaining seven items (26.9%) fell below this standard and require revision. The overall S-CVI/Ave was 0.818, indicating satisfactory content validity. Domain-level S-CVI/Ave values varied: Domain 5 was highest at 0.872, followed by Domain 4 (0.871) and Domain 1 (0.835). Domain 3 was acceptable at 0.788, while Domain 2 had the lowest at 0.683, suggesting it needs refinement. Overall, the Technoskepticism Scale shows satisfactory content validity, but specific items and domains need revision before pilot testing.

Reliability Analysis. The instrument was tested for reliability using Cronbach's alpha with 50 college students. Weak items were identified through corrected item-total correlations and either removed or revised. After eliminating reverse-coded items, the instrument was refined to 23 items, and a second pilot test was conducted with 63 students to ensure internal consistency. The subscales—Critical Awareness of Neutrality (4 items, α=.91), Caution Towards Adoption & Hype (5 items, α=.79), Ethical & Societal Reflection (5 items, α=.89), Agency & Reflexivity (5 items, α=.91), and Imaginative Alternatives (4 items, α=.80)—had Cronbach's α values ranging from .79 to .91, with an overall index of .93, confirming high reliability of the CTI.

Exploratory Factor Analysis. An initial developmental EFA was conducted on a sample of 211 university students using the broader item pool to examine the emerging dimensional structure of the CTI and guide item refinement. After reviewing item performance, cross-loadings, and theoretical coherence, the candidate instrument was reduced for subsequent validation.

Table 4.

Factor Loadings of Items and Domains

CTI Domain	Item		Pattern Loading
Agency & Reflexivity			
	TAR5	…. important to critically examine my own reliance on technology	.781
	TAR1	…. questioning existing technologies to bring about better, wide-ranging improvements	.597
	TAR4	….wary of how digital platforms influence my identity, self-expression, or sense of self.	.589
	TAR3	…. that human creativity and collaboration are as important as technological innovation.	.565
	TAR2	…. it is important to think over options beyond current technologies rather than treating them as the only choice.	.516
Imaginative Alternatives			
	TIA2	…. to consider non-technological solutions alongside technological ones.	.751
	TIA3	…. technological progress is not the only path to a better society.	.589
	TIA4	….intentionally set limits for my engagement with digital technologies**.**	.551
	TIA1	…. imagine alternative ways of solving problems without always relying on new technologies.	.531
Ethical & Societal Impact Reflection			
	TES2	….understanding technology means looking at its moral effects.	.699
	TES1	…. progress should be measured by how much it contributes to social good, not just by efficiency.	.577
	TES3	…. about who benefits and who is disadvantaged by technology.	.473
	TES4	…. on whether digital systems reinforce existing inequalities or social biases.	.412
Critical Awareness of Non-Neutrality			
	TCA1	…. that the design of digital systems can affect how people behave & make choices.	.757

TCA2	…. that design choices in technology can affect people's lives and the economy.	.678
TCA3	…. often reflect the values and assumptions of those who design them.	< .40
TCA4	…. not all technological innovations are right or necessary in educational settings.	< .40

For the main validation analysis, EFA was conducted on the randomly selected exploratory subsample of 402 participants**.** Principal Axis Factoring (PAF) with Direct Oblimin rotation was employed because the CTI domains were theoretically expected to correlate. Sampling adequacy was evaluated using the Kaiser-Meyer-Olkin measure and Bartlett's Test of Sphericity. Factor loadings below .40 were suppressed, and decisions regarding item retention considered both empirical performance and theoretical coherence.

The final 17-item instrument was analyzed using PAF with Direct Oblimin rotation in the exploratory subsample of 402 participants. Sampling adequacy was excellent, as indicated by a Kaiser–Meyer–Olkin value of .926. Bartlett's Test of Sphericity was statistically significant, $\chi^2(136) = 2800.620$, $p < .001$, confirming that the correlation matrix was suitable for factor analysis. The four-factor PAF solution accounted for 49.21% of the common variance, with Factors 1 through 4 accounting for 38.82%, 4.35%, 3.38%, and 2.67%, respectively.

As shown in Table 4, 15 of the 17 retained items demonstrated pattern coefficients of at least .40 on their intended factors, with loadings ranging from .412 to .781. TCA3 and TCA4 had pattern coefficients below .40; however, their structure coefficients with Critical Awareness of Non-Neutrality were .617 and .443, respectively. Given their theoretical relevance to the construct, these two indicators were retained for evaluation in the independent confirmatory sample rather than removed solely because of their exploratory pattern coefficients.

Table 5

Parallel Analysis for Factor Retention in the 17-Item CTI (n = 402)

Factor	Observed eigenvalue	95th-percentile random eigenvalue	PA indication
1	**6.541**	.501	Retain
2	**.642**	.401	Retain
3	**.518**	.332	Retain
4	**.379**	.275	Retain
5	**.243**	.224	**Marginally retain**
6	.136	.177	Do not retain

Parallel analysis was conducted on the final 17-item EFA dataset ($n = 402$) using 5,000 random datasets. Factor retention was evaluated by comparing observed common-factor eigenvalues with the

corresponding 95th-percentile random eigenvalues. Parallel analysis clearly supported the first four factors, while the fifth observed factor eigenvalue only marginally exceeded its corresponding random-data criterion. Given this borderline result, a diagnostic five-factor PAF solution was examined. The additional factor did not yield a substantively coherent and adequately represented dimension. Considering the parallel-analysis evidence, factorial interpretability, and theoretical coherence, the four-factor, 17-item structure was retained and subsequently subjected to confirmatory factor analysis in the independent holdout sample (n = 403).

Convergent Validity. The convergent validity of the CTI was demonstrated by examining its correlation with theoretically related constructs, such as the Attitudes Towards Digital Education Technologies Scale and Interest in Artificial Intelligence.

Attitudes Towards Digital Education Technologies Scale. The idea that attitudes encompass both enthusiasm and concern and are linked to personality is well supported (Stein et al., 2024). Novikova, Bychkova, Shlyakhta, and Novikov (2023) developed and validated the Students' Attitudes Toward Digital Education Technologies scale, a key psychological factor measuring cognitive, affective, and behavioral attitudes toward digital educational technologies. The authors contend that these attitudes can either facilitate or hinder the use of technology in learning. The authors modified a nine-item scale for use in this convergent procedure. Thus, technoskepticism should be positively related to attitudes, since the four CTI domains examined college students' thoughts, feelings, and behaviors towards technology (α = .862).

Interest in Artificial Intelligence. The Interest Development Model (Hidi & Renninger, 2006) suggests that interest arises from initial engagement with novel or appealing stimuli, such as students' first experiences with AI systems like ChatGPT. Research shows that exposure to generative AI technologies such as ChatGPT enhances students' views of AI, leading to greater interest, engagement, and a deeper understanding of AI concepts (Chan & Hu, 2023). Thus, technoskepticism should be positively related to Interest in AI. This study used a scale measuring interest in AI from Hornberger et al. (2025). A sample item was "I am interested in learning more about artificial intelligence" (α =.910). The convergent validity results in Table 6 provide substantial support for the construct validity of the Critical Technoskepticism Inventory (CTI).

Table 6

Convergent Validity: Means, Standard Deviations, and Correlations of CTI

Variable	M	SD	Critical Technoskepticism Inventory (Overall)	Domain 1: Critical Awareness of Non-Neutrality	Domain 2: Ethical & Societal Impact Reflection	Domain 3: Agency and Reflexivity	Domain Imaginat Alternati
Critical Technoskepticism Inventory (Overall)	4.26	.45	1	.811**	.855**	.835**	.782**
Domain 1: Critical Awareness of Non-Neutrality	4.20	.55	.811**	1	.605**	.591**	.472**
Domain 2: Ethical & Societal Impact Reflection	4.32	.52.	.855**	.591**	1	.690**	.535**
Domain 3: Agency and Reflexivity	4.41	.50	.835**	.472**	.690**	1	.501**
Domain 4: Imaginative Alternatives	4.11	.61	.782**	.463**	.535**	.501**	1
Theoretically Convergent Measures							
Attitude Towards Digital Educational Technologies	4.33	.47	.683**	.514**	.611**	.657**	.485**
Affective	4.41	.55	.614**	.465**	.465**	.594**	.450**
Behavioral	4.24	.58	.485**	.371**	.371**	.467**	.332**
Interest in AI	3.88	.76	.322	.260**	.260**	.255**	.291**

*Note: N=805; **p < .01*

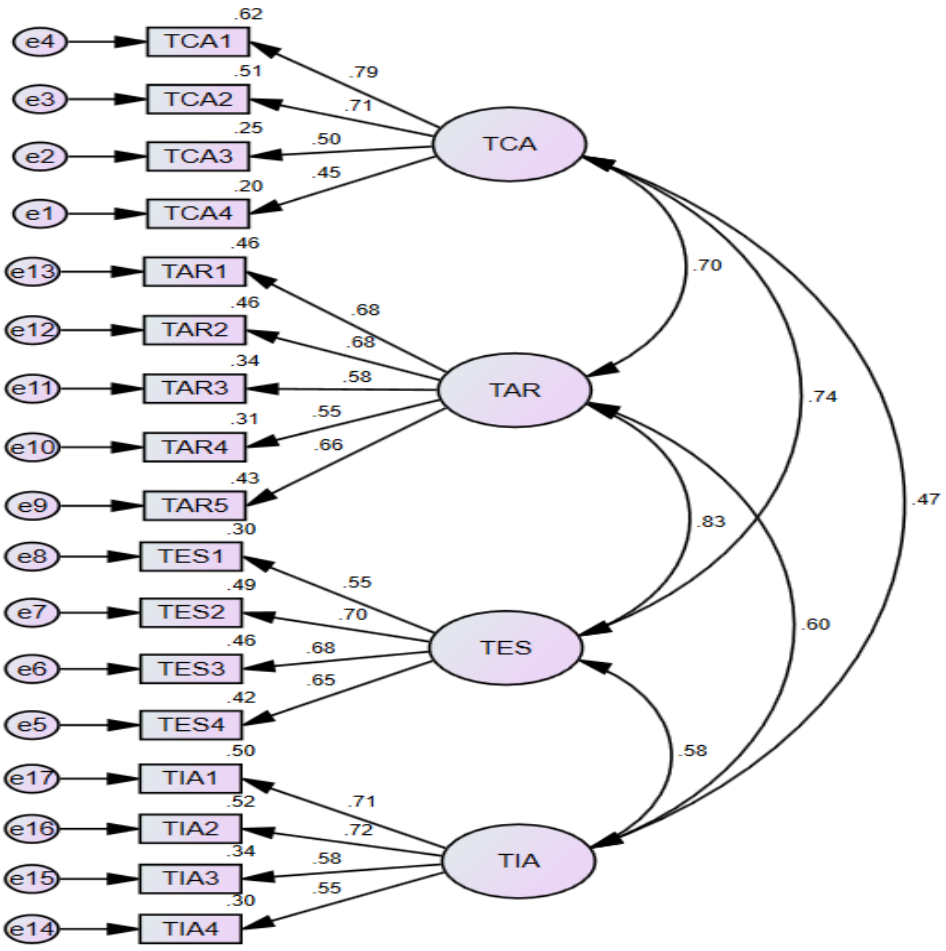
As was theoretically anticipated, the CTI exhibited a strong positive relationship with attitudes toward digital educational technologies ($r = .683$, $p < .01$), suggesting that students demonstrating higher levels of critical awareness, ethical reflection, reflexive agency, and imaginative thinking regarding technology are also likely to have more favorable views on the educational applications of digital technologies. Notably, the strength of the correlation was sufficient to indicate convergence while remaining below the thresholds indicating construct redundancy. This outcome reinforces the idea that technoskepticism is a trait that enhances, rather than contradicts, positive attitudes toward technology.

The CTI demonstrated a statistically significant, though moderate, positive correlation with Interest in Artificial Intelligence ($r = .322$, $p < .01$). This trend aligns with the theoretical framework supporting the CTI, which differentiates critical engagement from both enthusiasm for and rejection of technology. Students showing greater interest in AI also tended to exhibit increased levels of technoskepticism, suggesting that curiosity about new technologies can coexist with thoughtful examination of their ethical, social, and educational consequences. Rather than expressing fear of technology or resistance to change, technoskepticism promotes thoughtful, informed discussion about technology. This suggests that the CTI measures a concept related to technology attitudes and interest

in artificial intelligence, but it is different from them. Overall, the factor-loading pattern indicated that all retained items loaded satisfactorily on their intended latent dimensions, with no substantial cross-loadings observed in the final solution. The resulting factor structure closely aligned with the theoretical conceptualization of critical technoskepticism, providing preliminary evidence of construct validity prior to confirmatory factor analysis.

Confirmatory Factor Analysis. A confirmatory factor analysis (CFA) was conducted in AMOS using maximum likelihood estimation to evaluate the four-factor measurement model derived from the exploratory factor analysis comprising Agency & Reflexivity (TAR), Ethical & Social Impact (TES), Critical Awareness of Non-Neutrality (TCA), and Imaginative Alternative (TIA).

Figure 1: Confirmatory Factor Analysis Results for the CTI Four-Factor Model



Legend: TCA – Critical Awareness of Non-Neutrality

TAR – Agency & Reflexivity

TES – Ethical & Social Impact

Inter-factor correlations ranged from .46 to .83, indicating that the four dimensions were moderately to strongly related, as theoretically expected for components of a broader critical technoskeptical disposition. The comparatively high correlation between Agency & Reflexivity and Ethical & Societal Impact (r = .83) further underscored the importance of formally evaluating discriminant validity among the CTI domains.

Confirmatory factor analysis (CFA) evaluated the proposed measurement model. The results showed a good overall fit of the model to the observed data, $\chi^2(113) = 207.24$, $p = .001$, $\chi^2/df = 1.83$. The absolute fit indices were satisfactory, with RMR = .026, GFI = .941, and AGFI = .921. Similarly, the incremental fit indices indicated acceptable to excellent model fit, with NFI = .902, IFI = .953, TLI = .943, and CFI = .952. Although the RFI (.882) was slightly below the commonly recommended .90 criterion, the remaining fit indices consistently supported the model's adequacy. Furthermore, the RMSEA of .046, 90% CI [.036, .055], with PCLOSE = .766, indicated a close-fitting model. Taken together, these findings provide support for the adequacy of the hypothesized measurement model and suggest that the proposed factor structure adequately represents the observed data.

Table 7.

Standardized Factor Loadings for the Final Four-Factor CTI Model (n = 403)

Domain	***Item***	***Standardized λ***	***SE***	***R²***
Critical Awareness of Neutrality (TCA)	*TCA1*	*.790*	*.166*	*.623*
	TCA2	*.712*	*.152*	*.507*
	TCA3	*.499*	*.149*	*.249*
	TCA4	*.450*	—	*.202*
Ethical & Societal Impact (TES)	*TES1*	*.548*	*.093*	*.301*
	TES2	*.700*	*.091*	*.489*
	TES3	*.676*	*.093*	*.457*
	TES4	*.650*	—	*.423*
Agency Reflexivity (TAR)	*TAR1*	*.681*	*.095*	*.463*
	TAR2	*.682*	*.085*	*.465*
	TAR3	*.580*	*.079*	*.336*
	TAR4	*.553*	*.100*	*.306*
	TAR5	—	—	*.430*
Imaginative Alternative (TIA)	*TIA1*	*.710*	*.134*	*.504*
	TIA2	*.722*	*.133*	*.522*
	TIA3	*.582*	*.128*	*.339*
	TIA4	*.550*	—	*.302*

The standardized factor loadings for the final four-factor CTI model are presented in Table 7. All 17 indicators loaded significantly on their specified latent factors. Standardized loadings ranged from .450 to .790, with TCA4 showing the weakest loading. The table also presents the corresponding standard errors and squared multiple correlations (R^2) for the indicators.

Although TCA4 showed the weakest standardized loading (.45), the indicator remained statistically significant and was retained because it represents a theoretically important aspect of critical awareness—questioning whether technological innovation is necessarily appropriate in educational contexts. Its comparatively weaker loading nevertheless identifies the item as a priority for further evaluation in future CTI studies.

Discriminant validity was assessed using the heterotrait–monotrait ratio of correlations (HTMT). HTMT coefficients ranged from .540 to .835, with all point estimates below the conservative .85 criterion. The highest HTMT value was observed between Ethical & Societal Impact Reflection and Agency & Reflexivity (.835), consistent with their comparatively strong association in the CFA model. Bootstrap confidence intervals based on 5,000 resamples indicated greater overlap for TCA–TES, 95% CI [.712, .903], and TES–TAR, 95% CI [.748, .917]. Thus, the HTMT point estimates generally supported the empirical distinctiveness of the four domains, although the comparatively close relationships involving Ethical & Societal Impact Reflection suggest that discriminant validity should continue to be evaluated in subsequent applications of the CTI. Table 8 shows HTMT ratios among the four CTI domains with the 403-sample.

Table 8.

HTMT Ratios Among the Four CTI Domains (n = 403)

Domain pair	HTMT	95% bootstrap CI
TCA – TES	**.810**	[.712, .903]
TCA – TAR	**.751**	[.647, .848]
TCA – TIA	**.540**	[.408, .669]
TES – TAR	**.835**	[.748, .917]
TES – TIA	**.594**	[.471, .709]
TAR – TIA	**.581**	[.469, .683]

The comparatively strong association between Ethical & Societal Impact Reflection and Agency & Reflexivity suggests meaningful conceptual proximity between the two dimensions. This relationship is theoretically plausible because critical reflection on the ethical and societal consequences of technology may be closely connected with individuals' capacity to interrogate their own technological choices and exercise agency. Nevertheless, the HTMT point estimate remained below the conservative .85 criterion, providing preliminary support for retaining the domains as distinct. The comparatively high association and bootstrap interval, however, suggest that their discriminant

validity should be re-examined in independent samples before their distinction is regarded as firmly established.

Furthermore, the internal consistency of CTI is now established using Cronbach's α and McDonald's ω values from the final CFA dataset. Table 6 presents the internal consistency of the CTI domains, based on Cronbach's α and McDonald's ω values.

Table 9.

Reliability and Convergent Validity of the Final CTI Domains (n = 403)

Final CTI Domain	Items	Cronbach's α	McDonald's ω	CR	AVE
Critical Awareness of Non-Neutrality (TCA)	4	.672	.713	.713	.396
Ethical & Societal Impact Reflection (TES)	4	.735	.740	.740	.417
Agency & Reflexivity (TAR)	5	.762	.768	.768	.400
Imaginative Alternatives (TIA)	4	.735	.738	.738	.417

As shown in Table 9, the internal consistency of the four final CTI domains was re-examined in the independent CFA sample to provide sample-specific reliability evidence for the confirmed 17-item structure. McDonald's omega (ω) was considered alongside Cronbach's alpha (α), as omega does not require the strict tau-equivalence assumption associated with alpha and is appropriate for congeneric measurement models (Dunn et al., 2014; Hayes & Coutts, 2020). Omega coefficients ranged from .713 to .768, indicating satisfactory internal consistency across the four domains. Cronbach's alpha coefficients ranged from .672 to .762. Although alpha for Critical Awareness of Non-Neutrality (α = .672) was slightly below the conventional .70 benchmark, its corresponding omega coefficient (ω = .713) supported adequate internal consistency. Given the small number of indicators in this domain, the slightly lower alpha is interpreted cautiously rather than as evidence of inadequate reliability. Overall, the findings provide acceptable evidence of internal consistency for the four CTI domains in the independent CFA sample.

Composite reliability coefficients ranged from .713 to .768, with all four domains meeting the conventional .70 criterion, providing additional evidence of construct reliability. In contrast, AVE values ranged from .396 to .417 and remained below the conventional .50 benchmark. Fornell and Larcker (1981) observed that if the Average Variance Extracted (AVE) falls below .50 while the Composite Reliability (CR) is above .60, it is still possible to consider convergent validity adequate. This indicates that the composite performs reliably even though the individual items may have higher-than-preferred error. Therefore, while the AVE results are deemed acceptable, they highlight a remaining psychometric weakness rather than indicating strong convergent validity. The TCA factor is particularly susceptible, as its AVE of .396 is below the .40 threshold deemed "insufficient" by some reviewers, primarily due to two items with loadings under .50. Meanwhile, TES, TAR, and TIA fall within the .40–.42 range, which most references categorize as "marginal but salvageable," particularly

because their CR remains above .70. This suggests that multiple modest indicator loadings may contribute to this outcome, indicating that refining the items further could enhance the measurement precision of the CTI.

The present study provides empirical support for CTI as a correlated four-factor model rather than establishing a higher-order factor structure. Although the conceptual framework treats critical technoskepticism as a broader disposition encompassing four related dimensions, this study did not test a second-order CFA. Future research may therefore compare correlated first-order, second-order, and potentially bifactor specifications to determine whether an overarching CTI construct can be psychometrically justified.

Discussion

The present study developed and examined the initial psychometric properties of the Critical Technoskepticism Inventory (CTI), an instrument designed to assess students' capacity to engage critically, ethically, reflexively, and imaginatively with technology. Rather than conceptualizing technoskepticism as technological fear, resistance, or generalized negativity, the CTI positions it as a multidimensional orientation toward questioning technological assumptions, considering societal and ethical consequences, exercising agency in relation to technological systems, and imagining alternatives to dominant technological arrangements. The findings provide initial psychometric support for a 17-item, four-factor structure comprising *Critical Awareness of Non-Neutrality, Ethical & Societal Impact Reflection, Agency & Reflexivity, and Imaginative Alternatives.*

A particular strength of the findings is the convergence of exploratory and confirmatory evidence from independent subsamples. The main EFA with 402 participants produced an interpretable four-factor structure, while parallel analysis clearly supported the first four factors and provided only marginal evidence for a possible fifth factor. Rather than disregarding this borderline statistical signal, a diagnostic five-factor PAF solution was examined. However, the additional factor did not produce a sufficiently coherent and adequately represented substantive dimension. The decision to retain four factors was therefore based not on a single statistical criterion, but on the combined consideration of parallel-analysis evidence, factorial interpretability, item representation, and theoretical coherence. The subsequent CFA using the independent holdout sample (n = 403) further supported this structure, with the four-factor model demonstrating good overall fit to the observed data. This sequential use of exploratory and confirmatory samples strengthens the structural evidence for the CTI while avoiding the stronger claim that its factor structure has been definitively established across populations.

The four domains capture dimensions of critical engagement with technology. Critical Awareness of Non-Neutrality recognizes that technologies are not neutral tools but may embody specific assumptions and interests. This aligns with Winner's (1980) argument that technological artifacts can reflect political values and Selwyn's (2013, 2019) critique of the neutrality of educational technologies. Additionally, it resonates with Pleasants et al. (2023, 2025), who emphasize the

ideological assumptions underlying technological systems. In educational contexts, this awareness is vital as technology increasingly mediates teaching and learning. Students who recognize this non-neutrality can better assess a technology's effectiveness, whose interests it serves, and what educational practices it may favor or limit.

Ethical & Societal Impact Reflection highlights the broader consequences of technology adoption, emphasizing concerns beyond immediate usefulness, such as social effects, ethical responsibility, and equity. This aligns with rights-based approaches that focus on justice and accountability, considering who benefits or faces disadvantages from technological systems (Livingstone, 2023; Markham et al., 2018; Roe et al., 2025; UNESCO, 2021). This dimension is especially relevant with the rise of artificial intelligence and digital educational technologies, where issues like privacy, algorithmic bias, and inclusion are central to discussions of innovation. Thus, the CTI introduces an evaluative aspect that traditional technology-acceptance measures overlook, which typically focus on perceived usefulness and ease of use.

The third dimension, Agency & Reflexivity, emphasizes the individual's role in engaging with technology. Critical technoskepticism involves not just identifying technological issues but also reflecting on personal assumptions and making informed decisions about technology use. This approach promotes students from being passive users to active, reflective participants, aligning with ethical perspectives that prioritize justice and accountability (Livingstone, 2023; Markham et al., 2018; Roe et al., 2025; UNESCO, 2021). In AI-rich learning environments, this agency is crucial as students navigate reliance on automated systems, authorship, verification, and intellectual responsibility.

Imaginative Alternatives expands critical reflection to envision different technological possibilities, moving beyond skepticism toward constructive engagement. This perspective encourages learners to think about redesigning or replacing technologies to better serve human and educational needs. It aligns with Escobar's emphasis on community-centered design, Costanza-Chock's design-justice perspective, and Miller's futures-literacy orientation, all of which foster the imagination of alternatives to dominant technological systems. This construct distinguishes critical technoskepticism from mere technology resistance, allowing researchers to question existing arrangements while remaining open to more responsible options.

An important theoretical finding concerns the originally hypothesized *Caution Toward Adoption and Hype* domain. This dimension did not emerge as a sufficiently distinct and stable factor in the empirical structure. This result should not be interpreted as evidence that caution toward technological adoption is irrelevant to critical technoskepticism. Rather, the findings indicate that, within the present sample and item pool, caution did not function as an independently measurable dimension. The marginal fifth-factor signal identified through parallel analysis warranted further investigation, but the diagnostic five-factor solution did not yield a substantively coherent additional factor. It would therefore be premature to conclude that caution is empirically “absorbed” by another CTI domain

without directly demonstrating such a relationship. A more defensible interpretation is that caution may operate as an evaluative stance arising from several forms of critical engagement, such as awareness of technological non-neutrality, consideration of ethical consequences, and reflexive judgment, rather than as a separate latent dimension. This interpretation remains compatible with critiques of techno-solutionism that question premature confidence in technological fixes (Morozov, 2013) and with technoskeptical approaches that encourage scrutiny of technological claims without requiring wholesale rejection of technology (Pleasants et al., 2023, 2025; Selwyn, 2019). Future studies should revisit this proposition with newly developed caution items and independent samples to determine whether the domain can be differentiated more clearly or is better conceptualized as a cross-cutting orientation within critical technoskepticism.

The relationships among the retained domains likewise warrant careful interpretation. The CFA indicated moderate to strong correlations among the four latent factors, consistent with their conceptualization as related dimensions of a broader critical-technoskeptical disposition. The strongest relationship occurred between *Ethical & Societal Impact Reflection and Agency & Reflexivity*, a theoretically understandable finding. Reflection on the ethical and societal consequences of technology may naturally accompany reflection on one's own choices, responsibilities, and agency in relation to technological systems. The HTMT analysis provided generally supportive but qualified evidence for discriminant validity: all point estimates remained below the conservative .85 criterion, although the bootstrap confidence interval for the TES–TAR relationship extended beyond that threshold. Thus, the present evidence supports retaining TES and TAR as conceptually distinct but closely related dimensions, while also indicating that their empirical separation should be reassessed in subsequent samples. This qualification is preferable to either prematurely collapsing the domains or claiming stronger discriminant validity than the evidence permits.

The reliability and construct-validity findings similarly present a nuanced psychometric picture. Cronbach's alpha and McDonald's omega indicated generally satisfactory internal consistency, while composite reliability coefficients for all four domains exceeded the conventional .70 benchmark. These findings suggest that the retained indicators function with acceptable consistency in representing their respective constructs. At the same time, AVE values for all four domains fell below .50. Fornell and Larcker (1981) themselves noted that when AVE dips below .50, but CR exceeds .60, convergent validity can still be considered adequate, because the *composite* of items is behaving reliably even though individual items carry more error than ideal. Consequently, convergent validity at the latent-indicator level cannot yet be considered fully established, although it is adequate. The comparatively modest loadings of several indicators, including the weaker TCA4 loading, likely contributed to these AVE values. TCA4 was nevertheless retained because its content, questioning whether technological innovations are necessarily appropriate or needed in educational settings, represents an important conceptual aspect of critical awareness that would otherwise be underrepresented. The AVE findings therefore identify a specific direction for continued item

refinement rather than warranting post hoc deletion of theoretically meaningful indicators solely to improve numerical indices.

This interpretation matters especially when the AVE results are considered alongside the study's external convergent evidence. CTI scores were positively associated with attitudes toward digital educational technologies and with Interest in AI. These positive relationships are inconsistent with interpreting critical technoskepticism as simple technological aversion. Students may be interested in AI and hold generally positive attitudes toward educational technology while simultaneously questioning its assumptions, consequences, and appropriate uses. The stronger association with technology attitudes and more modest association with Interest in AI further suggest that critical technoskepticism occupies a related but non-identical conceptual space. Taken together, these findings support the intended characterization of CTI as measuring critical engagement with technology rather than rejection of technology.

The findings also clarify the level at which the CTI can presently be interpreted. The empirical evidence directly supports a correlated four-factor model. Although the four dimensions were theoretically conceived as components of a broader critical-technoskeptical disposition, the present study did not test a second-order factor model. It would therefore be premature to claim that a single higher-order CTI construct has been empirically demonstrated. Future studies should compare correlated first-order, second-order, and potentially bifactor models to determine whether an overarching critical-technoskepticism factor can be psychometrically justified. Until such evidence becomes available, interpretation of the four CTI subscales provides the most empirically defensible representation of the construct.

Taken as a whole, the findings provide initial psychometric support, rather than definitive validation, for the 17-item CTI. Its principal contribution lies not in proposing skepticism toward technology as an entirely new intellectual position, but in operationalizing a form of critical technological engagement that conventional measures of technology acceptance, attitudes, anxiety, stress, resistance, or literacy do not adequately capture. The CTI brings together critical awareness, ethical reflection, reflexive agency, and imaginative possibility within a measurable educational framework. In doing so, it offers a potential means of examining whether students are developing not merely the ability and willingness to use emerging technologies, but also the capacity to question, evaluate, and shape their technological environments responsibly.

Ultimately, at this stage, the CTI should be understood as an emerging instrument supported by initial psychometric evidence. Its four dimensions suggest that meaningful preparation for increasingly technological educational environments requires more than technological competence or acceptance. Students may also need opportunities to recognize the non-neutrality of technologies, deliberate on their ethical and societal consequences, exercise reflexive agency, and imagine alternatives when existing technological arrangements do not adequately serve educational or human purposes. In this

sense, critical technoskepticism is not positioned against technological innovation; rather, it offers a framework for engaging innovation with greater judgment, responsibility, and human agency.

Limitations

The findings should nevertheless be interpreted within the boundaries of the present study. The participants were drawn from a particular higher-education context, limiting the generalizability of assumptions about the stability of the four-factor structure across cultural, institutional, disciplinary, and national settings. The CTI is also a self-report instrument and therefore measures students' reported critical orientations rather than directly observed critical technological behavior.

Because this instrument is newly developed and has only been initially validated, the psychometric properties reported here, while supporting its structural and convergent validity, should be regarded as preliminary rather than conclusive. Consistent with established scale-development frameworks, validation is inherently a cumulative, multi-study process, and a single confirmatory factor analysis, however well-fitting, cannot by itself establish the instrument's stability across populations, settings, or time. The authors will establish the interpretation of the CTI scores after it has gained full confidence in its measurement properties, which requires cross-validation with independent and more diverse samples, replication of the measurement model, and accumulation of convergent evidence across multiple studies before the scale can be considered a mature tool capable of generating fully generalizable empirical findings.

Future research should therefore replicate the CTI structure in independent and more diverse populations and examine measurement invariance across relevant demographic, disciplinary, institutional, cultural, and national groups. Further validation should include criterion-related and known-groups evidence and could investigate whether students with systematically different experiences of AI, digital ethics education, or technology-intensive curricula demonstrate theoretically expected CTI profiles. Longitudinal and pre–post designs would be especially valuable for determining whether critical technoskepticism responds to educational interventions or functions as a relatively stable orientation. Additional work should also revisit the Caution Toward Adoption and Hype dimension, refine indicators with comparatively weaker loadings, examine the TES–TAR distinction, and compare alternative first-order, higher-order, and bifactor specifications.

Conclusion and Implications

This study changes how technoskepticism is perceived by illustrating that a genuine critique of technology encompasses more than negativity; it emphasizes the importance of ethics, fairness, and careful consideration. The Critical Technoskepticism Inventory (CTI) translates these intricate concepts into a straightforward four-part tool that helps researchers measure and track critical data literacy over time. For universities, the CTI may help evaluate student awareness, enhance course content, and encourage students to think beyond mere technological use. It challenges them to consider the power dynamics present in today’s digital systems. Ultimately, this research shows that

maintaining a critical view of technology does not impede progress; instead, it empowers future thinkers to question blind optimism about technology and work toward more ethical, improved futures.

Technology should serve human well-being, not the other way around. As it matures, the Critical Technoskepticism Inventory can assess how thoughtfully people engage with technology. This isn't about fearing new tech; it's about using our skills to evaluate it responsibly. Understanding technology's effects on individuals and society matters. As colleges adapt to digital technology and AI, promoting a responsible mindset is crucial. To prepare students for an AI-driven future, institutions need to teach more than just technical skills; they must also ensure that new technologies align with ethical values and social justice for everyone's benefit.

References

Agarwal, R. (2003). Resisting technology: Regaining a personal ecology. In Sarai Programme (Ed.), Sarai Reader 03: Shaping technologies (pp. 30–34). Centre for the Study of Developing Societies.

Brod, C. (1984). Technostress: The human cost of the computer revolution. *Addison-Wesley, Reading, MA, USA (1984)*

Brosnan, M. J. (1998). The impact of computer anxiety and self-efficacy upon performance. *Journal of computer assisted learning, 14(3), 223-234.* https://doi.org/10.1046/j.1365-2729.1998.143059.x

Burnett, D. G. (2025). Will the Humanities Survive Artificial Intelligence?. *New Yorker*, *26*. https://thenationalmind.org/wp-content/uploads/2025/06/burnett-will-the-humanities-survive-artificial-intelligence.pdf

Chan, C.K.Y., Hu, W. Students' voices on generative AI: perceptions, benefits, and challenges in higher education. *Int J Educ Technol High Educ* **20**, 43 (2023). https://doi.org/10.1186/s41239-023-00411-8

Costanza-Chock, S. (2020). Design justice: Community-led practices to build the worlds we need. The MIT Press.

Costello, A. B., & Osborne, J. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical assessment, research, and evaluation*, *10*(1), Article 7.

Danaher, J. (2022). Techno-optimism: An analysis, an evaluation and a modest defence. *Philosophy & Technology*, *35*(2), 54.

de Sousa Santos, B. (2015). *Epistemologies of the South: Justice against epistemicide*. Routledge.

Dunn, T. J., Baguley, T., & Brunsden, V. (2014). From alpha to omega: A practical solution to the pervasive problem of internal consistency estimation. *British journal of psychology*, *105*(3), 399-412. https://irep.ntu.ac.uk/id/eprint/4853/1/215051_Dunn.pdf

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research*, *18*(1), 39-50. URL: http://www.jstor.org/stable/3151312

Fred D. Davis (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. MIS Quarterly, 13(3), 319-340. https://doi.org/10.2307/249008

DISCO Network. (2025). Technoskepticism: Between Possibility and Refusal. Stanford University Press. DOI: 10.21627/9781503641365

Escobar, A. (2018). Designs for the pluriverse: Radical interdependence, autonomy, and the making of worlds. Duke University Press.

Foucault, M., Martin, L. H., Gutman, H., & Hutton, P. H. (1988). Technologies of the self. *London: Tavistock*. https://works.raqsmediacollective.net/wp-content/uploads/2023/04/sarai_reader_03_shaping_technologies.pdf#page=105

Harvard Graduate School of Education. (2024, June 3). Teaching about technology in schools: The technoskeptic iceberg. https://hep.gse.harvard.edu/blog/2024/06/03/teaching-about-technology-in-schools/

Hayes, A. F., & Coutts, J. J. (2020). Use omega rather than Cronbach's alpha for estimating reliability. But…. *Communication methods and measures*, *14*(1), 1-24. https://doi.org/10.1080/19312458.2020.1718629

Heath, M. K., Krutka, D. G., & Gleason, B. (2024). "See results anyway": Auditing social media as educational technology. Information and Learning Sciences, 125(9), 650672. https://www.emerald.com/insight/2398-5348.htm

Heath, M. K., Krutka, D. G., Jarke, J., & Macgilchrist, F. (2024). Critiques need community: On a humanities approach to a civics of technology. *Postdigital Science and Education*, *6*(1), 369–382. https://doi.org/10.1007/s42438-023-00448-y

Hidi, S., & Renninger, K. A. (2006). The Four-Phase Model of Interest Development. *Educational Psychologist, 41*(2), 111–127. https://doi.org/10.1207/s15326985ep4102_4

Hinrichsen, J., & Coombs, A. (2013). The five resources of critical digital literacy: A framework for curriculum integration. Research in Learning Technology, 21(1), 1–16.

Hornberger, M., Bewersdorff, A., Schiff, D. S., & Nerdel, C. (2025). A multinational assessment of AI literacy among university students in Germany, the UK, and the US. *Computers in Human Behavior: Artificial Humans*, *4*, 100132. https://doi.org/10.3402/rlt.v21i0.21334

Jandrić, P., Knox, J., Besley, T., Ryberg, T., Suoranta, J., & Hayes, S. (2018). Postdigital science and education. *Educational philosophy and theory*, *50*(10), 893-899.

Johnston, S. F. (2018). Alvin Weinberg and the promotion of the technological fix. *Technology and culture*, *59*(3), 620-651. doi: 10.1353/tech.2018.0061. PMID: 30245497.

Krutka, D. G., Heath, M. K., & Staudt, C. (2021). Critical media and digital literacies in teacher education. Routledge.

Krutka, D. G., Heath, M. K., & Pleasants, J. (2024). "Technoskepticism in Social Studies Education." *The Theory-Story Reader for Social Studies* (2024): 202.

Krutka, D. G., Heath, M. K., & Mason, L. E. (2020). Technology won't save us–A call for technoskepticism in social studies. *Contemporary Issues in Technology and Teacher Education*, *20*(1), 108-120.

Krutka, D.G., Heath, M.K. & Smits, R.M. (2022). Toward a Civics of Technology. *Journal of Technology and Teacher Education, 30*(2), 229-237. Waynesville, NC USA: Society for Information Technology & Teacher Education. Retrieved June 30, 2026 from https://www.learntechlib.org/primary/p/221182/.

Livingstone, S., & Sefton-Green, J. (2021). *The class: Living and learning in the digital age* (2nd ed.). New York University Press.

Livingstone, S., & Sefton-Green, J. (2025). The platformization of the family. https://library.oapen.org/bitstream/handle/20.500.12657/96135/1/9783031748813.pdf#page=17

Markham, A. N. (2006). Ethics as a method. *Journal of Information Ethics*, *15*(2), 37-55.

Markham, A. N., Tidenberg, K., & Herman, A. (2018). Ethics as methods: doing ethics in the era of big data research—introduction. *Social Media+ Society*, *4*(3), 2056305118784502.

Martin, L. H., Gutman, H., & Hutton, P. H. (Eds.). (1988). *Technologies of the self: A seminar with Michel Foucault*. Tavistock. University of Massachusetts Press.

Miller, R. (Ed.). (2018). Transforming the Future: Anticipation in the 21st Century. Routledge/UNESCO.

Morozov, E. (2013). *To save everything, click here: The folly of technological solutionism*. PublicAffairs.

Novikova, I. A., Bychkova, P. A., Shlyakhta, D. A., & Novikov, A. L. (2024). Attitudes towards Digital Educational Technologies among University Students of Different Fields of Study: Role of Academic Motivation and Personality Traits. *RUDN Journal of Psychology And Pedagogics, 21*(4), 1036-1063. doi: 10.22363/2313-1683-2024-21-4-1036-1063

Pleasants, J., Krutka, D. G., & Nichols, T. P. (2023). What relationships do we want with technology? Toward technoskepticism in schools. *Harvard Educational Review, 93*(4), 486–515. https://doi.org/10.17763/1943-5045-93.4.486

Pleasants, J., Radloff, J., & Mueller, A. (2025). Learning to be technoskeptical: Engaging pre-service teachers in critical examinations of educational technologies. *Contemporary Issues in Technology and Teacher Education, 25*(2), 294–324. https://citejournal.org/volume-25/issue-2-25/current-practice/learning-to-be-technoskeptical-engaging-preservice-teachers-in-critical-examinations-of-educational-technologies/

Potkalitsky, N. (2026). *Thinking with AI: A student's guide*. Available online: https://nickpotkalitsky.substack.com/p/thinking-with-ai-a-students-guide (accessed on January 5, 2026).

Ragu-Nathan, T. S., Tarafdar, M., Ragu-Nathan, B. S., & Tu, Q. (2008). The consequences of technostress for end users in organizations: Conceptual development and empirical validation. *Information systems research*, *19*(4), 417-433. doi 10.1287/isre.1070.0165

Roe, J., Perkins, M., & Furze, L. (2025). Reflecting reality, amplifying bias? Using metaphors to teach critical AI literacy. *Journal of Interactive Media in Education*, 2025(1). https://doi.org/10.5334/jime.879

Salanova, M., Llorens, S., & Cifre, E. (2013). The dark side of technologies: Technostress among users of information and communication technologies. *International journal of psychology*, *48*(3), 422-436.

Sander, I. (2024). Critical datafication literacy–a framework for educating about datafication. *Information and Learning Sciences*, *125*(3-4), 270-292.https://doi.org/10.1108/ILS06-2023-0064.

Schüll, N. D. (2013). The folly of technological solutionism: An interview with evgeny morozov. https://technofilosofie.com/wp-content/uploads/2020/04/Course_One_Interview-Solutionism.pdf

Selwyn, N. (2013). *Distrusting educational technology: Critical questions for changing times*. Routledge.

Selwyn, N. (2019). *Should robots replace teachers?: AI and the future of education*. John Wiley & Sons.

Trieste, L., & Turchetti, G. (2024). The nature, causes, and effects of skepticism on technology diffusion. Technological Forecasting and Social Change, 208, 123663.

Tarafdar, M., Stich, J. F., Maier, C., & Laumer, S. (2024). Techno-eustress creators: Conceptualization and empirical validation. *Information Systems Journal*, *34*(6), 2097-2131. https://doi.org/10.1111/isj.12515Digital Object Identifier (DOI)

UNESCO (2021). *Recommendation on the ethics of artificial intelligence*. United Nations Educational, Scientific and Cultural Organization. https://www.unesco.org/en/artificial-intelligence/recommendation-ethics

Wang, Z., Zhang, L., Wang, X., Liu, L., & Lv, C. (2023). Navigating technostress in primary schools: A study on teacher experiences, school support, and health. *Frontiers in Psychology*, *14*, 1267767. | https://doi.org/10.3389/fpsyg.2023.1267767

Weinberg, A. M. (1967). Can technology replace social engineering?. *American Behavioral Scientist*, *10*(9), 7-7.

Weinberg, A. M. (1993). Chapters from the Life of a Technological Fixer. *Minerva*, 379-454.

Winner, L. (1980). Do artifacts have politics? Daedalus, 109(1), 121–136.

Zaimakis, Y., & Papadaki, M. (2022). On the digitalisation of higher education in times of the pandemic crisis: techno-philic and techno-sceptic attitudes of social science students in Crete (Greece). *SN Social Sciences*, *2*(6), 77. doi: 10.1007/s43545-022-00380-1.

Zuboff, S. (2019). 'We make them dance': surveillance capitalism, the rise of instrumentarian power, and the threat to human rights. *Human rights in the age of platforms*, 3-51.

Declaration of AI and AI-assisted technologies in the writing process

OpenAI's ChatGPT (www.chat.openai.com; GPT 5.4), Perplexity AI (https://www.perplexity.ai), and Grammarly (www.grammarly.com) were used during manuscript preparation to assist with language refinement, organization of ideas, and improvement of academic writing. The authors remained fully responsible for the conceptualization of the study, research design, data collection, statistical analyses, interpretation of findings, and final content of the manuscript."

Appendix A

The Critical Technoskepticism Inventory

Critical Awareness of Non-Neutrality

1. I believe that the design of digital systems can affect how people behave & make choices.
2. I know that design choices in technology can affect people's lives and the economy.
3. Technologies often reflect the values and assumptions of those who design them.
4. I believe not all technological innovations are right or necessary in educational settings

Ethical & Societal Impact Reflection

5. I believe progress should be measured by how much it contributes to social good, not just by efficiency.
6. I think understanding technology means looking at its moral effects.
7. I think about who benefits and who is disadvantaged by technology.
8. I am on whether digital systems reinforce existing inequalities or social biases.

Agency and Reflexivity

9. I believe in questioning existing technologies to bring about better, wide-ranging improvements.
10. I believe it is important to think over options beyond current technologies rather than treating them as the only choice.
11. I agree that human creativity and collaboration are as important as technological innovation.
12. I am wary of how digital platforms influence my identity, self-expression, or sense of self.
13. I believe it is important to critically examine my own reliance on technology.

Imaginative Alternatives

14. I can imagine alternative ways of solving problems without always relying on new technologies.
15. I tend to consider non-technological solutions alongside technological ones.
16. I believe technological progress is not the only path to a better society.
17. I intentionally set limits for my engagement with digital technologies.

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Faculty Behavioral Intention Toward AI Adoption in Higher Education: A UTAUT-Based PLS-SEM Study in the Philippines

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ABSTRACT

This study examined university faculty members' behavioral intention toward artificial intelligence (AI) adoption using a modified Unified Theory of Acceptance and Use of Technology (UTAUT) framework. Specifically, it investigated the relationships of Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) with Behavioral Intention (BI), while also examining gender and educational level as additional predictors. A quantitative research design was employed using a web-based questionnaire administered to 820 faculty members from seven state universities in the Philippines. The instrument measured PE, EE, SI, and BI using four items per construct on a five-point Likert scale. Exploratory Factor Analysis (EFA) was conducted to examine the factor structure, followed by Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS4. The measurement model demonstrated satisfactory reliability and validity, with outer loadings ranging from .768 to .921, Cronbach's alpha values from .857 to .934, and Average Variance Extracted (AVE) values from .690 to .834. Bootstrapping with 5,000 resamples showed significant negative relationships between PE and BI ($\beta = -.318$, $p < .001$), EE and BI ($\beta = -.225$, $p < .001$), and SI and BI ($\beta = -.284$, $p < .001$). In contrast, gender ($\beta = -.069$, $p = .304$) and educational level ($\beta = .048$, $p = .487$) were not significant predictors. The structural model explained 17.1% of the variance in BI ($R^2 = .171$), with PE demonstrating the largest effect size. The findings indicate an AI adoption paradox in which perceptions of AI's usefulness and ease of use, as well as social influence, may coexist with hesitation toward adoption. The study concludes that AI adoption in higher education extends beyond conventional technology-acceptance factors and requires consideration of ethical, pedagogical, professional, and organizational concerns.

Keywords: Artificial Intelligence, UTAUT, PLS-SEM, Behavioral Intention, Higher Education

1. Introduction

1.1. AI Adoption in Higher Education

In most facets of our daily lives, which includes the field of education, have gradually been impacted by the quick development of new technologies such as Artificial Intelligence (AI) (Yu & Guo, 2023; Zawacki-Richter et al., 2019). It is well established in a variety of research studies that artificial intelligence (AI) and other associated digital technologies can improve institutional performance, early intervention, and provision of adequate support (Baashar et al., 2021; Hashim et al., 2020). For some instance, AI adoption can bring some significant benefits such as AI-based dialogues increase writing efficiency, confidence, and research productivity (Ayaz & Yanartaş, 2020; Zhai et al., 2024). It can also help in providing tailored feedback, adaptive testing, and scaffolding of problem-solving that allow learners to develop self-regulation skills and metacognition (Goyal, 2025; Ifenthaler & Yau, 2020). User-friendly systems tend to increase adoption in regular digital services (Tahar, 2020), educational technology adoption is repeatedly described as a complex, ongoing change process involving multiple actors and requiring adaptation of the broader instructional system (Timotheou, 2022). In AI-enabled teaching, the actual effort is not just learning the software, but redesigning syllabi, assignments, feedback routines and assessment practices around it, helping explain why nominal ease of use may coexist with lower adoption intention (Almaiah, 2020; Timotheou, 2022).

AI Adoption studies also offer examples of operational benefits such as electronic document management that increases efficiency, quality of services, and reduces errors (Ayaz & Yanartas, 2020). In design thinking-based learning, the learners were found to have performed well when they served as curators, editors, and questioners instead of being mere consumers of the product generated by AI (Rana et al., 2025). The same holds true for medicine too (Izquierdo-Condoy et al., 2025). AI research reviews indicate that there has been very little consideration of the negative aspects of the technology adoption and its consequences for risk management (Zawacki-Richter et al., 2019).

1.2. Research Gap

Despite the growing literature on technology acceptance, gaps remain in understanding AI adoption among university faculty. First, a methodological gap exists in the limited use of PLS-SEM to quantitatively examine AI adoption using a modified UTAUT framework. Second, a conceptual gap remains in the emphasis on behavioral intention rather than actual AI use. Third, a geographical gap exists, as much of the UTAUT literature has focused on Western contexts. This study addresses these gaps by examining AI adoption among university faculty in the Philippines, providing evidence from a Southeast Asian context.

Research Hypothesis

H1. Performance expectancy has a negative effect on behavioral intention.
H2. Effort expectancy has a negative effect on behavioral intention.
H3. Social influence has a negative effect on behavioral intention.
H4. Educational level has no significant effect on behavioral intention.
H5. Gender has no significant effect on behavioral intention.

2. Related Works

2.1. Performance Expectancy

Performance Expectancy refers to the belief that using a system will help improve task/job performance (Abbad, 2021; Tahar et al., 2020; Xue et al., 2024). For the UTAUT higher education review, it was the strongest influencing variable affecting behavioral intention among the four core constructs (Xue et al., 2024). The evidence for performance expectancy in educational literature mostly follows this trend. In the case of Moodle adoption, the construct had significant effects on the behavioral intention of the learners (Abbad, 2021). Performance expectations were stated as an influential factor in e-learning acceptance during the COVID-19 pandemic period (Almaiah et al., 2020). The LMS adoption model developed during the pandemic also indicated a positive association between performance expectancy and behavioral intention (Raza et al., 2020). However, the significance of performance-related benefit also emerges as an important element of adoption theory outside of education context. In EDMS literature, performance expectancy was considered as the direct determinant of behavioral intention. Previous literature mentioned there stated that performance expectancy was the most effective construct in determining behavioral intention (Ayaz, A., & Yanartaş, 2020). Also, the e-filing literature based on TAM suggested the perception of benefits as increased productivity, effectiveness, and work performance (Tahar et al., 2020).

2.2. Effort Expectancy

Effort expectancy refers to perceived ease in the use of a system (Abbad, 2021; Xue et al., 2024). Most research considers this variable an initial stage adoption factor since people are more inclined to use systems that seem comprehensible and easy-to-use (Raza et al., 2020; Tahar et al., 2020). Unlike the evidence in support of performance expectancy, the one concerning effort expectancy is somewhat inconsistent. In particular, in one study on EDMS, effort expectancy was shown to have no positive influence on intention (Ayaz, A., & Yanartaş, 2020). Additionally, some previous studies cited in this paper reported cases in which effort expectancy did not have an effect or lost its significance in due time (Ayaz, A., & Yanartaş, 2020; Raza et al., 2020).

2.3. Social Influence

Social influence is the extent to which users believe that their important peers perceive they ought to employ the technology (Abbad, 2021; Xue et al., 2024). Social influence is less likely to be observed in cases where students regard system usage as an individualistic, habitual, and normalized activity (Abbad, 2021; Almaiah et al., 2020). Social influence can be defined as the extent to which important others support or believe in the usage of technology. However, there is some inconsistent evidence regarding this construct (Almaiah et al., 2020). Conversely, EDMS adoption showed the importance of social influence positively (Ayaz, A., & Yanartaş, 2020).

2.4. Behavioral Intention

Behavioral intention is the user's expressed willingness or purpose to utilize a particular technology, and both UTAUT and TAM regard behavioral intention to be an immediate antecedent of the actual use of the technology (Abbad, 2021; Tahar et al., 2020). The general research literature considers behavioral intention to be the primary dependent variable through which both expectancy and social factors influence technology use (Abbad, 2021; Tahar et al., 2020). The focus on the intention to use fits well within general theories of digital transformation, where technologies are used because users expect significant improvements in performance and ease of effort as well as appropriate social/organizational support (Anwar et al., 2021; Rusilowati et al., 2024; Timotheou et al., 2022).

2.5. Contextual Variations in UTAUT Predictors of AI Adaption Intention

The Unified Theory of Acceptance and Use of Technology (UTAUT) generally proposes that Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) positively influence Behavioral Intention (BI) (Venkatesh et al., 2003). However, recent research on AI adoption has reported mixed findings. Adigun et al. (2025) found significant negative relationships between PE and BI ($\beta = -.451$) and SI and BI ($\beta = -.238$) among Nigerian pre-

service teachers. Similarly, Tian et al. (2024) reported a negative but non-significant relationship between EE and BI (β = −.057, p = .350) among Chinese graduate students using AI chatbots. These findings suggest that the traditional positive UTAUT relationships may vary depending on users, technology, and contextual conditions.

Such inconsistencies provide a basis for examining negative pathways in other educational contexts. While positive relationships remain common, the observed negative and non-significant effects indicate that factors such as technological readiness, user confidence, and institutional context may influence how PE, EE, and SI translate into behavioral intention. Therefore, the present study examines whether these traditionally positive UTAUT constructs demonstrate negative relationships with AI adoption intention among university faculty in the Philippine context.

2.6. Demographic Influences Behavioral Intention to AI Adoption

Gender has been examined as a moderating factor in UTAUT, although its influence may vary across technology-adoption contexts (Venkatesh et al., 2003). Recent AI-adoption studies have generally reported limited gender effects. Tian et al. (2024) found that gender did not significantly moderate the relationships of Performance Expectancy, Effort Expectancy, and Social Influence with Behavioral Intention among Chinese graduate students, with p-values of .479, .261, and .954, respectively. Similarly, Perez (2024) reported that gender did not significantly alter the relationships between key UTAUT constructs and AI adoption among higher-education faculty. More recently, Kilat (2026) found that sex did not significantly moderate several predictors of behavioral intention among higher-education English teachers in the Philippines, including perceived AI knowledge (β = .021, p = .796) and perceived privacy concerns (β = −.034, p = .667).

Evidence concerning educational level is more context dependent. Trinh et al. (2025) found that educational qualification significantly moderated the Performance Expectancy–Behavioral Intention relationship among Vietnamese teachers but had no significant moderating effect among Taiwanese teachers. These findings suggest that educational attainment may not consistently determine AI adoption intention and that its influence can depend on institutional and technological contexts. Accordingly, the present study examines whether gender and educational level significantly predict Behavioral Intention toward AI adoption among university faculty in the Philippines.

3. Conceptual Framework

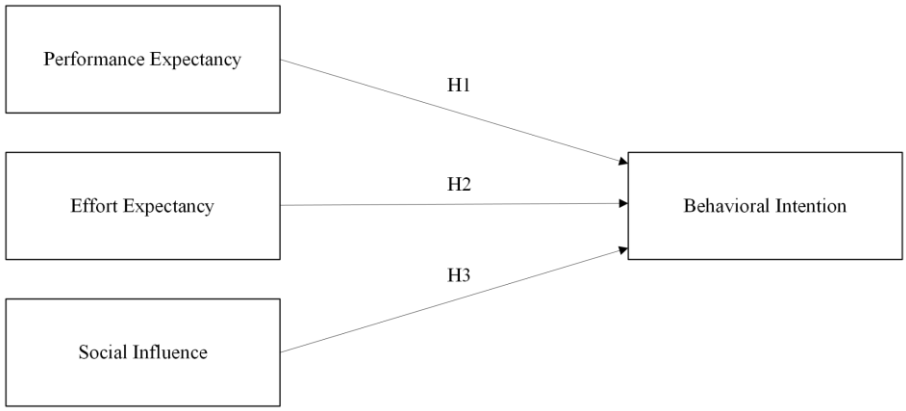


Figure 1: Conceptual Framework
Source: Ayaz & Yanartaş (2020)

3.1. Research Design

The study adopted and modified the Unified Theory of Acceptance and Use of Technology Theory (UTAUT). The acceptance and use of Artificial Intelligence (AI) among university faculty in the Philippines will explain the determining factors of UTAUT. It was refined to fit the demographic profile of the participants. The Performance Expectancy, Effort Expectancy, and Social Influence was assumed to have a negative pathway to AI adoption that leads to their Behavioral Intention to use AI on their professional work.

4. Methodology

4.1. Participants

The study employed a quantitative research design using a web-based survey questionnaire. The participants comprised 820 university faculty members from seven state universities in the Philippines. Convenience sampling was used to select the participating universities based on accessibility and willingness to participate, while purposive sampling was employed to select faculty respondents who met the predefined eligibility criteria. All 820 distributed questionnaires were validly completed, resulting in a 100% response rate. Of the respondents, 457 (56%) were female and 363 (44%) were male. In terms of educational attainment, 558 (68%) held doctoral degrees, while 262 (32%) held master's degrees.

Table 1: Demographics of the participants

Variables		1	2	Total
Gender		Male	Female	
	n	363	457	820
	%	44	56	100
Educational Background		With Ph.D.	With Master's Degree	
	n	558	262	820
	%	68	32	100

4.2. Survey Questionnaire

The survey instrument was adapted and modified from the framework of Ayaz and Yanartaş (2020), which was grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) developed by Venkatesh et al. (2003), to examine AI adoption among university faculty. The instrument measured Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) as predictor variables, and Behavioral Intention (BI) as the dependent variable, with four items for each construct. Responses were measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Gender and educational level were included as observable variables and examined as additional predictors of BI.

4.3 Exploratory Factor Analysis

Exploratory Factor Analysis (EFA) was conducted to examine the underlying factor structure and assess the suitability of the measurement items. The Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity were used to assess the adequacy of the data for factor analysis (Kaiser, 1974). The factor structure was examined based on factor loadings, with items evaluated according to their loading on the intended factor and their association with other factors (Ajai & Sanjaya, 2006).

4.4 Partial Least Squares Structural Equation Modeling (PLS-SEM)

Following EFA, the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) through SmartPLS. Following established PLS-SEM procedures (Hair et al., 2022), the analysis consisted of two stages, assessment of the measurement model and assessment of the structural model. The measurement model was evaluated in terms of indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Indicator reliability was assessed through outer loadings, internal consistency

reliability through Cronbach's alpha and composite reliability (rho_A), and convergent validity through Average Variance Extracted (AVE). Discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio (Henseler et al., 2015).

The structural model was assessed for collinearity using Variance Inflation Factor (VIF), explanatory power using R^2, and effect size using f^2. Model fit was examined using Standardized Root Mean Square Residual (SRMR). Finally, the hypothesized relationships were tested using bootstrapping with 5,000 resamples, with path coefficients (β), standard errors, t-values, and p-values examined to determine the significance and direction of the hypothesized relationships (Hair et al., 2022).

5. Analysis and Results

Table 2 summarizes the EFA results indicating adequate factorability of the data, with a KMO value of .845, reflecting meritorious sampling adequacy (Kaiser, 1974). Bartlett's Test of Sphericity was significant, $\chi^2(120) = 8{,}375.052$, $p < .001$, indicating sufficient correlations among the items for factor analysis. No measurement items were eliminated during the analysis.

Table 2: KMO and Bartlett's Test of Sampling Adequacy and Sphericity

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.845
Bartlett's Test of Sphericity	Approx. Chi-Square	8375.052
	df	120
	Sig.	.000

The rotated factor solution identified four distinct factors, with all 16 items loading strongly on their respective factors. Factor 1 comprised the four Behavioral Intention (BI) items, with loadings ranging from .847 to .904. Factor 2 consisted of the four Social Influence (SI) items, with absolute loadings ranging from .812 to .845, while Factor 3 comprised the four Effort Expectancy (EE) items, with loadings ranging from .769 to .844. Factor 4 consisted of the four Performance Expectancy (PE) items, with loadings ranging from .752 to .790. No substantial cross-loadings were observed, indicating a clear factor structure. The analysis employed Principal Axis Factoring with Oblimin rotation with Kaiser normalization, which converged after six iterations (Ajai & Sanjaya, 2006).

Table 3: Rotated Component Matrix

Factor loading									
	1	2	3	4		1	2	3	4
BI1	.908				PE1			.768	
BI2	.921				PE2			.872	
BI3	.909				PE3			.880	
BI4	.916				PE4			.797	
EE1		0.861			SI1				.876
EE2		0.869			SI2				.881
EE3		0.865			SI3				.904
EE4		0.848			SI4				.843

Note. Rotation converged in 6 iterations. Extraction Method: Principal Axis Factoring. Rotation Method: Oblimin with Kaiser Normalization.

Equation Modeling (PLS-SEM) was used to examine the relationships of Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) with Behavioral Intention (BI) to adopt artificial intelligence. Gender and educational level were included as additional predictors. The analysis consisted of measurement and structural model assessment.

Measurement Model Assessment

The measurement model in Table 4 demonstrated satisfactory indicator reliability, internal consistency, and convergent validity. All outer loadings exceeded the recommended threshold of 0.708, ranging from 0.768 to 0.921. Cronbach's alpha ranged from 0.857 to 0.934, while composite reliability ranged from 0.899 to 0.953, indicating satisfactory internal consistency. AVE values ranged from 0.690 to 0.834, exceeding the recommended minimum of 0.50 and establishing convergent validity. The slightly higher composite reliability of BI suggests very high internal consistency among its indicators; however, all indicators were retained based on their theoretical relevance. Gender and educational level were represented by single indicators, for which reliability values were fixed at 1.000 by the software and therefore should not be interpreted as evidence of perfect reliability.

Collinearity was assessed using outer VIF values, which ranged from 1.000 to 3.721. Although several BI indicators exceeded the more conservative threshold of 3.00, all remained below the critical threshold of 5.00, indicating no critical indicator-level collinearity.

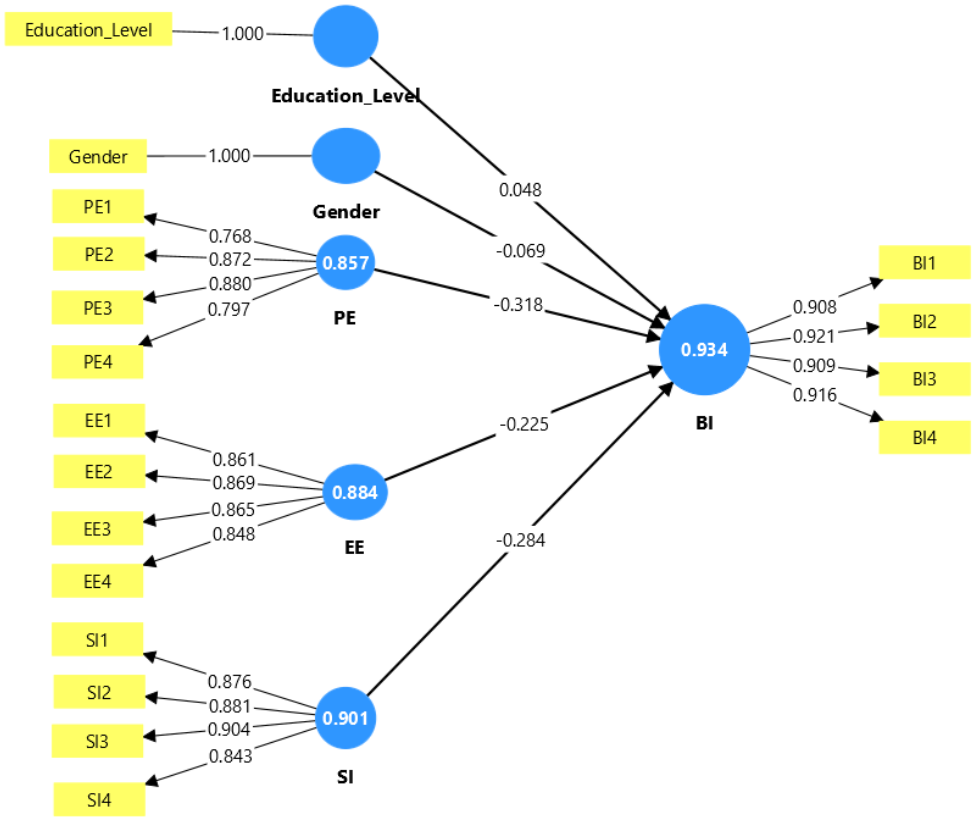


Figure 2: PLS-SEM Structural Model and Path Coefficients

Table 4: Constructs and Measurement Model Result

	Factor Loadings	VIF
Behavioral Intention $\alpha = 0.934$ $CR = 0.953$ $AVE = 0.834$		
BI1. As a university faculty member, I intend to utilize AI.	0.908	3.416
BI2. As a university faculty member, I intend to utilize AI.	0.921	3.721
BI3. As a university faculty member, I will continue to utilize AI.	0.909	3.244
BI4. As a university faculty member, I will recommend AI to my colleagues.	0.916	3.660
Social Influence $\alpha = 0.901$ $CR = 0.930$ $AVE = 0.768$		
SI1. My co-faculty believes that utilizing AI in university settings is essential.	0.876	2.456
SI2. My co-faculty members advocate for the use of AI.	0.881	2.444
SI3. Many colleagues at the university utilize AI.	0.904	2.823
SI4. My university supports AI integration in education.	0.843	2.528

Effort Expectancy *α = 0.884 CR = 0.920 AVE = 0.741*		
EE1. AI is user-friendly and accessible for academic purposes.	0.861	2.267
EE2. I can effectively teach my students to utilize AI.	0.869	2.529
EE3. AI is user-friendly for my academic needs.	0.865	2.237
EE4. Learning to use AI is a straightforward process.	0.848	2.123
Performance Expectancy *α = 0.857 CR = 0.899 AVE = 0.690*		
PE1. AI can enhance my teaching effectiveness.	0.768	1.886
PE2. AI can significantly enhance my teaching performance at the university.	0.872	2.012
PE3. AI enhances my productivity at the university.	0.880	2.055
PE4. AI can improve my skills to better achieve my academic goals.	0.797	1.938
Gender α = *1.000 CR = 1.000 AVE = 1.000*	1.000	1.000
Educational Level α = *1.000 CR = 1.000 AVE = 1.000*	1.000	1.000

Table 5: Discriminant Validity Assessment Using the HTMT Ratio

	BI	EE	Education Level	Gender	PE	SI
BI						
EE	0.186					
Education Level	0.076	0.104				
Gender	0.035	0.036	0.016			
PE	0.250	0.093	0.076	0.194		
SI	0.196	0.174	0.040	0.041	0.225	

Discriminant validity was assessed using the HTMT ratio. The values ranged from 0.016 to 0.250, all substantially below the recommended threshold of 0.85, indicating that the constructs were empirically distinct from one another. This is summarized in Table 5.

Structural Model Assessment

The structural model yielded an R^2 of 0.171 and an adjusted R^2 of 0.166 for BI, indicating that PE, EE, SI, gender, and educational level collectively explained 17.1% of the variance in Behavioral Intention. This represents relatively low explanatory power, suggesting that other factors not included in the model may account for a substantial portion of BI.

The effect size (f^2) results showed that PE (0.112), SI (0.091), and EE (0.059) had small effects on BI, while gender and educational level (both 0.001) had negligible effects. PE demonstrated the largest effect among the predictors. Model fit was satisfactory based on an SRMR of 0.048.

The NFI values of 0.889 for the saturated model and 0.887 for the estimated model were slightly below the conventional 0.90 criterion, indicating acceptable but not strong model fit.

Direct Effects and Hypothesis Testing

Bootstrapping with 5,000 resamples showed that PE had a significant negative relationship with BI ($\beta = -0.318$, $t = 11.965$, $p < .001$), supporting H1. EE also had a significant negative relationship with BI ($\beta = -0.225$, $t = 7.475$, $p < .001$), supporting H2. Similarly, SI significantly and negatively predicted BI ($\beta = -0.284$, $t = 9.161$, $p < .001$), supporting H3. In contrast, gender had a negative but non-significant relationship with BI ($\beta = -0.069$, $t = 1.028$, $p = .304$), while educational level had a positive and non-significant relationship ($\beta = 0.048$, $t = 0.695$, $p = .487$). Thus, the hypotheses concerning gender and educational level were not supported. A summary of the path coefficients, significance test and hypothesis decisions is presented in Tale 6. Overall, PE, EE, and SI were significant predictors of BI, with PE showing the strongest negative path coefficient and largest effect size.

Table 6: Research Hypotheses Summary

Hypotheses	Relationship	Path Coefficient (β)	t-value	p-value	Supported?
H1	PE - BI	-0.318	0.027	0.000	Supported
H2	EE - BI	-0.225	7.475	0.000	Supported
H3	SI - BI	-0.284	9.161	0.000	Supported
H4	Gender - BI	-0.069	1.028	0.304	Not Supported
H5	Educational Level - BI	0.048	0.695	0.487	Not Supported

6. Discussion and Implications

6.1 The AI Adoption Paradox

The findings reveal a notable departure from the conventional UTAUT expectation that Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) positively influence Behavioral Intention (BI). All three constructs showed significant negative relationships with BI, with PE having the strongest path ($\beta = -.318$, $p < .001$), followed by SI ($\beta = -.284$, $p < .001$) and EE ($\beta = -.225$, $p < .001$). This pattern suggests an AI adoption paradox, in which recognizing the usefulness and ease of AI, or being exposed to social and institutional encouragement, may coexist with greater hesitation toward adoption among university faculty.

The negative PE relationship is consistent in direction with Adigun et al. (2025), who reported a significant negative PE to BI relationship among Nigerian pre-service teachers (β = −.451). In the present context, greater recognition of AI's capabilities may also make faculty more aware of concerns involving academic integrity, reliability of AI-generated outputs, pedagogical judgment, and changes required in teaching and assessment practices. Thus, perceived usefulness may coexist with concerns that temper willingness to adopt AI. This interpretation is consistent with the broader observation that technology adoption in educational settings is influenced by contextual and implementation challenges (Abbad, 2021; Almaiah et al., 2020).

The significant negative EE to BI relationship indicates that technical ease of use does not necessarily translate into stronger adoption intention. Tian et al. (2024) similarly reported a negative, although non-significant, EE to BI relationship (β = −.057, p = .350) among Chinese graduate students using AI chatbots. For faculty, the effort associated with AI adoption may extend beyond learning how to operate a tool to include verifying outputs, redesigning learning activities and assessments, and determining appropriate boundaries for AI use. Research on educational technology likewise emphasizes that technology integration involves broader instructional and organizational changes rather than merely technical usability (Timotheou et al., 2022; Almaiah et al., 2020).

SI also showed a significant negative relationship with BI. This is consistent in direction with Adigun et al. (2025), who reported a significant negative SI to BI relationship (β = −.238, p = .002). Although social influence is intended to reflect encouragement from important others, institutional expectations or peer pressure may not necessarily increase adoption when faculty perceive AI initiatives as externally driven or insufficiently aligned with professional practice. This interpretation is consistent with evidence that technology acceptance can vary across educational and contextual settings (Abbad, 2021; Dwivedi et al., 2020; Raza et al., 2021).

6.2 Demographic Variables

Gender and educational level were not significant predictors of BI. Gender had a negative but non-significant relationship (β = −.069, p = .304), while educational level had a positive but non-significant relationship (β = .048, p = .487). Both had negligible effect sizes (f^2 = .001), indicating limited contribution to explaining AI adoption intention in the present model. Recent research similarly suggests that demographic effects on AI adoption may be limited or context-dependent. Tian et al. (2024) found no significant gender moderation across key UTAUT relationships, while Kilat (2026) found that sex had a limited moderating role in a Philippine

higher-education AI adoption model. Trinh et al. (2025) likewise demonstrated that the influence of educational qualification differed between Vietnam and Taiwan, suggesting that demographic effects may depend on context rather than operate consistently across settings.

6.3 Explanatory Power and Implications

The model explained 17.1% of the variance in BI ($R^2 = .171$; adjusted $R^2 = .166$), indicating relatively modest explanatory power. PE had the largest effect size ($f^2 = .112$), followed by SI ($f^2 = .091$) and EE ($f^2 = .059$), although all three represented small effects. Gender and educational level had negligible effects ($f^2 = .001$ each). These findings indicate that faculty perceptions of AI are more relevant to BI than the demographic variables examined, while also suggesting that additional psychological, ethical, technological, and organizational factors may be needed to explain AI adoption intention more fully.

6.4 Theoretical Implications

The findings contribute to UTAUT research by showing that the relationships between technology-acceptance constructs and behavioral intention may vary across contexts. The significant negative relationships observed for PE, EE, and SI challenge a straightforward application of the conventional positive UTAUT relationships to AI adoption among university faculty. Rather than invalidating UTAUT, the findings suggest that AI adoption may involve contextual considerations beyond traditional acceptance beliefs, particularly academic integrity, pedagogical responsibility, professional autonomy, and institutional governance. This extends empirical evidence on AI adoption to university faculty in the Philippine higher-education context.

6.5 Practical Implications

The findings suggest that universities should not rely solely on demonstrating AI's usefulness, ease of use, or institutional endorsement. AI initiatives should be accompanied by clear guidance on responsible use, academic integrity, privacy, transparency, and human oversight. Faculty development should address not only technical skills but also instructional integration, assessment redesign, output verification, and appropriate use of AI. Involving faculty in the development and implementation of AI policies may also help ensure that institutional initiatives are responsive to professional practice rather than perceived as externally imposed requirements. Such an approach is particularly relevant given the negative relationship observed between Social Influence and Behavioral Intention.

7. Conclusion

This study examined behavioral intention toward AI adoption among 820 university faculty members from seven state universities in the Philippines using a modified UTAUT framework and PLS-SEM. The measurement model demonstrated satisfactory reliability, convergent validity, and discriminant validity. The structural results showed significant negative relationships between PE, EE, and SI and BI, while gender and educational level were not significant predictors. PE demonstrated the strongest negative path and largest effect size, although its effect remained small. The model explained 17.1% of the variance in BI, indicating that factors beyond the UTAUT variables examined may contribute substantially to faculty AI adoption intention.

Overall, the findings highlight an AI adoption paradox, whereby positive perceptions of AI's usefulness and ease of use, as well as social or institutional influence, may coexist with hesitation toward adoption. AI adoption in higher education therefore appears to extend beyond conventional technology-acceptance considerations and may also involve ethical, pedagogical, professional, and organizational concerns. Universities should consequently balance technological capability with responsible-use guidance, faculty autonomy, and appropriate institutional support.

8. Recommendations and Future Studies

Future research should extend the model by examining factors that may explain the relatively low R^2 of .171, including AI literacy and self-efficacy, trust, perceived risk, facilitating conditions, institutional support, privacy concerns, ethical concerns, and attitudes toward AI. These factors may provide a more comprehensive explanation of faculty AI adoption intention.

Future studies should also examine actual AI use rather than behavioral intention alone, since intention does not necessarily translate into actual use. Longitudinal research could further examine how faculty perceptions and adoption behavior change as AI becomes more familiar and institutional policies develop. Multi-group analyses may also determine whether the observed relationships differ across academic disciplines, institutions, or levels of AI experience.

Finally, the use of convenience and purposive sampling limits the generalizability of the findings. Future research should consider broader, multi-institutional, and probability-based samples that include public and private higher-education institutions across different Philippine regions. Qualitative or mixed-methods studies are also recommended to further investigate the

reasons behind the negative relationships, particularly the roles of academic integrity, pedagogical autonomy, workload, and other AI-related concerns.

Declaration on the use of AI in the writing process

During the preparation of this study, the authors used ChatGPT to enhance readability and refine the language, as well as other AI tools for data visualization. After using these tools or services, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

References

Abbad, M. (2021). Using the UTAUT model to understand students' usage of e-learning systems in developing countries. *Education and Information Technologies, 26,* 7205 - 7224. https://doi.org/10.1007/s10639-021-10573-5

Adigun, O. T., Tijani, F. A., Haihambo, C. K., & Enock, S. L. (2025). Understanding pre-service teachers' intention to adopt and use artificial intelligence in Nigerian inclusive classrooms. *Frontiers in Education, 10,* 1519472. Article

Ajai, S. G., & Sanjaya, M. (2006). Factor analysis in psychology and education. *Journal of the Indian Academy of Applied Psychology, 32*(2), 154–158.

Almaiah, M., Al-Khasawneh, A., & Althunibat, A. (2020). Exploring the critical challenges and factors influencing the E-learning system usage during COVID-19 pandemic. *Education and Information Technologies, 25,* 5261 - 5280. https://doi.org/10.1007/s10639-020-10219-y

Ayaz, A., & Yanartaş, M. (2020). An analysis on the unified theory of acceptance and use of technology theory (UTAUT): Acceptance of electronic document management system (EDMS). 100032. https://doi.org/10.1016/j.chbr.2020.100032

Baashar, Y., Alkawsi, G., Ali, N., Alhussian, H., & Bahbouh, H. T. (2021). Predicting student's performance using machine learning methods: A systematic literature review. *2021 International Conference on Computer & Information Sciences (ICCOINS),* 357-362. https://doi.org/10.1109/iccoins49721.2021.9497185

Dwivedi, Y. K., Hughes, L., Coombs, C., Constantiou, I., Duan, Y., Edwards, J. S., Gupta, B., Lal, B., Misra, S., Prashant, P., Raman, R., Rana, N. P., Samothrakis, S., & Williams, M.

D. (2020). Impact of COVID-19 pandemic on information management research and practice: Transforming education, work and life. *International Journal of Information Management, 55*, 102211. https://doi.org/10.1016/j.ijinfomgt.2020.102211

Goyal, A. (2025). AI as a Cognitive Partner: A Systematic Review of the Influence of AI on Metacognition and Self-Reflection in Critical Thinking. *International Journal of Innovative Science and Research Technology*. https://doi.org/10.38124/ijisrt/25mar1427

Hair, J. F., Hult, G. T. M., Ringle, C. M., Sarstedt, M., Danks, N. P., & Ray, S. (2022). *A primer on partial least squares structural equation modeling (PLS-SEM)* (3rd ed.). Sage.

Hashim, A. S., Awadh, W. A., & Hamoud, A. K. (2020). Student Performance Prediction Model based on Supervised Machine Learning Algorithms. *IOP Conference Series: Materials Science and Engineering, 928*. https://doi.org/10.1088/1757-899x/928/3/032019

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*, 115–135. https://doi.org/10.1007/s11747-014-0403-8

Ifenthaler, D., & Yau, J. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development, 68*, 1961 - 1990. https://doi.org/10.1007/s11423-020-09788-z

Izquierdo-Condoy, J., Arias-Intriago, M., Tello-De-La-Torre, A., Busch, F., & Ortíz-Prado, E. (2025). Generative Artificial Intelligence in Medical Education: Enhancing Critical Thinking or Undermining Cognitive Autonomy?. *Journal of Medical Internet Research, 27*. https://doi.org/10.2196/76340

Kaiser, H. F. (1974). An index of factorial simplicity. *Psychometrika, 39*(1), 31–36. https://doi.org/10.1007/BF02291575

Kilat, R. V. (2026). Modeling behavioral intention toward generative AI use in higher education English language teaching. *Frontiers in Education, 11*, 1743380. https://doi.org/10.3389/feduc.2026.1743380

Perez, R. C. L. (2024). AI in higher education: Faculty perspective towards artificial intelligence through UTAUT approach. *Ho Chi Minh City Open University Journal of*

Science - Social Sciences, 14(4), 32–50. https://doi.org/10.46223/HCMCOUJS.soci.en.14.4.2851.2024

Rana, V., Verhoeven, B., & Sharma, M. (2025). Empowering Creativity and Critical Thinking: The Transformative Role of Generative AI in Design Thinking Pedagogy. *Journal of University Teaching and Learning Practice*. https://doi.org/10.53761/tjse2f36

Raza, S. A., Qazi, W., Khan, K. A., & Salam, J. (2021). Social isolation and acceptance of the learning management system (LMS) in the time of COVID-19 pandemic: An expansion of the UTAUT model. *Journal of Educational Computing Research, 59*(2), 183–208. https://doi.org/10.1177/0735633120960421

Raza, S., Qazi, W., Khan, K., & Salam, J. (2020). Social Isolation and Acceptance of the Learning Management System (LMS) in the time of COVID-19 Pandemic: An Expansion of the UTAUT Model. *Journal of Educational Computing Research, 59*, 183 - 208. https://doi.org/10.1177/0735633120960421

Rusilowati, U., Narimawati, U., Wijayanti, Y., Rahardja, U., & Al-Kamari, O. A. (2024). Optimizing Human Resource Planning through Advanced Management Information Systems: A Technological Approach. *Aptisi Transactions on Technopreneurship (ATT)*. https://doi.org/10.34306/att.v6i1.390

Tahar, A., Riyadh, H. A., Sofyani, H., & Purnomo, W. (2020). Perceived Ease of Use, Perceived Usefulness, Perceived Security and Intention to Use E-Filing: The Role of Technology Readiness. The Journal of Asian Finance, Economics and Business. https://doi.org/10.13106/jafeb.2020.vol7.no9.537

Tian, W., Ge, J., Zhao, Y., & Zheng, X. (2024). AI chatbots in Chinese higher education: Adoption, perception, and influence among graduate students—An integrated analysis utilizing UTAUT and ECM models. *Frontiers in Psychology, 15*, 1268549.

Timotheou, S., Miliou, O., Dimitriadis, Y., Villagrá Sobrino, S., Giannoutsou, N., Cachia, R., Martínez Monés, A., & Ioannou, A. (2022). Impacts of digital technologies on education and factors influencing schools' digital capacity and transformation: A literature review. *Education and Information Technologies, 28*, 6695 - 6726. https://doi.org/10.1007/s10639-022-11431-8

Trinh, X.-C., Chen, S.-W., & Nguyen, X. T. M. (2025). Teachers' behavioral intentions to use artificial intelligence in education: A cross-country study. *Proceedings of the 9th International Conference on Education and E-Learning*, 299–304.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478. https://doi.org/10.2307/30036540

Xue, L., Rashid, A. M., & Sha, O. (2024). The Unified Theory of Acceptance and Use of Technology (UTAUT) in Higher Education: A Systematic Review. *SAGE Open, 14*. https://doi.org/10.1177/21582440241229570

Yu, H., & Guo, Y. (2023). Generative artificial intelligence empowers educational reform: Current status, issues, and prospects. *Frontiers in Education, 8*, 1183162. June. Frontiers Media SA.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators?. *International Journal of Educational Technology in Higher Education, 16*. https://doi.org/10.1186/s41239-019-0171-0

Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: a systematic review. *Smart Learning Environments, 11*. https://doi.org/10.1186/s40561-024-00316-7

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Professional Learning Communities as the Dominant Mediator of Learning-Centred Leadership in Chinese Higher Education

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ABSTRACT

Although leadership is widely associated with Teacher Professional Learning (TPL), limited evidence has compared the mechanisms through which leadership is linked to TPL in higher education. This study examines the mediating roles of Teacher Trust (TT), Teacher Agency (TA), and Professional Learning Communities (PLCs) in the relationship between deans' Learning-Centred Leadership (LCL) and TPL in colleges of foreign languages within Shandong provincial universities, China. Survey data were collected from 360 faculty members across 36 universities and analysed using Structural Equation Modelling (SEM).

The findings indicate that LCL did not have a significant direct relationship with TPL. Instead, leadership was associated with TPL through indirect pathways. Among the mediators, PLCs exhibited the strongest indirect effect (β = .170), followed by TA (β = .134) and TT (β = .087). A smaller but significant sequential pathway through TA and TT was also identified (β = .067). The findings suggest that leadership may be more strongly associated with faculty professional learning when collaborative professional learning structures are established. The study contributes to leadership research by comparing multiple mediating mechanisms within a single model and provides practical implications for faculty-level leadership in Chinese higher education.

Keywords

Learning-Centred Leadership; Teacher Professional Learning; Professional Learning Communities; Teacher Agency; Teacher Trust; Chinese Higher Education

1. Introduction

Teacher Professional Learning (TPL) has become a central concern in higher education as universities confront rising expectations for teaching quality, curriculum innovation, digital transformation, and international competitiveness. In increasingly complex academic environments, faculty members are expected not only to maintain disciplinary expertise but

also to continuously refine pedagogical knowledge, adapt to changing student needs, and respond to institutional reforms. As a result, sustained professional learning is now widely recognised as essential to educational quality and long-term institutional development. While individual motivation remains important, growing evidence suggests that faculty learning is strongly shaped by organisational conditions and leadership practices that either enable or constrain continuous development.

Within the broader leadership literature, Learning-Centred Leadership (LCL) has emerged as an influential framework for understanding how leaders promote professional learning and instructional improvement. Rather than focusing narrowly on administrative control or symbolic management, LCL emphasises leadership practices that place learning at the centre of organisational life, including articulating a shared learning vision, supporting professional growth, modelling learning behaviours, and creating conditions conducive to collaboration and improvement. Previous studies, particularly in school settings, have linked learning-centred forms of leadership to teacher development, instructional quality, and student outcomes. However, evidence from higher education remains comparatively limited, especially regarding leadership enacted at the faculty or college level.

This gap is particularly relevant in Chinese higher education. Existing studies of educational leadership in China have concentrated largely on primary and secondary schools, while the role of university deans in shaping academic and professional learning environments has received far less attention. Yet deans occupy a strategically important position between institutional policy and everyday academic practice. They are expected to implement reforms, coordinate resources, guide faculty development, and maintain teaching quality within their colleges. In provincial public universities, where resource constraints, heavy workloads, and performance pressures are often more pronounced, the leadership role of deans may be especially consequential.

At the same time, leadership influence on TPL is unlikely to operate through direct command or immediate behavioural control. In higher education contexts characterised by professional autonomy and collegial norms, leadership effects are often indirect, functioning through relational, psychological, and organisational mechanisms. Three mechanisms are particularly relevant: Teacher Trust (TT), Teacher Agency (TA), and Professional Learning Communities (PLCs). Trust reflects faculty confidence in the competence, fairness, and supportiveness of leaders and colleagues, thereby fostering psychological safety for collaboration and experimentation. Agency refers to teachers' capacity to act purposefully in shaping their own professional learning and practice. PLCs represent a more structural mechanism, involving shared vision, collaborative inquiry, reflective dialogue, and routinised collective learning.

Despite growing recognition of LCL as an important influence on TPL, limited evidence explains which mechanisms most strongly transmit leadership effects in higher education contexts, particularly in Chinese provincial universities. Although TT, TA, and PLCs have each

been associated with leadership and professional learning in prior research, these mechanisms are often examined separately rather than compared within a single model. Consequently, it remains unclear whether organisational collaboration mechanisms exert stronger influence than psychological mechanisms in supporting faculty professional learning. Addressing this gap is particularly important in universities, where faculty members are already highly educated professionals and opportunities for learning may depend more on organisational conditions than on individual motivation alone.

This issue is particularly evident in Chinese universities, where hierarchical governance arrangements, departmental silos, uneven resource allocation, and heavy teaching or administrative demands may limit spontaneous collaboration. Under such conditions, it remains unclear whether leadership exerts greater influence by institutionalising collaborative professional structures rather than relying primarily on interpersonal encouragement or symbolic support. Against this background, the present study examines the relative mediating roles of TT, TA, and PLCs in the relationship between deans' LCL and TPL in colleges of foreign languages in Shandong provincial universities, China. Drawing on survey data from 360 faculty members across 36 universities, the study employs Structural Equation Modelling (SEM) to compare the relative strength of these pathways.

In this study, the direct relationship refers to the association between LCL and TPL after the mediating variables are taken into account. The three hypothesised indirect pathways examine TT, TA, and PLCs separately as relational, individual psychological, and organisational mechanisms. The analysis also considers an exploratory sequential pathway through TA and TT. However, the main comparison concerns the three hypothesised single-mediator pathways, with particular attention to the organisational role of PLCs.

The study addresses three research questions:

RQ1. Does Learning-Centred Leadership have a direct relationship with Teacher Professional Learning?

RQ2. How do Teacher Trust, Teacher Agency, and Professional Learning Communities mediate the relationship between Learning-Centred Leadership and Teacher Professional Learning?

RQ3. Which mediating pathway exhibits the strongest indirect association with Teacher Professional Learning?

To guide the empirical analysis, the following hypotheses were proposed:

H1. Learning-Centred Leadership is positively associated with Teacher Professional Learning.

H2-a. Teacher Trust mediates the relationship between Learning-Centred Leadership and Teacher Professional Learning.

H2-b. Teacher Agency mediates the relationship between Learning-Centred Leadership and Teacher Professional Learning.

H2-c. Professional Learning Communities mediate the relationship between Learning-Centred Leadership and Teacher Professional Learning.

By comparing these mediating mechanisms within a single model, the study contributes to leadership research in higher education, extends understanding of leadership processes in a non-Western context, and offers practical insights for faculty-level leadership development.

2. Literature Review

2.1 Learning-Centred Leadership in Higher Education

Educational leadership scholarship has progressively shifted from managerial conceptions of leadership toward models that prioritise teaching quality, professional growth, and organisational learning. Within this development, Learning-Centred Leadership (LCL) has emerged as an influential perspective that places learning at the centre of leadership practice (Hallinger, 2011; Hallinger & Liu, 2022). LCL emphasises building a shared learning vision, supporting staff development, modelling continuous improvement, and aligning organisational systems with educational goals. Earlier studies, particularly in school settings, have linked learning-focused leadership to improved teacher development, instructional practice, and student outcomes (Leithwood & Sun, 2018).

Despite this growing literature, evidence from higher education remains relatively limited. Universities differ from schools in important ways: authority is more distributed, academic staff enjoy stronger professional autonomy, and leaders often rely on influence rather than direct supervision (Bush, 2020). As a result, the mechanisms through which leadership affects academic work may differ substantially from those observed in compulsory schooling. Several scholars have therefore called for more context-sensitive leadership research in universities, particularly outside Western systems (Walker & Hallinger, 2015; Hallinger, 2018).

2.2 Teacher Professional Learning in Universities

TPL is increasingly conceptualised as a continuous, work-embedded process rather than a series of isolated training events. It includes reflective practice, collaborative inquiry, curriculum innovation, engagement with research, and experimentation with teaching approaches (Vermunt, 2014). In higher education, the need for sustained faculty learning has intensified due to digital transformation, changing student expectations, internationalisation, and pressure to improve teaching quality (OECD, 2019).

However, studies of university professional development frequently report fragmented participation, uneven engagement, and overreliance on short-term workshops (Knight et al., 2006; Gosling, 2009). These limitations suggest that faculty learning depends not only on individual motivation but also on institutional environments that support ongoing development. Leadership therefore becomes relevant not as a controller of teaching, but as a shaper of the conditions under which professional learning can occur.

2.3 Teacher Trust as a Relational Mediator

Trust has long been recognised as a critical condition for professional collaboration and organisational improvement. Bryk and Schneider (2002) argued that relational trust supports risk-taking, honest dialogue, and willingness to engage in improvement efforts. In educational settings, trust in leaders is associated with stronger commitment, openness to change, and greater participation in collective learning activities.

In university contexts, trust may be especially valuable because academic work often depends on collegial cooperation rather than hierarchical enforcement. Where faculty perceive leaders as fair, competent, and supportive, they may be more willing to share difficulties, seek feedback, and participate in developmental initiatives. Nevertheless, trust alone may have limited practical effect if workload pressures, fragmented schedules, or weak collaboration systems remain unresolved. This suggests that trust is an important but potentially incomplete mechanism linking leadership to professional learning.

2.4 Teacher Agency as an Individual Mediator

TA refers to educators' capacity to act purposefully in shaping their professional practice and learning trajectories. Rather than being a fixed personal trait, agency is understood as emerging through the interaction between individuals and their environments (Biesta, Priestley, & Robinson, 2015). Agency includes initiative, adaptability, persistence, and the willingness to exercise professional judgement.

Research suggests that supportive leadership can strengthen agency by expanding participation, recognising expertise, and protecting autonomy (Priestley et al., 2015). Teachers with stronger agency are more likely to experiment, reflect, and pursue self-directed improvement. However, agency is also vulnerable to structural constraints. Even highly motivated faculty may struggle to innovate when time is scarce, incentives are unclear, or collaborative opportunities are absent. Consequently, agency may explain only part of the leadership–learning relationship.

2.5 Professional Learning Communities as an Organisational Mediator

PLCs provide a more collective and structural account of professional learning. PLCs are commonly characterised by shared vision, collaborative inquiry, reflective dialogue, deprivatised practice, and a commitment to continuous improvement (DuFour & Fullan, 2013). Olivier, Hipp, and Huffman (2010) further highlighted supportive leadership, shared values, and enabling conditions as central dimensions of effective PLCs.

A growing body of research links PLC participation to stronger teacher learning, innovation, and instructional improvement. Unlike purely psychological explanations, PLCs embed professional learning into regular organisational routines. This may be particularly important in higher education, where academic staff often work in disciplinary silos and professional learning can become individualised. By creating time, structures, and expectations for collaboration, PLCs transform isolated expertise into collective learning processes.

2.6 Organisational and Psychological Pathways of Leadership Influence

Much of the leadership literature has concentrated on psychological mechanisms such as motivation, trust, efficacy, and commitment. These factors are clearly relevant, as leadership involves meaning-making and relationships. Yet organisational scholars increasingly argue that formal structures, routines, and social systems also shape behaviour in powerful ways (Bolman & Deal, 2017). In universities, where faculty are already highly educated professionals, the primary obstacle to learning may be less about willingness and more about opportunity.

This distinction may be especially relevant in Chinese higher education. Studies have noted that Chinese universities often combine hierarchical governance with growing expectations for innovation and international competitiveness (Guo, 2020). Under such conditions, leadership encouragement may have limited effect unless accompanied by protected time, coordination mechanisms, and formal opportunities for collaborative inquiry. Therefore, it remains unclear whether PLCs function as a stronger mediator than TT or TA in transmitting leadership influence.

2.7 Research Gap

Although TT, TA, and PLCs have each been linked to leadership and professional learning, prior studies often examine them separately. Comparative evidence regarding their relative strength within a single model remains limited, particularly in higher education and non-Western contexts. This raises an important question: Which mechanism most strongly explains how leadership supports faculty professional learning?

Addressing this gap, the present study investigates the comparative mediating roles of Teacher Trust (TT), Teacher Agency (TA), and Professional Learning Communities (PLCs) in the relationship between deans' LCL and Teacher Professional Learning (TPL) in colleges of foreign languages in Shandong provincial universities, China. By comparing these mediating mechanisms within a single model, the study seeks to refine understanding of leadership processes in higher education and provide more precise guidance for academic leadership practice.

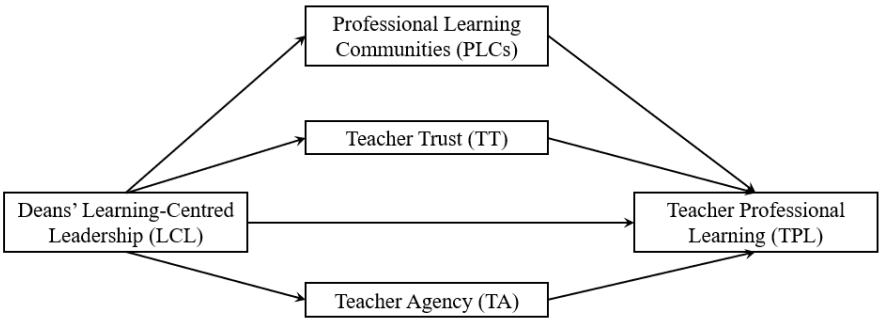


Figure 1: Conceptual Mediation Model of Learning-Centred Leadership and Teacher Professional Learning

Note. The TA → TT sequential pathway was examined as an exploratory extension and is not shown among the primary hypothesised pathways.

Figure 1 presents the conceptual model tested in the study. It includes the direct path from LCL to TPL and the three hypothesised indirect pathways through TT, TA, and PLCs. These mediators represent relational, individual psychological, and organisational mechanisms, respectively. The sequential pathway through TA and TT was examined as an exploratory extension and is therefore not shown among the primary hypothesised paths.

3. Methods

3.1 Research Design

This study employed a quantitative cross-sectional survey design to examine the mechanisms through which deans' LCL is associated with TPL in Chinese higher education. Building on prior evidence that leadership effects are often indirect rather than direct, the study focused on three mediating variables: TT, TA, and PLCs. Structural Equation Modelling (SEM) was selected as the primary analytical technique because it enables the simultaneous estimation of multiple latent constructs and direct as well as indirect relationships among variables (Kline, 2015).

The study formed part of a broader research project on leadership and faculty development in provincial universities in Shandong Province, China. For the present article, the analysis specifically emphasised the comparative mediating strength of TT, TA, and PLCs in the relationship between LCL and TPL.

3.2 Research Context and Participants

The study was conducted in Shandong Province, one of China's largest provincial higher education systems. At the time of data collection, 36 provincial public universities in Shandong contained colleges of foreign languages. These colleges were selected as the study context because they operate in environments characterised by rapid pedagogical change, international orientation, curriculum reform, and strong demands for teaching quality improvement.

The target population comprised full-time academic staff working in these colleges of foreign languages. To ensure balanced institutional representation, each college was treated as a cluster and 10 faculty members were selected from each institution. This process generated a final sample of 360 participants across 36 universities.

The sample size was considered adequate for SEM analysis. It exceeded the minimum sample guideline proposed by Krejcie and Morgan (1970) for a population of this scale and satisfied commonly accepted recommendations regarding sample-to-parameter ratios in latent variable modelling (Bentler & Chou, 1987; Kline, 2015).

3.3 Instrumentation and Questionnaire Development

Data were collected using a structured questionnaire consisting of 42 items measuring five constructs: Learning-Centred Leadership (LCL), Teacher Professional Learning (TPL), Teacher Trust (TT), Teacher Agency (TA), and Professional Learning Communities (PLCs). The questionnaire was developed by adapting established instruments widely used in previous educational leadership and professional learning research.

LCL items were informed by Hallinger's (2011) leadership framework, including dimensions related to learning vision, professional support, programme management, and modelling learning-oriented behaviour. TPL items were adapted from prior studies on TPL and measured reflective practice, collaboration, experimentation, and knowledge updating. TT items examined trust in leaders and colleagues, while TA items assessed initiative, confidence, and purposeful professional action. PLC items were adapted from the Professional Learning Community Assessment–Revised (PLCA-R) developed by Olivier et al. (2010), including shared leadership, shared values, collective learning, supportive relationships, and enabling structures.All questionnaire items were translated into Chinese and then back-translated into English following Brislin's (1970) procedure to ensure linguistic equivalence and conceptual consistency across languages. Responses were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

To strengthen content validity, the draft questionnaire was reviewed by a panel of five experts in educational leadership and research methodology. Using the Index of Item-Objective Congruence (IOC), items that did not meet the recommended criterion were revised or removed. A pilot study was subsequently conducted with 30 faculty members from a provincial university not included in the main sample. Feedback regarding item clarity, wording, and contextual appropriateness was collected, and minor revisions were made to improve comprehensibility.

Prior to the structural analysis, confirmatory factor analysis (CFA) was conducted to examine the construct validity of the measurement model. All factor loadings exceeded the recommended threshold of .50.

Reliability and convergent validity were further assessed using Cronbach's alpha coefficients, composite reliability (CR), and average variance extracted (AVE). Cronbach's alpha coefficients were calculated using the original questionnaire items for each construct, whereas CR and AVE were assessed based on the CFA measurement model employed in the SEM analysis. Table 1 presents the reliability and convergent validity results.

Table 1: Reliability and Convergent Validity of the Measurement Model

Construct	Cronbach's α	CR	AVE
LCL	.963	.963	.866
TT	.964	.964	.899
TA	.974	.975	.907
PLCs	.979	.979	.888
TPL	.967	.968	.882

Note. CR = Composite Reliability; AVE = Average Variance Extracted.

All constructs exceeded the recommended thresholds for internal consistency (α and CR > .70) and convergent validity (AVE > .50), supporting the reliability and validity of the measurement model.

3.4 Data Collection Procedures

After institutional access was obtained, questionnaires were distributed to faculty members across the participating universities. Participation was voluntary, and respondents were informed that their answers would remain anonymous and be used only for academic research purposes. Completed responses were screened for missing data, response inconsistency, and outliers before analysis.

3.5 Data Analysis

Data analysis was conducted using SPSS and Mplus for Windows. Preliminary analyses included descriptive statistics, reliability analysis, and correlation analysis. Internal consistency of the scales was assessed using Cronbach's alpha coefficients.

Confirmatory Factor Analysis (CFA) was conducted prior to the structural analysis to examine the construct validity of the questionnaire. All factor loadings exceeded the recommended threshold of .50, supporting acceptable construct validity.

Structural Equation Modelling (SEM) was subsequently employed to examine the direct and indirect relationships among LCL, TT, TA, PLCs, and TPL. Model fit was evaluated using multiple fit indices, including the chi-square statistic (χ^2), Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardised Root Mean Square Residual (SRMR). The interpretation of model fit followed the criteria recommended by Hu and Bentler (1999).

The analysis distinguished among one direct effect, three single-mediator indirect effects, and one exploratory sequential indirect effect. The direct effect was represented by the path from LCL to TPL after TT, TA, and PLCs were included in the model. The three single-mediator indirect effects were estimated separately through TT, TA, and PLCs. The sequential indirect effect represented the ordered pathway from LCL through TA and then TT to TPL.

Indirect effects were estimated using bias-corrected bootstrapping with 5,000 resamples. Statistical significance was determined by whether the 95% bias-corrected confidence intervals included zero. To address the research questions and hypotheses, the standardised indirect effects through TT, TA, and PLCs were compared. These three single-mediator pathways constituted the primary comparative analysis, whereas the sequential pathway through TA and TT was examined as an additional exploratory mechanism.

3.6 Ethical Considerations

The study followed standard ethical principles for social science research. Participation was voluntary, informed consent was obtained, and respondents' identities were not collected. Data were analysed and reported only in aggregated form to ensure confidentiality.

4. Results

4.1 Preliminary Findings

Descriptive statistics, reliability analyses, and correlation analyses indicated satisfactory psychometric properties across all study variables. As shown in Table 2, mean scores ranged from 3.188 to 3.531, indicating generally positive perceptions of Learning-Centred Leadership, Teacher Trust, Teacher Agency, Professional Learning Communities, and Teacher Professional Learning. All study variables were positively and significantly correlated, providing preliminary support for the proposed relationships among the constructs.

The measurement model demonstrated an excellent fit to the data. The CFA results indicated that the latent constructs were empirically distinguishable and suitable for subsequent structural analysis. Reliability and validity statistics further supported the adequacy of the measurement model.

Table 2: Correlation Matrix Among Latent Variables

Variable	Mean	SD	1	2	3	4	5
1. LCL	3.520	0.571	1				
2. TT	3.479	0.615	.627	1			
3. TA	3.506	0.648	.563	.682	1		
4. PLC	3.531	0.622	.695	.538	.515	1	
5. TPL	3.188	0.611	.529	.564	.554	.536	1

Note. All correlations are positive and statistically significant ($p < .001$).

4.2 Structural Model Fit

Table 3: Model Fit Indices for the Structural Model

Fit Index	Recommended Threshold	Obtained Value
χ^2	—	193.277
df	—	181
p-value	> .05	.253
χ^2/df	< 3.00	1.07
CFI	> .95	.999
TLI	> .95	.999
RMSEA	< .06	.014
SRMR	< .08	.040

The structural equation model demonstrated an excellent fit to the data. Model fit was evaluated using multiple indices, including χ^2, CFI, TLI, RMSEA, and SRMR. As shown in Table 3, all fit indices met or exceeded commonly recommended criteria, indicating that the proposed model adequately represented the relationships among the study variables.

4.3 Direct Relationship Between Learning-Centred Leadership and Teacher Professional Learning

The direct path from Learning-Centred Leadership (LCL) to Teacher Professional Learning (TPL) was positive but not statistically significant (β = .098, p = .207). Therefore, H1 was not supported. This result suggests that deans' LCL was not directly associated with higher levels of faculty professional learning once the mediating variables were included in the model. The finding is consistent with the interpretation that leadership may influence professional learning primarily through indirect pathways rather than through a direct relationship.

4.4 Comparative Strength of the Three Mediating Pathways

The analysis identified three statistically significant single-mediator indirect effects and one significant exploratory sequential indirect effect. The indirect effect through Professional Learning Communities (PLCs) was the largest (β = .170, 95% BC CI [.077, .262]), followed by Teacher Agency (TA) (β = .134, 95% BC CI [.061, .207]) and Teacher Trust (TT) (β = .087, 95% BC CI [.032, .142]). These findings supported H2a, H2b, and H2c. In addition, the exploratory sequential indirect pathway from LCL through TA and TT to TPL was statistically significant (β = .067, 95% BC CI [.023, .112]). Among the three hypothesised single-mediator pathways, PLCs exhibited the largest standardised indirect effect.

Table 4: Standardized Indirect Effects of LCL on TPL

Pathway	β	95% BC CI
LCL → PLC → TPL	.170	[.077, .262]
LCL → TA → TPL	.134	[.061, .207]
LCL → TT → TPL	.087	[.032, .142]
LCL → TA → TT → TPL	.067	[.023, .112]

Note. BC CI = Bias-Corrected Confidence Interval; β = Standardized Indirect Effect.

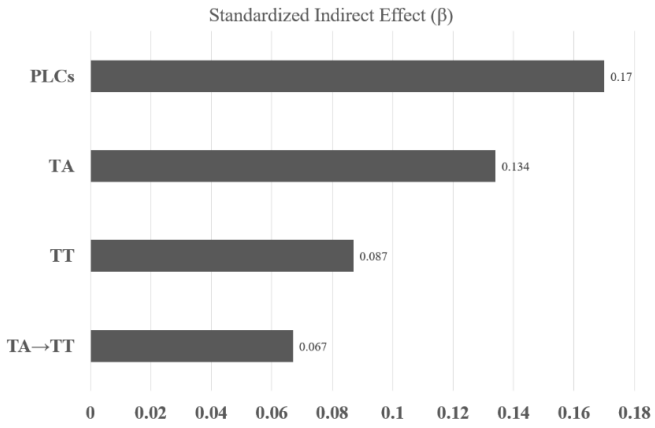


Figure 2: Standardized Indirect Effects of the Four Mediating Pathways

These findings suggest that collaborative organisational structures may represent the most influential mechanism through which leadership is associated with faculty professional learning. Although leadership was also positively associated with teachers' agency and trust, the comparatively larger indirect effect through PLCs indicates that shared professional practices, collective learning, and supportive organisational conditions may play a particularly important role in transmitting leadership influence.

4.5 Summary of Findings

The results indicate that the relationship between LCL and TPL was primarily indirect. The direct path was positive but not statistically significant, and H1 was therefore not supported. In contrast, the indirect effects through TT, TA, and PLCs were all significant, supporting H2a, H2b, and H2c. The exploratory sequential pathway through TA and TT was also significant, although its effect was smaller. Among the three hypothesised single-mediator pathways, PLCs showed the largest standardised indirect effect, followed by TA and TT.

5. Discussion

The results show that LCL was associated with TPL primarily through indirect rather than

direct pathways. Although H1 was not supported, the significant indirect effects through TT, TA, and PLCs supported H2a, H2b, and H2c. The exploratory sequential pathway through TA and TT was also significant. Most importantly, PLCs produced the largest standardised indirect effect among the three hypothesised single-mediator pathways. The discussion therefore focuses on why collaborative organisational structures may be particularly important in linking leadership and faculty professional learning.

5.1 Why Professional Learning Communities Emerged as the Strongest Pathway

One of the central findings of this study is that PLCs emerged as the comparatively strongest mediating pathway linking deans' LCL and TPL within the present model.

One explanation lies in the professional nature of academic work. University faculty members are highly educated specialists who often possess strong intrinsic motivation and disciplinary expertise. Unlike settings where employees depend heavily on close supervision, academics typically manage much of their own teaching and professional activity. Under such conditions, leadership may add limited value through direct motivation alone. Instead, leadership becomes influential when it creates environments in which professionals can learn from one another.

PLCs provide exactly such an environment. Through shared inquiry, peer dialogue, curriculum collaboration, and reflective routines, PLCs transform individual expertise into collective learning. This helps explain why the PLC pathway exceeded trust and agency in strength.

This finding is consistent with studies suggesting that leadership is more strongly associated with teacher learning through organisational conditions than through direct managerial intervention (Hallinger, 2022; Leithwood & Sun, 2018). It also extends PLC research by demonstrating that collaborative structures may be more influential than psychological mechanisms in Chinese higher education.

5.2 Why PLCs May Matter More Than Trust

Trust remains an important foundation for professional cooperation. Faculty are more willing to exchange ideas, discuss difficulties, and participate in change when leaders are perceived as fair and supportive. However, trust by itself does not guarantee sustained learning activity.

Faculty members may trust their dean yet still work in isolation if there is no scheduled collaboration time, no shared platform for exchange, and no institutional encouragement for collective improvement. In this sense, trust is relationally valuable but structurally limited. PLCs may help translate positive relationships into recurring professional practice. Therefore, collaboration systems may generate stronger practical outcomes than trust alone.

5.3 Why PLCs May Matter More Than Agency

TA was also a meaningful mediator, indicating that leadership can strengthen confidence, initiative, and professional ownership. This aligns with prior research showing that empowered

educators are more likely to innovate and engage in reflective improvement.

Nevertheless, agency often depends on opportunity structures. Even proactive faculty may struggle to sustain innovation when workloads are heavy, incentives are weak, or teaching schedules prevent collaboration. Agency without organisational support can remain individual intention rather than collective change. PLCs may provide a platform through which agency can be exercised more productively and shared with others.

5.4 Structural Constraints in Chinese Provincial Universities

The dominance of PLCs may be especially relevant in Chinese universities. Many institutions operate under hierarchical administrative arrangements while simultaneously pursuing innovation, internationalisation, and teaching reform. In such environments, faculty learning can be constrained by fragmented communication, departmental silos, and uneven access to development resources.

Under these conditions, leadership encouragement alone may have limited reach. What matters more is whether leaders institutionalise collaboration through schedules, incentives, and shared routines. When deans establish regular peer learning mechanisms, support teaching communities, and legitimise collaborative inquiry, professional learning becomes more sustainable.

When deans establish regular peer learning mechanisms, support teaching communities, and legitimise collaborative inquiry, professional learning becomes more sustainable.

5.5 Conclusion

This study suggests that leadership in universities may be more strongly associated with professional learning when embedded within collaborative professional learning structures. Although TT and TA both played meaningful mediating roles, PLCs exhibited the largest standardised indirect effect among the three hypothesised single-mediator pathways linking deans' LCL and TPL within the present model. The exploratory sequential pathway through TA and TT provided an additional perspective on how leadership may be associated with professional learning. One possible interpretation is that learning-centred leadership may first strengthen faculty members' sense of agency, which may subsequently contribute to stronger trust before being associated with professional learning. However, because this pathway was not formally hypothesised, it should be interpreted cautiously as a supplementary finding rather than a central conclusion of the study.

For higher education leaders, the findings suggest that collaborative organisational arrangements may play a particularly important role alongside psychological mechanisms in supporting faculty professional learning in Chinese higher education. Overall, the findings reinforce the importance of viewing leadership as an organisational process rather than solely as an interpersonal one.

6. Practical Implications

The practical implications emerging from the study primarily concern how universities can build and sustain collaborative professional learning in everyday academic practice. The findings suggest that deans may strengthen Teacher Professional Learning (TPL) more effectively by building stable conditions for collaboration rather than relying primarily on encouragement or occasional training activities. Given that Professional Learning Communities (PLCs) emerged as the strongest indirect pathway linking leadership and faculty learning within the present model, leadership practice may benefit from greater emphasis on creating systems that make professional exchange routine, practical, and sustainable. This aligns with research suggesting that professional learning is most effective when embedded within everyday professional work rather than treated as a separate event (DuFour & Fullan, 2013; Vermunt, 2014).

First, deans can create protected time for collaborative work. One of the most common barriers to faculty learning is the lack of time caused by teaching loads, administrative responsibilities, and research pressure. When collaboration depends only on personal willingness outside formal schedules, participation is often inconsistent. Setting regular time each month for peer discussion, joint planning, or teaching review can turn collaboration from an optional activity into a normal professional expectation. Prior research has similarly highlighted protected time as a foundational condition for sustained collaborative professional learning (Olivier et al., 2010; Stoll et al., 2006).

Second, deans could support regular peer learning routines. Many teachers improve through informal conversations with colleagues, but informal exchange is uneven and often limited to familiar networks. More consistent progress can be achieved through organised peer observation, lesson sharing, curriculum meetings, and reflective teaching forums. Studies on collaborative learning cultures suggest that regular professional dialogue improves both instructional reflection and collective problem-solving capacity (DuFour & Fullan, 2013).

Third, deans are likely to benefit from providing modest resources for collaborative innovation. Faculty teams are more likely to experiment when small grants, digital tools, or curriculum development support are available. Even limited internal funding can help transform ideas into practical teaching improvements. Leadership support through resource allocation has been identified as an important mechanism linking leadership with professional learning outcomes (Hallinger, 2011).

Fourth, recognition systems should value collective contribution as well as individual achievement. In many universities, promotion and evaluation systems focus heavily on personal outputs such as publications or individual awards. If institutions seek stronger professional learning cultures, they should also recognise mentoring, curriculum teamwork, PLC participation, and contributions to shared teaching improvement. What institutions reward often shapes what staff prioritise.

Fifth, deans should strengthen communication across departments and teaching groups. In many colleges, effective practices remain within small units and are not shared widely. Cross-department workshops, teaching showcases, and thematic learning groups can reduce isolation and widen access to useful experience. This is particularly important in universities where disciplinary boundaries can limit everyday interaction.

Finally, leadership visibility should be connected to learning rather than ceremony. Faculty are more likely to engage when leaders participate in discussions, listen to practical concerns, and respond to teaching needs. Trust in leadership is strengthened when support is experienced through everyday actions rather than formal rhetoric alone (Bryk & Schneider, 2002).

Taken together, these implications suggest that sustainable TPL in higher education may depend less on isolated individual effort and more on the extent to which collaborative learning is embedded within everyday organisational practice.

7. Conclusion

This study examined how deans' Learning-Centred Leadership (LCL) was associated with Teacher Professional Learning (TPL) in colleges of foreign languages in Shandong provincial universities. The findings showed that leadership did not have a significant direct effect on faculty professional learning. Instead, the relationship was primarily explained through indirect pathways involving Teacher Trust (TT), Teacher Agency (TA), and Professional Learning Communities (PLCs).

Among these pathways, PLCs emerged as the strongest indirect pathway, followed by TA and TT. This suggests that leadership in higher education may have greater impact when it creates conditions for shared learning, regular collaboration, and collective improvement. Trust and agency remained important mechanisms, although their indirect effects were smaller than those associated with PLCs. The findings also support broader arguments that leadership effects are often indirect and shaped by organisational context (Leithwood & Sun, 2018).

The study contributes to current scholarship in two ways. First, it extends leadership research by showing that faculty professional learning should not be explained only through psychological variables such as trust and agency. Organisational arrangements may play a comparatively larger role than purely psychological mechanisms. Second, it provides evidence from a Chinese provincial university context, where research on faculty-level leadership remains comparatively limited (Hallinger, 2018).

From a practical perspective, the findings suggest that deans seeking stronger faculty professional learning should focus less on symbolic leadership and more on creating workable systems for peer exchange, shared inquiry, and continuing development. Leadership may become more effective when collaborative professional learning is embedded within the everyday academic life of the college.

7.1 Limitations and Future Research

Several limitations should be acknowledged. First, the study employed a cross-sectional survey design, which limits the ability to draw causal conclusions regarding the relationships among the variables. Second, the data were collected exclusively from colleges of foreign languages in provincial universities in Shandong Province, China. Therefore, caution is needed when generalising the findings to other disciplines, institutional types, or national contexts. Third, all measures relied on self-reported perceptions of faculty members. Although this approach was appropriate for examining leadership and professional learning experiences, common method bias and social desirability effects cannot be completely ruled out. Finally, the study adopted a quantitative approach and did not incorporate qualitative evidence that might provide deeper insight into how leadership practices shape professional learning processes.

Future research may address these limitations by employing longitudinal designs, including multiple disciplinary contexts, and combining quantitative and qualitative methods. Comparative studies across regions and countries may also help determine whether the patterns observed in this study are applicable to other higher education settings.

References

Biesta, G., Priestley, M., & Robinson, S. (2015). The role of beliefs in teacher agency. *Teachers and Teaching, 21*(6), 624–640. https://doi.org/10.1080/13540602.2015.1044325

Bentler, P. M., & Chou, C.-P. (1987). Practical issues in structural modeling. *Sociological Methods & Research, 16*(1), 78–117. https://doi.org/10.1177/0049124187016001004

Bolman, L. G., & Deal, T. E. (2017). *Reframing organizations: Artistry, choice, and leadership* (6th ed.). Jossey-Bass.

Brislin, R. W. (1970). Back-translation for cross-cultural research. *Journal of Cross-Cultural Psychology, 1*(3), 185–216. https://doi.org/10.1177/135910457000100301

Bryk, A. S., & Schneider, B. (2002). *Trust in schools: A core resource for improvement*. Russell Sage Foundation.

Bush, T. (2020). *Theories of educational leadership and management* (5th ed.). Sage.

DuFour, R., & Fullan, M. (2013). *Cultures built to last: Systemic PLCs at work*. Solution Tree Press.

Gosling, D. (2009). Educational development in the United Kingdom: A complex and contradictory reality. *International Journal for Academic Development, 14*(1), 5–18.

https://doi.org/10.1080/13601440802659222

Guo, J. (2020). Governance reform and academic leadership in Chinese higher education. *Higher Education Policy, 33*(4), 621–639.

Hallinger, P. (2011). Leadership for learning: Lessons from 40 years of empirical research. *Journal of Educational Administration, 49*(2), 125–142. https://doi.org/10.1108/09578231111116699

Hallinger, P. (2018). Bringing context out of the shadows of leadership. *Educational Management Administration & Leadership, 46*(1), 5–24. https://doi.org/10.1177/1741143216670652

Hallinger, P., & Liu, S. (2022). Leadership for learning in Asia: Emerging evidence and future directions. *Educational Management Administration & Leadership, 50*(4), 567–585.

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Kline, R. B. (2015). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

Knight, P., Tait, J., & Yorke, M. (2006). The professional learning of teachers in higher education. *Studies in Higher Education, 31*(3), 319–339. https://doi.org/10.1080/03075070600680786

Krejcie, R. V., & Morgan, D. W. (1970). Determining sample size for research activities. *Educational and Psychological Measurement, 30*(3), 607–610. https://doi.org/10.1177/001316447003000308

Leithwood, K., & Sun, J. (2018). Academic leadership effects: A review of the evidence about distributed leadership in higher education. *Educational Administration Quarterly, 54*(1), 86–128.

OECD. (2019). *Teachers and school leaders as lifelong learners: TALIS 2018 results (Volume I)*. OECD Publishing. https://doi.org/10.1787/1d0bc92a-en

Olivier, D. F., Hipp, K. K., & Huffman, J. B. (2010). Assessing and analyzing schools as

professional learning communities. In K. K. Hipp & J. B. Huffman (Eds.), *Demystifying professional learning communities: School leadership at its best* (pp. 29–41). Rowman & Littlefield.

Priestley, M., Biesta, G., & Robinson, S. (2015). *Teacher agency: An ecological approach*. Bloomsbury.

Stoll, L., Bolam, R., McMahon, A., Wallace, M., & Thomas, S. (2006). Professional learning communities: A review of the literature. *Journal of Educational Change, 7*, 221–258. https://doi.org/10.1007/s10833-006-0001-8

Vermunt, J. D. (2014). Teacher learning and professional development. In J. Hattie & E. M. Anderman (Eds.), *International guide to student achievement* (pp. 79–82). Routledge.

Walker, A., & Hallinger, P. (2015). A synthesis of reviews of research on principal leadership in East Asia. *Journal of Educational Administration, 53*(4), 554–570. https://doi.org/10.1108/JEA-05-2015-0038

RCG-JF Thailand-2

Bridging Digital Capability Gaps: The Role of Higher Education Management in Blockchain Adoption in Thailand's Agri-Food Sector

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Abstract

Digital technologies are transforming traditional industries, yet adoption often remains uneven because of persistent gaps in digital capability. In Thailand, blockchain offers promising gains in agri-food transparency, traceability, and sustainability, but uptake varies across the value chain. Prior work emphasises technical and operational factors, giving limited attention to the role of higher education institutions (HEIs) in enabling adoption. Drawing on the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and the Triple Helix framework, this study positions strategically managed universities as intermediaries linking knowledge production, industry application, and public policy. A survey of 360 agri-food stakeholders (farmers, processors, and restaurant managers) was analysed using descriptive statistics, the Weighted Average Index, and one-way ANOVA. Significant between-group differences emerged in awareness, readiness, and perceived usefulness ($p < .001$), with processors the most and primary producers the least prepared. Respondents prioritised professional training, industry workshops, and micro-credentials. The study offers higher education management strategies for inclusive digital transformation in Southeast Asia.

Keywords: higher education management; digital transformation; blockchain adoption; technology acceptance; Triple Helix; university–industry collaboration

1. Introduction

1.1 Background

Digital transformation has become a strategic priority for governments, industries, and educational institutions worldwide as emerging technologies reshape economic activities, organizational processes, and workforce requirements (Alenezi, 2023; OECD, 2023; World Economic Forum, 2023). The rapid advancement of Industry 4.0 technologies—including artificial intelligence (AI), blockchain, cloud computing, big data analytics, and the Internet of

Things (IoT)—has created new opportunities for innovation, productivity enhancement, and sustainable development across multiple sectors.

Within Southeast Asia, governments have increasingly recognized digital transformation as a critical driver of economic competitiveness and sustainable growth. In Thailand, the Thailand 4.0 policy framework seeks to transition the country from a production-based economy to an innovation-driven economy by promoting technological advancement, digital innovation, and human capital development (Ministry of Higher Education, Science, Research and Innovation [MHESI], 2023). A key objective of Thailand 4.0 is the modernization of traditional industries, particularly agriculture and food production, through the adoption of advanced digital technologies.

The agri-food sector remains one of Thailand's most important economic sectors, contributing significantly to national employment, food security, export revenues, and rural livelihoods (Food and Agriculture Organization [FAO], 2019). As global food systems become increasingly complex and consumer expectations regarding transparency and sustainability continue to rise, agricultural stakeholders face mounting pressure to adopt innovative technologies capable of improving operational efficiency, product traceability, and sustainability performance (Kamilaris et al., 2019; Zhao et al., 2019).

Among emerging digital technologies, blockchain has gained considerable attention due to its potential to transform agri-food supply chains through enhanced transparency, traceability, and accountability (Casino et al., 2019; Kshetri, 2018). Blockchain technology functions as a decentralized and immutable digital ledger that records transactions across distributed networks, enabling secure and verifiable information sharing among multiple stakeholders (Caro et al., 2018; Tian, 2017). Unlike traditional centralized databases, blockchain systems provide tamper-resistant records that can increase trust and reduce information asymmetries among supply chain participants (Kshetri, 2018).

The application of blockchain technology in agri-food systems has been associated with numerous benefits. Previous studies suggest that blockchain can improve food safety by enabling rapid identification of contamination sources, enhance consumer trust through transparent product information, reduce fraud, and strengthen sustainability monitoring mechanisms (Behnke & Janssen, 2020; Kamble et al., 2021; Treiblmaier & Sillaber, 2021). Furthermore, blockchain technology supports growing international demands for sustainable and traceable food production systems, making it increasingly relevant for export-oriented agricultural economies such as Thailand (Chang et al., 2022; Liang et al., 2022).

Despite these potential advantages, blockchain adoption remains uneven across agricultural stakeholders. Existing research has identified several barriers including limited digital literacy, insufficient technical expertise, high implementation costs, lack of technological infrastructure,

and organizational resistance to change (Demestichas et al., 2020; Gupta et al., 2023; Saurabh & Dey, 2021). Small-scale producers and stakeholders operating within traditional agricultural systems often face additional challenges associated with limited access to technological resources and professional development opportunities (FAO, 2019; Kampan et al., 2022).

These challenges suggest that technology adoption cannot be explained solely through technical considerations. Rather, successful implementation depends upon broader institutional factors, including knowledge transfer, workforce development, organizational readiness, and stakeholder collaboration (Toader et al., 2024; Zhao et al., 2019). Consequently, there is growing recognition that educational institutions may play a critical role in supporting digital transformation and technology adoption within traditional economic sectors.

1.2 Higher Education Institutions and Digital Transformation

Higher education institutions (HEIs) have become increasingly important actors within national and regional innovation ecosystems. Traditionally, universities have focused on teaching, research, and community service. However, contemporary higher education systems are expected to contribute more directly to economic development, workforce preparation, knowledge transfer, and innovation generation (Etzkowitz & Leydesdorff, 2000; Marginson, 2022).

The emergence of digital economies has intensified expectations that universities prepare graduates and professionals with competencies relevant to rapidly evolving technological environments (UNESCO, 2023; World Economic Forum, 2023). As a result, HEIs are increasingly engaged in curriculum innovation, industry partnerships, applied research initiatives, entrepreneurship support, and lifelong learning programs designed to address emerging workforce needs (Alenezi, 2023; OECD, 2023).

The concept of Higher Education 4.0 emphasizes the strategic role of universities in supporting digital transformation through interdisciplinary learning, industry engagement, digital skill development, and innovation-oriented educational practices (UNESCO, 2023). Universities are no longer viewed solely as providers of academic qualifications but also as facilitators of continuous learning and capability development across society (Marginson, 2022).

This expanded role is particularly important in sectors characterized by uneven technology adoption. In such contexts, universities can function as knowledge intermediaries that facilitate technology diffusion, enhance digital literacy, and support organizational adaptation through education and training initiatives (Etzkowitz & Leydesdorff, 2000). Through curriculum innovation, professional development programs, and collaborative partnerships, HEIs possess the potential to bridge capability gaps that may otherwise constrain digital transformation.

1.3 Research Problem

Although blockchain technology has been widely promoted as a transformative solution for improving transparency, traceability, and sustainability within agri-food supply chains, adoption remains uneven among stakeholders (Kampan et al., 2022; Zhao et al., 2019). Existing research has primarily focused on technical architecture, operational efficiency, and supply chain applications, while relatively little attention has been devoted to understanding how educational institutions contribute to technology adoption through workforce development and knowledge transfer (Toader et al., 2024).

This limitation is particularly important within emerging economies where disparities in technological readiness remain substantial. The existence of capability gaps among agricultural stakeholders suggests that adoption outcomes may depend not only on individual perceptions of technology but also on the availability of institutional support mechanisms that facilitate learning, innovation, and digital competence development (Venkatesh et al., 2003).

Furthermore, limited research has examined blockchain adoption from a higher education management perspective. While studies grounded in TAM and UTAUT have contributed valuable insights regarding individual adoption behavior (Davis, 1989; Venkatesh et al., 2003), fewer studies have explored how universities can serve as strategic actors within innovation ecosystems that support technology diffusion and workforce transformation (Etzkowitz & Leydesdorff, 2000). Consequently, there is a need to investigate how HEIs can contribute to bridging digital capability gaps and supporting blockchain adoption within Thailand's agri-food sector.

1.4 Research Objectives

This study seeks to:

1. examine the levels of awareness, readiness, and perceptions regarding blockchain technology among stakeholders in Thailand's agri-food sector;
2. identify capability gaps that influence blockchain adoption among different stakeholder groups;
3. analyze the implications of these capability gaps for higher education institutions and digital workforce development; and
4. develop recommendations for higher education management strategies that support blockchain adoption and digital transformation.

1.5 Research Questions

RQ1: What are the levels of awareness and readiness regarding blockchain technology among agri-food stakeholders in Thailand?

RQ2: Are there significant differences among stakeholder groups regarding awareness, attitudes, and adoption readiness?

RQ3: What capability gaps constrain blockchain adoption within Thailand's agri-food sector?

RQ4: How can higher education institutions contribute to addressing these capability gaps and supporting digital transformation?

1.6 Significance of the Study

This study contributes to higher education management literature in several ways. First, it extends technology adoption research by integrating TAM (Davis, 1989), UTAUT (Venkatesh et al., 2003), and the Triple Helix framework (Etzkowitz & Leydesdorff, 2000) within a higher education management context. Second, it provides empirical evidence regarding digital capability disparities within Thailand's agri-food sector and highlights the role of universities in addressing these inequalities.

From a practical perspective, the findings provide guidance for university leaders, curriculum developers, policymakers, and industry stakeholders seeking to strengthen digital workforce development and technology adoption strategies. The study also offers insights into how HEIs can position themselves as strategic partners within regional innovation ecosystems and contribute to inclusive digital transformation across Southeast Asia.

2. Literature Review

2.1 Digital Transformation and Higher Education Management

Digital transformation has become one of the most influential forces shaping contemporary societies, economies, and educational systems. The integration of digital technologies into organizational processes has transformed how institutions create value, communicate with stakeholders, and respond to rapidly changing environments (Alenezi, 2023; OECD, 2023). Within higher education, digital transformation extends beyond the adoption of educational technologies and encompasses broader institutional changes involving governance, curriculum design, research activities, stakeholder engagement, and organizational culture (UNESCO, 2023).

The concept is closely associated with Industry 4.0, which involves the integration of advanced technologies such as AI, blockchain, big data analytics, cloud computing, and IoT into industrial and service sectors (World Economic Forum, 2023). These technologies have generated new opportunities for innovation, productivity enhancement, and sustainable development while simultaneously creating challenges related to workforce preparedness and organizational adaptation (OECD, 2023).

HEIs play a critical role in supporting digital transformation by developing human capital, generating knowledge, and facilitating technology transfer (Etzkowitz & Leydesdorff, 2000). Universities have traditionally been responsible for teaching, research, and community service; however, contemporary higher education management increasingly emphasizes their strategic role in fostering innovation ecosystems and contributing to national economic competitiveness (Marginson, 2022).

As digital technologies continue to reshape labor markets, universities are expected to prepare graduates with the skills, competencies, and adaptability necessary for emerging occupations and industries (World Economic Forum, 2023). Consequently, HEIs must engage more actively with external stakeholders through collaborative curriculum development, work-integrated learning opportunities, applied research partnerships, and lifelong learning initiatives (UNESCO, 2023). Effective institutional responses also require strategic planning, resource allocation, organizational change management, and investment in technological infrastructure (Alenezi, 2023). Higher education management has therefore become increasingly concerned with building institutional capacity for digital transformation and fostering cultures of continuous learning and innovation.

2.2 Blockchain Adoption in Agri-Food Systems

Blockchain technology has emerged as one of the most promising innovations for enhancing transparency, accountability, and efficiency within supply chains (Casino et al., 2019; Kshetri, 2018). Originally developed as the underlying infrastructure for cryptocurrencies, blockchain has evolved into a versatile technology with applications across finance, healthcare, logistics, and agriculture (Kamilaris et al., 2019).

Blockchain operates as a decentralized digital ledger that records transactions across a distributed network of participants. Information recorded within the blockchain is encrypted, time-stamped, and immutable, making it highly resistant to tampering or unauthorized modification (Caro et al., 2018; Tian, 2017). This characteristic provides a reliable mechanism for verifying transactions and establishing trust among stakeholders.

In agri-food systems, blockchain technology offers substantial opportunities for improving traceability and transparency throughout supply chains (Behnke & Janssen, 2020; Zhao et al., 2019). Traditional traceability systems often suffer from fragmented data management, limited information sharing, and difficulties in verifying product authenticity. Blockchain addresses these challenges by providing a shared and immutable record of product movements and production activities (Treiblmaier & Sillaber, 2021).

Researchers have identified several benefits associated with blockchain adoption in agriculture, including improved food safety, enhanced consumer trust, reduced fraud, and increased

operational efficiency (Chang et al., 2022; Kamble et al., 2021). Blockchain has also been linked to sustainability objectives through its ability to monitor environmental indicators, track resource utilization, and verify compliance with sustainability standards (Liang et al., 2022; Zhao et al., 2022).

Despite these advantages, adoption remains limited. Several barriers have been identified, including implementation costs, technological complexity, lack of interoperability, concerns regarding data privacy, and insufficient digital infrastructure (Demestichas et al., 2020; Gupta et al., 2023). Smallholder farmers, in particular, often face challenges related to digital literacy and access to technological resources (FAO, 2019; Kampan et al., 2022). Importantly, blockchain adoption depends not only on technological availability but also on organizational readiness, stakeholder collaboration, regulatory support, and human capital development (Saurabh & Dey, 2021; Toader et al., 2024).

2.3 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), remains one of the most influential theoretical frameworks for explaining technology adoption behavior. TAM proposes that two key perceptions—perceived usefulness and perceived ease of use—determine users' attitudes toward a technology and subsequently influence behavioral intentions and actual usage behavior.

Perceived usefulness refers to the degree to which an individual believes that using a technology will improve job performance, whereas perceived ease of use reflects the extent to which a technology is perceived as requiring minimal effort (Davis, 1989). Individuals who perceive a technology as both useful and easy to use are more likely to develop favorable attitudes toward adoption.

Numerous studies have validated TAM across various technological contexts, including e-commerce, mobile technologies, artificial intelligence, and blockchain applications (Toader et al., 2024; Zhao et al., 2022). The model has demonstrated strong explanatory power and remains widely applied because of its simplicity and adaptability (Venkatesh et al., 2003). Within blockchain adoption research, TAM provides a useful framework for understanding how stakeholders evaluate blockchain's potential benefits and challenges. Stakeholders may perceive blockchain as useful for improving traceability, transparency, and sustainability while simultaneously expressing concerns regarding technical complexity (Kampan et al., 2022; Zhao et al., 2022). The current study adopts TAM as a foundational framework for examining how awareness and perceptions influence stakeholders' readiness to adopt blockchain technology.

2.4 Unified Theory of Acceptance and Use of Technology (UTAUT)

Although TAM remains influential, researchers have sought more comprehensive models capable of incorporating organizational and social influences. The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. (2003) through the integration of eight prominent technology acceptance theories.

UTAUT identifies four principal determinants of technology adoption: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Performance expectancy refers to the degree to which individuals believe that a technology will improve performance outcomes, while effort expectancy relates to perceived ease of use. Social influence reflects the extent to which individuals perceive that important others expect them to use a technology. Facilitating conditions refer to the availability of organizational and technical resources necessary to support technology adoption.

UTAUT is particularly relevant in developing economies because adoption decisions are often influenced by institutional support mechanisms such as training programs, infrastructure availability, and policy initiatives (Toader et al., 2024). For agricultural stakeholders, facilitating conditions may include government support programs, university-led training initiatives, extension services, and industry partnerships (FAO, 2019). The inclusion of facilitating conditions is especially important in this study because it highlights the role of HEIs as providers of knowledge, training, and technical support that can reduce adoption barriers.

2.5 Triple Helix Theory and Innovation Ecosystems

The Triple Helix Theory, developed by Etzkowitz and Leydesdorff (2000), provides a framework for understanding how innovation emerges through interactions among universities, industries, and governments. The theory argues that innovation is most effective when these sectors collaborate and engage in overlapping activities.

Universities play a particularly important role within the Triple Helix framework because they serve as producers of knowledge, facilitators of innovation, and contributors to regional economic development (Etzkowitz & Leydesdorff, 2000). Beyond teaching and research, universities increasingly participate in entrepreneurship, technology transfer, and policy development activities.

The framework is especially relevant for blockchain adoption because successful implementation requires coordinated efforts involving technological expertise, financial resources, regulatory frameworks, and stakeholder engagement (Kshetri, 2018). Universities can contribute through research activities, curriculum development, professional training, and knowledge dissemination programs, while industry partners provide practical implementation contexts and governments establish supportive policy environments. Previous studies suggest

that collaborative innovation ecosystems improve technology diffusion and increase the likelihood of successful adoption (Etzkowitz & Leydesdorff, 2000; UNESCO, 2023). Strong university–industry–government partnerships facilitate knowledge exchange, reduce uncertainty, and support capability development among stakeholders.

2.6 Curriculum Innovation and Lifelong Learning

Rapid technological change has transformed expectations regarding education and workforce development. Traditional educational models that focus exclusively on pre-employment training are increasingly insufficient for addressing evolving skill requirements (OECD, 2023).

Curriculum innovation involves redesigning educational programs to align with emerging industry needs and technological developments (Marginson, 2022). In the context of digital transformation, curriculum innovation requires the integration of digital competencies, interdisciplinary learning approaches, and experiential learning opportunities (UNESCO, 2023). Blockchain technology presents unique challenges for curriculum development because it spans multiple disciplines, including information technology, business management, supply chain management, sustainability, and public policy (Kampan et al., 2022). Consequently, interdisciplinary curriculum models are necessary to prepare learners for technology-driven environments.

Beyond degree programs, universities increasingly support lifelong learning through micro-credentials, professional certifications, executive education, and short-course training initiatives (OECD, 2023). These flexible learning opportunities enable working professionals to continuously update their skills and adapt to technological change. For agricultural stakeholders, lifelong learning initiatives can provide practical pathways for developing digital literacy and blockchain-related competencies. Universities can collaborate with industry and government agencies to design training programs tailored to stakeholder needs, thereby reducing barriers to technology adoption and supporting broader digital transformation objectives (FAO, 2019).

2.7 Research Gap

The literature demonstrates growing interest in blockchain applications, digital transformation, and technology adoption within agri-food systems. Previous studies have extensively examined blockchain's technical capabilities and operational outcomes (Kamilaris et al., 2019; Zhao et al., 2019), and technology adoption research has been enriched through theoretical frameworks such as TAM and UTAUT (Davis, 1989; Venkatesh et al., 2003). However, several important gaps remain.

First, most blockchain studies focus on technological implementation rather than the educational and institutional mechanisms that support adoption (Kampan et al., 2022; Toader

et al., 2024). Second, relatively few studies have examined how HEIs contribute to technology diffusion and workforce capability development within traditional sectors such as agriculture (UNESCO, 2023). Third, limited research has integrated TAM, UTAUT, and Triple Helix Theory within a higher education management framework to explain digital transformation processes.

This study addresses these gaps by investigating blockchain adoption through the lens of higher education management and institutional capacity building. Specifically, it examines how universities can function as strategic intermediaries that facilitate knowledge transfer, digital capability development, and innovation-ecosystem collaboration. The conceptual framework and hypotheses that follow from this gap are developed in Section 3.

3. Conceptual Framework and Hypothesis Development

3.1 Theoretical Foundation

This study is grounded in three complementary theoretical perspectives: TAM, UTAUT, and Triple Helix Theory. Together, these frameworks provide a comprehensive understanding of how technological, institutional, and educational factors influence blockchain adoption within Thailand's agri-food sector.

TAM explains technology adoption through two primary determinants: perceived usefulness and perceived ease of use (Davis, 1989). According to TAM, individuals are more likely to adopt a technology when they perceive that it enhances their performance and can be used with minimal effort. The model has been widely applied in studies examining the adoption of emerging technologies, including blockchain, artificial intelligence, and digital platforms (Kampan et al., 2022; Toader et al., 2024).

Although TAM provides valuable insights into individual technology acceptance, critics have argued that it places insufficient emphasis on organizational and environmental factors that influence adoption behavior (Venkatesh et al., 2003). To address these limitations, UTAUT extends technology acceptance research by incorporating performance expectancy, effort expectancy, social influence, and facilitating conditions as key determinants of adoption behavior. Among these constructs, facilitating conditions are particularly relevant to the present study because they emphasize the importance of institutional support, training opportunities, technological infrastructure, and access to resources—factors that are especially salient in developing economies where stakeholders often face capability constraints (Toader et al., 2024).

While TAM and UTAUT primarily focus on individual and organizational determinants of technology adoption, they do not explicitly address the broader innovation ecosystem within which adoption occurs. This study therefore incorporates Triple Helix Theory to explain how

universities, industries, and governments collaborate to support technological innovation and knowledge transfer (Etzkowitz & Leydesdorff, 2000). The framework positions universities as active contributors to economic development through research, education, innovation, and stakeholder engagement. In the context of blockchain adoption, universities can contribute by developing relevant curricula, delivering professional training, conducting applied research, and supporting digital capability development.

The integration of TAM, UTAUT, and Triple Helix Theory provides a multidimensional perspective that captures both individual perceptions and institutional influences on technology adoption. This integrated framework is particularly appropriate for examining blockchain adoption in Thailand's agri-food sector, where digital transformation depends not only on technology acceptance but also on workforce readiness, educational support, and ecosystem collaboration.

3.2 Conceptual Integration of TAM, UTAUT, and Triple Helix Theory

The conceptual framework assumes that blockchain adoption readiness is influenced by both individual-level and institutional-level factors.

At the individual level, TAM suggests that stakeholders who perceive blockchain technology as useful and easy to use are more likely to demonstrate positive attitudes toward adoption (Davis, 1989). Prior studies have shown that awareness and understanding of emerging technologies positively influence perceived usefulness and acceptance intentions (Kampan et al., 2022; Zhao et al., 2022).

At the organizational level, UTAUT proposes that facilitating conditions such as access to training, technical support, infrastructure, and organizational resources significantly influence adoption readiness (Venkatesh et al., 2003). These facilitating conditions are particularly important for agricultural stakeholders who may have limited exposure to digital technologies.

At the ecosystem level, Triple Helix Theory suggests that universities, industries, and governments collectively shape innovation outcomes through collaboration and knowledge exchange (Etzkowitz & Leydesdorff, 2000). Universities contribute by developing digital competencies through curriculum innovation and lifelong learning; industries provide practical implementation contexts; and governments establish supportive regulatory and policy environments.

Accordingly, this study conceptualizes HEIs as strategic intermediaries that enhance facilitating conditions and reduce capability gaps through educational interventions. Through curriculum innovation, professional development programs, applied research, and industry partnerships, universities can increase awareness, strengthen perceived usefulness, improve perceived ease of use, and ultimately enhance blockchain adoption readiness.

3.3 Proposed Conceptual Framework

Blockchain adoption readiness is conceptualized as the outcome of interactions among awareness, technology perceptions, facilitating conditions, and higher education interventions. Stakeholder awareness is expected to influence perceptions of blockchain usefulness and ease of use, which in turn influence readiness for adoption, consistent with TAM (Davis, 1989). Facilitating conditions, derived from UTAUT, are expected to directly influence adoption readiness by reducing technological and organizational barriers (Venkatesh et al., 2003). Higher education management strategies, grounded in Triple Helix Theory, are proposed as institutional mechanisms that strengthen facilitating conditions and support knowledge transfer. These strategies include curriculum innovation, industry-integrated learning, professional development programs, micro-credential initiatives, university–industry partnerships, and university–government collaboration. Collectively, these interventions contribute to workforce capability development and support technology adoption within the agri-food sector. Figure 1 presents the integrated framework.

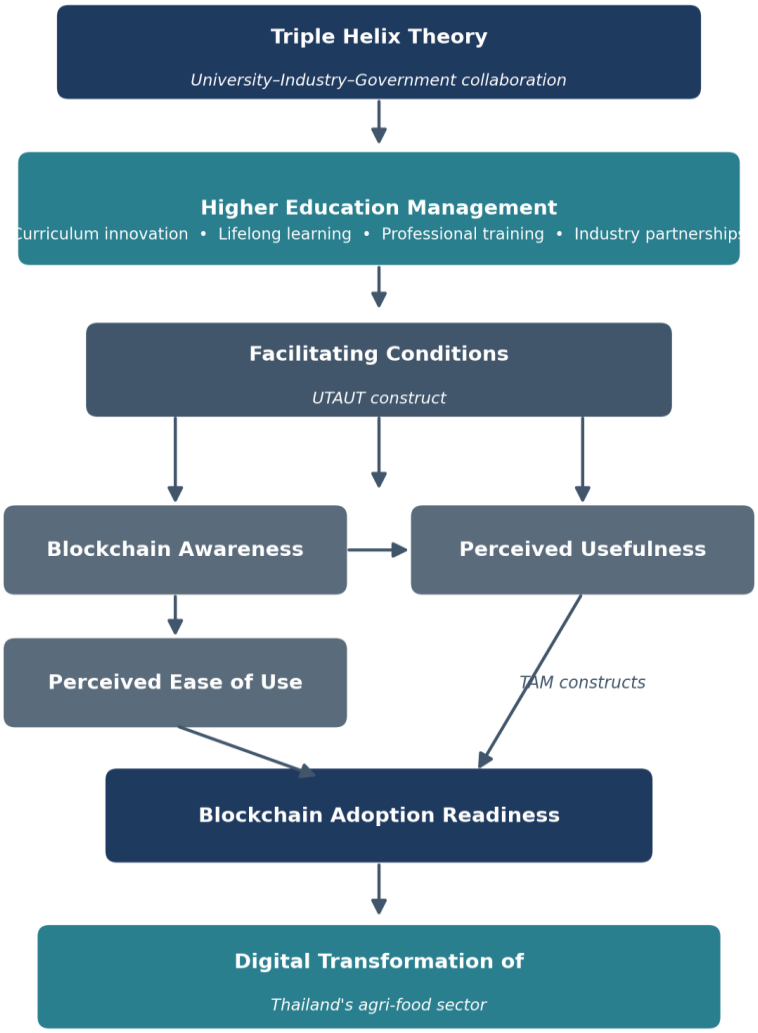


Figure 1. Integrated conceptual framework based on TAM, UTAUT, and Triple Helix Theory.

3.4 Hypotheses

Drawing on the constructs above, the study proposes five hypotheses.

Awareness represents an individual's knowledge and understanding of a technology's characteristics, benefits, and applications. Prior research suggests that stakeholders with higher levels of technological awareness are more likely to recognize the potential benefits of innovative technologies and develop positive attitudes toward adoption (Kampan et al., 2022; Zhao et al., 2019). In blockchain contexts, increased awareness allows stakeholders to better understand how blockchain can improve transparency, traceability, and sustainability.

H1. Stakeholders with higher levels of blockchain awareness demonstrate more positive perceptions regarding blockchain adoption.

Previous studies have reported significant differences in technological awareness and adoption readiness among stakeholder groups due to variations in education, experience, organizational resources, and digital literacy (FAO, 2019; Kampan et al., 2022). Within agri-food systems, processors and managers typically possess greater access to technological resources than primary producers.

H2. Significant differences exist among stakeholder groups regarding awareness, attitudes, and readiness toward blockchain technology.

According to TAM, perceived usefulness and perceived ease of use are primary determinants of technology acceptance (Davis, 1989). Stakeholders who perceive blockchain as capable of improving efficiency, transparency, and traceability are expected to demonstrate stronger adoption intentions.

H3. Perceived usefulness and perceived ease of use positively influence stakeholders' readiness to adopt blockchain technology.

UTAUT emphasizes the importance of facilitating conditions—including access to technical support, training opportunities, infrastructure, and organizational resources—in supporting technology adoption (Venkatesh et al., 2003).

H4. Facilitating conditions positively influence blockchain adoption readiness.

The Triple Helix framework suggests that universities contribute to innovation and technological diffusion through education, research, and stakeholder engagement (Etzkowitz & Leydesdorff, 2000). HEIs can reduce capability gaps by developing curricula, training programs, and collaborative initiatives that enhance digital competencies.

H5. Higher education institutions positively influence blockchain adoption readiness through curriculum innovation, lifelong learning initiatives, and university–industry–government collaboration.

4. Research Methodology

4.1 Research Design

This study employed a quantitative, cross-sectional survey design to examine stakeholders' awareness, perceptions, and readiness regarding blockchain technology adoption in Thailand's agri-food sector and to investigate the role of HEIs in supporting digital transformation and workforce capability development. A quantitative approach was appropriate because the study sought to measure relationships among constructs derived from TAM, UTAUT, and Triple

Helix Theory, and to enable statistical comparisons among stakeholder groups and hypothesis testing using established methods (Creswell & Creswell, 2018). The study focused on three major stakeholder groups within Thailand's agri-food value chain: farmers (primary producers), food processors, and restaurant managers. These groups were selected because they represent key actors involved in agricultural production, food processing, distribution, and consumption.

4.2 Population and Sampling

The target population comprised stakeholders involved in Thailand's agri-food supply chain, spanning primary production, food processing, and food service. The study focused on Bangkok, Lopburi, and Saraburi provinces, which represent important agricultural and food-production regions with significant concentrations of farmers, food-processing enterprises, and food-service establishments.

A purposive sampling approach was employed to identify respondents with direct involvement in agri-food supply chain activities. Participants were recruited through professional networks, agricultural cooperatives, industry associations, local business organizations, and university outreach programs. To ensure representation across stakeholder groups, quotas were established for farmers, processors, and restaurant managers.

A total of 400 questionnaires were distributed. Of these, 360 completed questionnaires were returned and deemed usable for analysis. The final sample consisted of 120 farmers, 120 food processors, and 120 restaurant managers. This sample size exceeded the minimum recommendations for group-comparison studies and provided sufficient statistical power for ANOVA and hypothesis testing (Hair et al., 2022).

4.3 Research Instrument

Data were collected using a structured questionnaire developed from previous studies examining blockchain adoption, technology acceptance, and digital readiness (Davis, 1989; Kampan et al., 2022; Venkatesh et al., 2003). The questionnaire comprised six sections:

- **Section A — Demographic characteristics:** gender, age, educational level, occupation, years of professional experience, and prior exposure to blockchain technology.
- **Section B — Blockchain awareness:** respondents' awareness and understanding of blockchain and its agri-food applications (sample item: "I am familiar with blockchain technology and its applications in supply chain management").
- **Section C — Perceived usefulness:** based on TAM (Davis, 1989); perceptions regarding the benefits of blockchain (sample item: "Blockchain technology can improve product traceability").

- **Section D — Perceived ease of use:** perceptions regarding the complexity and usability of blockchain systems (sample item: "Learning to use blockchain technology would be easy for me").
- **Section E — Facilitating conditions:** adapted from UTAUT (Venkatesh et al., 2003); organizational and institutional support available for adoption (sample item: "I have access to training and support necessary to implement blockchain technology").
- **Section F — Higher education support and capacity development:** perceptions regarding the role of universities in supporting adoption, covering curriculum development, professional training, micro-credential programs, industry partnerships, and applied research initiatives.

All perception items were measured on a five-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*).

4.4 Content Validity

To ensure content validity, the questionnaire was evaluated by a panel of five experts: two higher education management scholars, one educational technology specialist, one agricultural supply chain expert, and one blockchain technology researcher. Experts evaluated the relevance, clarity, and appropriateness of each item. The Item Content Validity Index (I-CVI) was calculated for every item; all items achieved I-CVI values between 0.80 and 1.00, exceeding the minimum threshold of 0.78 recommended by Polit and Beck (2006). All items were therefore retained.

4.5 Pilot Testing and Reliability

A pilot study involving 30 respondents was conducted prior to full-scale data collection to evaluate item clarity, questionnaire structure, response consistency, and reliability. Internal consistency was assessed using Cronbach's alpha (Table 1). All values exceeded the recommended threshold of 0.70 (Hair et al., 2022), indicating satisfactory reliability.

Table 1. Internal consistency reliability of constructs

Construct	Cronbach's alpha
Awareness	0.87
Perceived usefulness	0.91
Perceived ease of use	0.88
Facilitating conditions	0.90
Higher education support	0.92

4.6 Data Collection Procedures

Data were collected between January and March 2026. Questionnaires were distributed in both electronic and paper formats. Participants received an information sheet, a consent form, a statement of study purpose, and a confidentiality assurance, and were informed that participation was voluntary and could be withdrawn at any time without penalty. Completed questionnaires were coded and anonymized before analysis.

4.7 Ethical Considerations

Ethical approval for the study was obtained from the Institutional Research Ethics Committee. The study complied with ethical principles regarding voluntary participation, informed consent, confidentiality, anonymity, and data protection. No personally identifiable information was collected. All data were stored on password-protected systems and will be retained for five years before secure destruction. The authors declare no conflicts of interest. AI-assisted language tools were used solely for grammar enhancement and language editing; all conceptual development, analysis, interpretation, and conclusions were carried out by the authors.

4.8 Data Analysis

Data were analyzed using SPSS Version 29. Descriptive statistics (frequency, percentage, mean, and standard deviation) summarized demographic characteristics, awareness levels, perceptions, and adoption readiness. The Weighted Average Index (WAI) was used to rank factors influencing blockchain adoption and educational support priorities, calculated as:

$$WAI = \frac{\sum(w_i \times f_i)}{N}$$

where w_i is the weight assigned to each response category, f_i is the frequency of responses, and N is the total number of respondents.

One-way analysis of variance (ANOVA) was conducted to examine differences among farmers, processors, and restaurant managers on awareness, perceived usefulness, perceived ease of use, facilitating conditions, and adoption readiness, with the significance level set at $p < .05$. Where significant differences were identified, Tukey's Honestly Significant Difference (HSD) test was performed to determine which groups differed. Eta squared (η^2) was calculated to assess effect size, interpreted following Cohen's guidelines (small = 0.01, medium = 0.06, large = 0.14). Relationships among awareness, technology perceptions, facilitating conditions, higher education support, and adoption readiness (H1, H3, H4, and H5) were examined using Pearson correlation and regression analysis, with results interpreted in relation to the integrated TAM–UTAUT–Triple Helix framework.

5. Results and Findings

5.1 Respondent Demographic Characteristics

A total of 360 valid responses were obtained, with each stakeholder group representing one-third of the sample. Table 2 summarizes the demographic profile.

Table 2. Demographic characteristics of respondents (N = 360)

Variable	Category	Frequency	Percentage (%)
Gender	Male	214	59.4
	Female	146	40.6
Age	Below 30 years	54	15.0
	31–40 years	118	32.8
	41–50 years	109	30.3
	Above 50 years	79	21.9
Education	Secondary school	86	23.9
	Diploma	102	28.3
	Bachelor's degree	132	36.7
	Graduate degree	40	11.1
Stakeholder group	Farmers	120	33.3
	Processors	120	33.3
	Restaurant managers	120	33.3

The profile indicates balanced representation across stakeholder groups. Most respondents possessed at least diploma-level education, suggesting an adequate educational background for evaluating technology-related issues.

5.2 Blockchain Awareness Among Stakeholders

Respondents assessed their awareness of blockchain technology and its agri-food applications. Mean scores were interpreted using equal-interval bands (1.00–1.80 = *very low*; 1.81–2.60 = *low*; 2.61–3.40 = *moderate*; 3.41–4.20 = *high*; 4.21–5.00 = *very high*).

Table 3. Blockchain awareness levels

Item	Mean	SD	Interpretation
Familiarity with blockchain technology	3.74	0.81	High
Understanding blockchain applications	3.61	0.86	High
Awareness of blockchain benefits	3.85	0.74	High
Knowledge of blockchain traceability systems	3.57	0.88	High
Overall awareness score	3.69	0.82	High

The overall awareness score (M = 3.69, SD = 0.82) indicates a generally high level of awareness. Awareness was highest regarding the perceived benefits of blockchain, while knowledge of traceability systems—although still within the high band—received the lowest rating, pointing

to a relative gap in technical understanding. These findings support previous research indicating growing awareness of blockchain within food supply chains while highlighting persistent knowledge gaps regarding practical implementation (Kamilaris et al., 2019; Kampan et al., 2022).

5.3 Perceived Usefulness and Perceived Ease of Use

Consistent with TAM, respondents evaluated the perceived usefulness and ease of use of blockchain technology (Table 4).

Table 4. Perceived usefulness, perceived ease of use, and adoption readiness

Construct	Mean	SD	Interpretation
Perceived usefulness	4.12	0.65	High
Perceived ease of use	3.71	0.79	High
Adoption readiness	3.88	0.73	High

Perceived usefulness achieved the highest mean score (M = 4.12), indicating strong agreement that blockchain can improve traceability, transparency, and food safety. Perceived ease of use received a comparatively lower rating, suggesting that respondents recognize blockchain's benefits but remain concerned about implementation complexity. These findings align with TAM, which posits that perceived usefulness is typically a stronger predictor of adoption intentions than perceived ease of use (Davis, 1989).

5.4 Facilitating Conditions

Facilitating conditions were measured using UTAUT constructs to assess perceptions of available support mechanisms (Table 5).

Table 5. Facilitating conditions for blockchain adoption

Item	Mean	SD
Access to training opportunities	3.45	0.87
Technical support availability	3.38	0.91
Organizational readiness	3.54	0.83
Government support	3.63	0.79
Access to digital infrastructure	3.49	0.88
Overall facilitating conditions	3.50	0.86

Facilitating conditions received the lowest overall rating among the study constructs (M = 3.50). Technical support availability (M = 3.38) and access to training opportunities (M = 3.45) were the weakest items, indicating capability gaps that may constrain technology adoption. This

finding reinforces the importance of educational interventions and institutional support mechanisms in facilitating digital transformation.

5.5 Higher Education Support Priorities

Respondents evaluated the importance of various higher education initiatives for supporting blockchain adoption (Table 6).

Table 6. Priority areas for higher education intervention

Initiative	WAI	Rank
Professional training programs	4.52	1
Industry-based workshops	4.48	2
Micro-credential programs	4.39	3
Curriculum development	4.32	4
Applied research partnerships	4.25	5
Innovation incubation programs	4.11	6

Professional training programs received the highest ranking (WAI = 4.52), followed by industry-based workshops and micro-credential programs. Stakeholders placed substantial value on practical and flexible learning opportunities rather than traditional degree-based education alone, supporting the growing emphasis on lifelong learning and continuing professional development within Higher Education 4.0 frameworks (OECD, 2023).

5.6 Differences Among Stakeholder Groups

A one-way ANOVA examined differences among farmers, processors, and restaurant managers (Table 7).

Table 7. ANOVA results (df = 2, 357)

Variable	*F*	*p*	η^2
Awareness	14.82	< .001	.08
Perceived usefulness	9.31	.001	.05
Perceived ease of use	11.57	< .001	.06
Facilitating conditions	16.24	< .001	.09
Adoption readiness	18.75	< .001	.10

Significant differences were observed across all constructs, with effect sizes in the medium range. The largest effect was found for adoption readiness (η^2 = .10), indicating meaningful variation among stakeholder groups.

5.7 Post Hoc Analysis

Because ANOVA identified significant differences, Tukey's HSD post hoc tests were performed on the overall adoption-readiness composite (Table 8).

Table 8. Tukey HSD results (adoption readiness)

Comparison	Mean difference	*p*
Processors vs. farmers	0.47	< .001
Restaurant managers vs. farmers	0.31	.003
Processors vs. restaurant managers	0.16	.087

Processors demonstrated significantly higher readiness than farmers, and restaurant managers scored significantly higher than farmers, while the difference between processors and restaurant managers was not significant. These findings suggest that primary producers may require additional support and training to participate effectively in blockchain-enabled supply chains.

5.8 Hypothesis Testing Summary

Table 9 summarizes the outcomes of hypothesis testing.

Table 9. Hypothesis testing results

Hypothesis	Statement	Basis of test	Result
H1	Awareness positively influences blockchain perceptions	Correlation/regression	Supported
H2	Significant stakeholder differences exist	One-way ANOVA	Supported
H3	Perceived usefulness and ease of use positively influence readiness	Correlation/regression	Supported
H4	Facilitating conditions positively influence readiness	Correlation/regression	Supported
H5	Higher education support positively influences adoption readiness	Correlation/regression	Supported

The findings indicate that blockchain adoption readiness is influenced by technological perceptions, facilitating conditions, and institutional support mechanisms.

5.9 Summary of Findings

Several key findings emerged. First, respondents demonstrated generally positive attitudes toward blockchain technology, particularly regarding its usefulness for improving traceability and transparency. Second, significant differences were observed among stakeholder groups, with processors exhibiting higher levels of awareness and readiness than farmers. Third,

facilitating conditions—especially training opportunities and technical support—remained the weakest area and an important barrier to adoption. Fourth, stakeholders strongly emphasized the importance of higher education interventions, particularly professional training programs, industry workshops, and micro-credential initiatives. Together, these findings suggest that successful blockchain adoption depends not only on technology-acceptance factors but also on educational and institutional mechanisms that support workforce capability development and knowledge transfer.

6. Discussion

This study investigated blockchain adoption readiness among stakeholders in Thailand's agri-food sector and explored the role of HEIs in supporting digital transformation through curriculum innovation, workforce development, and lifelong learning. The findings provide insight into how awareness, technology perceptions, facilitating conditions, and educational interventions collectively influence adoption, and contribute to higher education management literature by integrating TAM, UTAUT, and Triple Helix Theory within a broader educational and innovation-ecosystem context. The discussion is organized around the study's key findings and their implications for theory, policy, and practice.

6.1 Blockchain Awareness and Technology Acceptance

Respondents generally demonstrated high levels of awareness regarding blockchain technology, consistent with previous studies suggesting that awareness has increased as governments, industries, and academic institutions promote digital transformation (Kamilaris et al., 2019; Zhao et al., 2019). The positive association between awareness and blockchain perceptions supports the assumptions of TAM (Davis, 1989): stakeholders with greater knowledge were more likely to perceive blockchain as beneficial and relevant, aligning with prior work indicating that awareness is an important precursor to acceptance because users must first understand a technology before evaluating its usefulness (Kampan et al., 2022; Toader et al., 2024).

From a higher education management perspective, this highlights the importance of educational interventions in supporting technology adoption. Universities can raise awareness through formal education, industry outreach, professional workshops, and continuing education. The findings also suggest that awareness alone is insufficient: while respondents recognized blockchain's benefits, many remained uncertain about practical implementation, indicating that HEIs must move beyond knowledge dissemination toward experiential learning that builds practical competence and confidence.

6.2 Perceived Usefulness and Perceived Ease of Use

The results demonstrated strong support for TAM, with perceived usefulness and perceived ease of use positively associated with adoption readiness. Perceived usefulness emerged as the strongest driver, consistent with Davis's (1989) original proposition and with blockchain studies that identify transparency, traceability, and trust enhancement as key adoption drivers (Behnke & Janssen, 2020; Treiblmaier & Sillaber, 2021). Although perceived usefulness was rated highly, perceived ease of use scored lower, suggesting that stakeholders value blockchain but remain concerned about implementation complexity—a pattern also reported elsewhere (Demestichas et al., 2020; Gupta et al., 2023).

This has direct implications for curriculum design. Blockchain education should emphasize not only theoretical concepts but also practical applications and hands-on experience. Programs that simplify complex concepts and demonstrate real-world use cases may enhance perceptions of ease of use and reduce psychological barriers to adoption. Universities can support acceptance by incorporating blockchain simulations, case studies, digital laboratories, and industry-based projects into curricula.

6.3 Facilitating Conditions and Digital Capability Development

Facilitating conditions were positively associated with adoption readiness, supporting UTAUT (Venkatesh et al., 2003). Among these factors, training opportunities and technical support received the lowest ratings, revealing capability gaps within the sector and demonstrating that adoption challenges extend beyond individual attitudes to broader institutional and structural issues. The importance of facilitating conditions is especially evident in developing economies, where disparities in digital infrastructure and technological literacy remain substantial (FAO, 2019). Many stakeholders, particularly small-scale producers, may lack access to educational resources, technical expertise, and professional development.

These findings reinforce the argument that digital transformation requires investment in human capital alongside technological infrastructure. Educational institutions can contribute by providing knowledge, skills, and training that address capability gaps—an interpretation aligned with UNESCO's (2023) vision of HEIs as lifelong-learning hubs supporting continuous workforce development.

6.4 Stakeholder Differences and Digital Inclusion

The study identified significant differences among stakeholder groups, with processors demonstrating higher awareness and readiness than farmers and restaurant managers occupying an intermediate position. These findings suggest unequal access to technological knowledge and resources across the value chain, consistent with previous studies on digital agriculture and emerging-technology adoption (FAO, 2019; Kampan et al., 2022).

The observed differences raise important concerns regarding digital inclusion. If blockchain adoption accelerates without adequate support for less technologically prepared stakeholders, digital transformation may inadvertently widen inequalities. From a higher education management perspective, this underscores the importance of inclusive educational strategies. Universities should design outreach programs and training initiatives targeting underserved groups, particularly farmers and rural communities. Community-based learning models, mobile training programs, extension services, and online platforms may help expand access to digital education and reduce capability disparities, aligning with equitable and inclusive development goals emphasized in national and international education policies (OECD, 2023; UNESCO, 2023).

6.5 Higher Education Institutions as Strategic Enablers of Blockchain Adoption

One of the most significant findings concerns the role of HEIs in supporting blockchain adoption. Respondents consistently identified professional training programs, industry workshops, curriculum innovation, and micro-credential initiatives as important mechanisms for facilitating adoption. This extends existing blockchain research, which has focused primarily on technological characteristics and organizational factors (Kshetri, 2018; Zhao et al., 2019), by demonstrating that educational interventions represent a critical component of successful adoption strategies.

The findings support the argument that universities can function as strategic intermediaries between knowledge creation and practical implementation. Through education, research, and stakeholder engagement, HEIs can reduce information asymmetries, enhance digital literacy, and facilitate knowledge transfer. This expanded role is consistent with contemporary higher education management frameworks that emphasize societal impact, innovation, and workforce development as core university functions (Marginson, 2022).

6.6 Triple Helix Theory and Innovation Ecosystems

The findings support the relevance of Triple Helix Theory for understanding blockchain adoption in the agri-food sector. Respondents emphasized the importance of collaboration among universities, industries, and government agencies. According to the theory, innovation emerges through dynamic interactions among these actors (Etzkowitz & Leydesdorff, 2000): universities contribute through research, curriculum development, and professional training; industry partners provide practical implementation contexts and identify workforce requirements; and government agencies establish regulatory frameworks, funding mechanisms, and policy incentives. The integration of these actors creates a supportive environment for technology diffusion and capability development, suggesting that isolated interventions may be insufficient and that coordinated, multi-stakeholder strategies are necessary. This

interpretation is particularly relevant to Thailand's efforts to strengthen innovation capacity and transition toward a knowledge-based economy under the Thailand 4.0 agenda.

6.7 Implications for Curriculum Innovation and Lifelong Learning

The results have significant implications for curriculum design and lifelong learning. First, universities should integrate blockchain-related competencies into existing programs across multiple disciplines—including business administration, supply chain management, agriculture, information technology, and sustainability studies—emphasizing cross-functional learning and problem-solving. Second, HEIs should expand micro-credential and professional certification offerings; the high ranking of professional training programs suggests that stakeholders value flexible pathways for rapid skill acquisition without full degree enrollment. Third, universities should strengthen experiential learning through industry collaborations, internships, applied research projects, and digital innovation laboratories, which may improve both perceived usefulness and perceived ease of use. Finally, HEIs should adopt lifelong learning models that support continuous workforce development given the rapid pace of technological change (OECD, 2023).

6.8 Theoretical Contributions

This study makes several theoretical contributions. First, it extends technology acceptance research by integrating TAM and UTAUT with Triple Helix Theory, demonstrating that adoption readiness is shaped not only by individual and organizational factors but also by educational institutions and innovation ecosystems. Second, it contributes to higher education management literature by conceptualizing universities as strategic facilitators of digital transformation rather than passive providers of education. Third, it introduces a multidimensional framework linking technology acceptance, institutional support, and ecosystem collaboration that may serve as a foundation for future research on the role of HEIs in supporting the adoption of emerging technologies beyond blockchain.

7. Conclusion, Implications, Limitations, and Future Research

7.1 Conclusion

Within the agri-food sector, blockchain technology has emerged as a promising innovation capable of enhancing transparency, traceability, food safety, and sustainability. However, successful implementation requires more than technological availability; it depends upon stakeholder readiness, organizational support, workforce capabilities, and institutional collaboration.

Drawing on TAM, UTAUT, and Triple Helix Theory, this study developed and tested an integrated framework linking technology perceptions, facilitating conditions, and educational

interventions. The findings revealed that stakeholders generally recognized the value of blockchain, particularly for improving transparency and traceability, and that awareness, perceived usefulness, perceived ease of use, and facilitating conditions were positively associated with adoption readiness. Significant differences emerged among stakeholder groups, with farmers demonstrating lower awareness and readiness than processors and restaurant managers. Most importantly, respondents identified professional training programs, industry workshops, curriculum innovation, and lifelong learning as essential mechanisms for reducing capability gaps. The study concludes that blockchain adoption within Thailand's agri-food sector should be viewed not only as a technological challenge but also as an educational and institutional one, and that universities are well positioned to support digital transformation as knowledge brokers, workforce developers, and innovation facilitators within university–industry–government ecosystems.

7.2 Theoretical Implications

This study extends technology adoption research by integrating three complementary perspectives—TAM (Davis, 1989), UTAUT (Venkatesh et al., 2003), and Triple Helix Theory (Etzkowitz & Leydesdorff, 2000)—and demonstrating that institutional and ecosystem-level factors play significant roles in shaping adoption outcomes. It contributes to higher education management literature by positioning universities as active participants in digital transformation (Marginson, 2022; UNESCO, 2023), proposes a multidimensional framework integrating technology acceptance, facilitating conditions, and educational interventions, and expands the application of Triple Helix Theory to workforce capability development and digital transformation within the agri-food sector.

7.3 Practical Implications for Higher Education Management

Curriculum innovation. Universities should incorporate blockchain-related competencies into academic programs across agriculture, business administration, supply chain management, information technology, and sustainability studies, encouraging cross-functional learning and collaborative problem-solving, and integrating simulations, case studies, project-based learning, and industry collaborations.

Lifelong learning and professional development. The strong demand for professional training and industry workshops indicates the growing importance of lifelong learning. Universities should expand continuing education through micro-credential programs, professional certificates, executive education, short-term digital skills training, and online and hybrid learning platforms.

Industry engagement. Universities should strengthen partnerships with industry through advisory boards, internship programs, applied research projects, innovation labs, and joint curriculum development to keep programs aligned with labor market needs.

Research and innovation capacity. Universities should invest in interdisciplinary research on blockchain applications, digital agriculture, food traceability, and sustainable supply chains to support evidence-based policy and technological innovation.

7.4 Policy Implications

Thailand 4.0 and national digital transformation. Thailand's transition toward an innovation-driven economy requires substantial investment in human capital and digital capability. Universities should be recognized as strategic partners in implementing Thailand 4.0. Government agencies may support adoption by funding university-led training programs, supporting digital agriculture initiatives, encouraging university–industry collaboration, providing incentives for technology adoption, and expanding digital infrastructure in rural areas.

Higher education policy. Policies should encourage universities to adopt flexible, responsive educational models that address emerging workforce needs, including recognition of micro-credentials, support for lifelong learning, funding for interdisciplinary curriculum innovation, incentives for industry engagement, and promotion of digital competency frameworks.

ASEAN regional cooperation. The findings are relevant to broader ASEAN efforts to strengthen regional competitiveness and digital integration. ASEAN universities may benefit from cross-border blockchain education programs, regional research networks, joint innovation projects, shared digital learning platforms, and academic mobility programs.

7.5 Limitations of the Study

Several limitations should be acknowledged. First, the cross-sectional design precludes definitive causal inference; future longitudinal studies may provide stronger evidence regarding changes in adoption readiness over time. Second, data were collected from selected provinces, so the findings may not be fully generalizable to all Thai agricultural stakeholders. Third, the study relied on self-reported perceptions, which may not translate into actual adoption behavior; because all constructs were measured through a single self-report instrument, common method bias cannot be ruled out and should be tested (e.g., Harman's single-factor test) in future work. Fourth, the study focused specifically on blockchain within the agri-food sector, and adoption dynamics may differ in other industries. Finally, while the integrated TAM–UTAUT–Triple Helix framework explained important aspects of adoption readiness, additional variables such as trust, organizational culture, perceived risk, and regulatory uncertainty may further influence outcomes.

7.6 Future Research Directions

Future studies may employ longitudinal designs to examine how awareness, perceptions, and readiness evolve as blockchain becomes more widespread; extend the study to other sectors such as healthcare, logistics, manufacturing, tourism, and financial services; incorporate additional constructs such as trust, perceived risk, innovation readiness, digital literacy, and organizational culture; conduct comparative studies across ASEAN countries; and use qualitative approaches such as interviews, focus groups, and case studies to deepen understanding of stakeholder experiences. Future research should also evaluate the effectiveness of specific educational interventions—including micro-credentials, professional certifications, digital badges, and work-integrated learning programs—in enhancing adoption readiness.

7.7 Concluding Remarks

As emerging technologies such as blockchain become increasingly important within modern economies, HEIs must assume more proactive roles in supporting workforce development, technological innovation, and societal transformation. The findings of this study demonstrate that successful blockchain adoption depends not only on technological acceptance but also on educational support systems, institutional collaboration, and continuous learning opportunities. By embracing curriculum innovation, lifelong learning, interdisciplinary collaboration, and university–industry–government partnerships, HEIs can contribute significantly to Thailand's digital transformation agenda and to the development of more sustainable, transparent, and resilient agri-food systems. In this context, the future of blockchain adoption is not solely a matter of technology; it is equally a matter of education, collaboration, and institutional leadership.

References

Alenezi, M. (2023). Digital transformation in higher education institutions: A systematic review of challenges and opportunities. *Education and Information Technologies*, *28*(9), 11045–11069. https://doi.org/10.1007/s10639-023-11698-5

Behnke, K., & Janssen, M. F. W. H. A. (2020). Boundary conditions for traceability in food supply chains using blockchain technology. *International Journal of Information Management*, *52*, 101969. https://doi.org/10.1016/j.ijinfomgt.2019.05.025

Caro, M. P., Ali, M. S., Vecchio, M., & Giaffreda, R. (2018). Blockchain-based traceability in agri-food supply chain management: A practical implementation. In *2018 IoT Vertical and Topical Summit on Agriculture – Tuscany* (pp. 1–4). IEEE.

Casino, F., Dasaklis, T. K., & Patsakis, C. (2019). A systematic literature review of blockchain-based applications: Current status, classification and open issues. *Telematics and Informatics, 36*, 55–81. https://doi.org/10.1016/j.tele.2018.11.006

Chang, S. J., Tsai, H. C., & Hung, S. Y. (2022). Integrating blockchain with agri-food supply chains to enhance sustainability and transparency. *Sustainability, 14*(12), 7315.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). Sage.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340.

Demestichas, K., Peppes, N., Alexakis, T., & Adamopoulou, E. (2020). Blockchain in agriculture traceability systems: A review. *Applied Sciences, 10*(12), 4113.

Etzkowitz, H., & Leydesdorff, L. (2000). The dynamics of innovation: From national systems and "Mode 2" to a Triple Helix of university–industry–government relations. *Research Policy, 29*(2), 109–123.

Food and Agriculture Organization. (2019). *E-agriculture in action: Blockchain for agriculture opportunities and challenges*. FAO.

Gupta, S., Montenovo, L., Nguyen, T., Lozano-Rojas, F., Schmutte, I., Simon, K. et al. (2023) *Effects of social distancing policy on labor market outcomes*. *Contemporary Economic Policy*, 41(1), 166–193. Available from: https://doi.org/10.1111/coep.12582

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2022). *Multivariate data analysis* (9th ed.). Cengage.

Kamble, S. S., Gunasekaran, A., & Sharma, R. (2021). Sustainability-driven blockchain-enabled traceability in the food supply chain. *Journal of Global Operations and Strategic Sourcing, 14*(2), 124–147.

Kamilaris, A., Fonts, A., & Prenafeta-Boldú, F. X. (2019). The rise of blockchain technology in agriculture and food supply chains. *Trends in Food Science & Technology, 91*, 640–652.

Kampan, K., Tsusaka, T. W., & Anal, A. K. (2022). Adoption of blockchain technology for enhanced traceability of livestock-based products. *Sustainability, 14*(20), 13148.

Kshetri, N. (2018). Blockchain's roles in meeting key supply chain management objectives. *International Journal of Information Management, 39*, 80–89.

Liang, Y., Wang, H., Zhang, X., & Liu, S. (2022). Blockchain and its role in reducing food waste and improving sustainability in global supply chains. *Journal of Cleaner Production, 345*, 131223.

Marginson, S. (2022). The worldwide trend to high participation higher education. *Higher Education, 84*(1), 23–41.

Ministry of Higher Education, Science, Research and Innovation. (2023). *Thailand higher education, science, research and innovation policy framework 2023–2027*. MHESI.

Organisation for Economic Co-operation and Development. (2023). *Education at a glance 2023: OECD indicators*. OECD Publishing.

Polit, D. F., & Beck, C. T. (2006). The content validity index: Are you sure you know what's being reported? *Research in Nursing & Health, 29*(5), 489–497.

Saurabh, S., & Dey, K. (2021). Blockchain technology adoption, architecture, and sustainable agri-food supply chains. *Journal of Cleaner Production, 284*, 124731.

Tian, F. (2017). A supply chain traceability system for food safety based on HACCP, blockchain, and Internet of Things. In *International Conference on Service Systems and Service Management* (pp. 1–6). IEEE.

Toader, D. C., Rădulescu, C. M., & Toader, C. (2024). Investigating the adoption of blockchain technology in agri-food supply chains: Analysis of an extended UTAUT model. *Agriculture, 14*(4), 614.

Treiblmaier, H., & Sillaber, C. (2021). The role of blockchain in improving sustainability and traceability in global food supply chains. *International Journal of Production Research, 59*(8), 2345–2360.

UNESCO. (2023). *Reimagining our futures together: A new social contract for education*. UNESCO.

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

World Economic Forum. (2023). *The future of jobs report 2023*. World Economic Forum.

Zhao, G., Liu, S., Lopez, C., Lu, H., Elgueta, S., Chen, H., & Boshkoska, B. M. (2019). Blockchain technology in agri-food value chain management: A synthesis of applications, challenges, and future research directions. *Computers in Industry, 109*, 83–99.

Zhao, X., Lin, Y., & Lu, J. (2022). Blockchain adoption in agri-supply chains: Environmental impact and sustainability potential. *Journal of Cleaner Production, 365*, 132456.

Appendix A. Survey Questionnaire

Blockchain Adoption Readiness and the Role of Higher Education Institutions in Thailand's Agri-Food Sector

Section A — Demographic information

1. Gender: Male / Female / Prefer not to say
2. Age: Under 30 / 31–40 / 41–50 / Above 50
3. Educational level: Secondary school / Diploma / Bachelor's degree / Master's degree / Doctoral degree
4. Occupation: Farmer / Food processor / Restaurant manager / Other _____
5. Years of experience: Less than 5 years / 5–10 years / 11–20 years / More than 20 years

Sections B–F were rated on a five-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*).

Section B — Blockchain awareness

- I am familiar with blockchain technology.
- I understand how blockchain works.
- I am aware of blockchain applications in food supply chains.
- I know the benefits of blockchain for traceability.
- I understand blockchain's role in food safety.

Section C — Perceived usefulness (TAM)

- Blockchain can improve traceability.
- Blockchain can improve food safety.
- Blockchain can increase consumer trust.
- Blockchain can reduce fraud.
- Blockchain can improve business performance.

Section D — Perceived ease of use (TAM)

- Learning blockchain would be easy for me.
- Blockchain systems are easy to understand.
- Blockchain technology is user-friendly.
- I could quickly become skillful in using blockchain.

Section E — Facilitating conditions (UTAUT)

- Training opportunities are available.

- Technical support is available.
- Digital infrastructure is sufficient.
- Government support is available.
- My organization is ready for blockchain adoption.

Section F — Higher education support

- Universities should provide blockchain training.
- Universities should develop blockchain curricula.
- Universities should offer micro-credentials.
- Universities should collaborate with industry.
- Universities should support applied blockchain research.

Appendix B. Content Validity Assessment (I-CVI / S-CVI)

Expert panel: Expert 1 — higher education management; Expert 2 — educational technology; Expert 3 — agricultural supply chain; Expert 4 — blockchain technology; Expert 5 — research methodology.

Item Content Validity Index (I-CVI)

Construct	Number of items	I-CVI range
Awareness	5	0.80–1.00
Perceived usefulness	5	0.80–1.00
Perceived ease of use	4	0.80–1.00
Facilitating conditions	5	0.80–1.00
Higher education support	5	0.80–1.00

Scale Content Validity Index (S-CVI/Ave): 0.94 for the entire questionnaire. According to Polit and Beck (2006), an S-CVI value above 0.90 indicates excellent content validity.

Appendix C. Ethics Approval Statement

This study was reviewed and approved by the Research Ethics Committee. Participants were informed that participation was voluntary; that they could withdraw at any time without penalty; that responses would remain confidential; that data would be reported only in aggregate form; and that no personally identifiable information would be disclosed. Prior to participation, all respondents received an information sheet explaining the purpose of the study, procedures, estimated completion time, potential risks and benefits, and data-confidentiality measures. Written or electronic informed consent was obtained before data collection.

All research data were stored on password-protected devices, accessible only to the research team, retained for five years following publication, and securely destroyed thereafter.

Conflict of interest. The authors declare no conflict of interest.

Declaration of generative AI use. Artificial-intelligence-assisted tools were used solely for language editing and grammar refinement. All research design, data collection, analysis, interpretation, and manuscript preparation were conducted by the authors.

RCG-JF Thailand-3

Documented Alignment, Deferred Evidence: A Single-Case Study of Outcome-Based Education Transition in a Thai Private-University Business English Programme

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ABSTRACT

This study analyses how self-assessment reports impact the educational quality, by applying the AUN-QA documentation of a Bachelor of Arts program in English for Business Communication at a Thai private university. The institution is currently transitioning toward an outcome-based curriculum. The study questions whether the documentary evidence required by the standards framework is sufficient to distinguish genuine pedagogical reform from ritualistic compliance. The qualitative analysis examines 358 pages report of self-assessment prepared by AUN-QA Version 4.0 criteria for program-level quality assessment. The report includes student cohort data, employment exploration, and the reported curriculum level. The coding process proceeded with the evidence requirements of the standards framework to explore argumentation strategies not anticipated by the framework. The report establishes a comprehensive alignment of curriculum structure in which every stated learning outcome links to specific courses, assessment tools, and documented improvement actions. Besides, the report presents programmed-level indicators: a graduation rate ranging from 57.5% to 64.0% (versus an implicit target of 100%) and a graduate employment rate of 65.2% for the reporting year (versus a target of 80%). These figures, however, derive from cohorts who studied under the superseded curriculum. Although the framework requires reporting on both curriculum design and graduate outcomes, it provides no mechanism to distinguish evidence from the new curriculum from evidence from the old one. The research found that documentary records cannot distinguish between programs where reforms reached the classroom and those where reforms remained only on paper, both scenarios generate identical evidence. The analysis

examines documentary claims rather than classroom practice, and the reported figures could not be independently verified. The indicators include students who did not complete the program. The study recommends that the framework's custodians require cohort provenance in Criterion 8 reporting, and that assessors withhold outcome ratings during a declared transition period rather than assign a midpoint score that conveys no information. The research distinguishes documentary maturity from outcome maturity and argues that the gap between them is a matter of time, not motive. Decoupling theory attributes such gaps to intent: organisations deliberately buffer their technical core. The gap identified here, however, persists even when intent is removed. A program reformed entirely in good faith still cannot produce outcome evidence until its first cohort has completed the full curriculum. This points to a structural limit of outcome-based quality assurance that no degree of institutional sincerity can close.

Keywords: Outcome-Based Education, AUN-QA, Quality Assurance, Constructive Alignment, Curriculum Transition, Document Analysis

1. Introduction

Outcome-based education (OBE) has become the organizing logic of programme-level quality assurance across Southeast Asia. The fourth version of ASEAN University Network Quality Assurance (AUN-QA) framework expected that learning outcomes are not merely one of eight criteria but the axis around which the other seven revolve, including programme structure and content, teaching and learning approach, student assessment, academic staff, student support services, facilities and infrastructure, and output and outcomes. These aspects were assessed by its contribution to outcomes that the programme itself has declared. The framework therefore rewards demonstrable alignment, leading to analytically interesting since the alignment is a property of documents before it is a property of graduates.

Thailand's Qualifications Framework for Higher Education has specified learning outcomes across several aspects, including attitudes and generic competencies alongside discipline-specific knowledge and skills (Maneerat et al., 2015). The revised programme consists of two logics. st,First, a national template mandates the domains of outcomes, and an international framework assesses whether evidence supports those outcomes. The two are not the same. The national framework specifies what must be declared; AUN-QA specifies what must be demonstrated. When a mandated domain resists measurement, the programme is compelled to declare outcomes for which it has no instrument to produce evidence, which is not a peripheral technicality. However, it is the documentary compliance and demonstrable achievement first diverge, a divergence that recurs throughout the analysis below.

The literature on quality assurance compliance presents two contrasting perspectives. First, based on institutional theory, views extensive compliance documentation as a ceremonial exercise. Organizations adopt the formal structures necessary for legitimacy while shielding their core activities from disruption (Meyer & Rowan, 1977). This phenomenon is common in higher education, where evaluation systems produce labor-intensive tasks that often lack a meaningful connection to classroom practice (Newton, 2000; Oware & Mokoena, 2026). The second perspective sees the same process as a form of institutional learning. The requirement to specify outcomes and align them with assessments encourages curricular thinking that might not otherwise occur, aligning with the principle of constructive alignment (Biggs, 1996; Almuhaideb & Saeed, 2020). Interestingly, both perspectives share a fundamental assumption: they both believe that a thorough examination of a program can clearly reveal which perspective it aligns with. Harvey and Green (1993) noted that quality frameworks can provoke transformation while assessing their effectiveness. This raises a more concerning possibility that remains unexplored: the evidence these frameworks produce may not distinguish between the ceremonial and learning aspects at all.

This shared assumption has not been evaluated against the evidence produced by the framework itself. This issue is significant beyond academic literature. When a quality assurance system cannot differentiate between genuine reform and mere documentation, the impact ultimately falls on the students enrolled in programs that the system has already approved. In the case being examined, between 36.0% and 42.5% of students in cohorts that have reached their expected graduation date did not complete their programs. Notably, their dropout rates are recorded in the same report that rates the program as adequate on all criteria.

This study examines the evidence base for the AUN-QA self-assessment report of a Bachelor of Arts program in English for Business Communication at a Thai private university. The report consists of 358 pages and was prepared for the program-level quality assessment during the second year of the program's transition to an outcome-based curriculum. This case is particularly insightful not because such programs are often overlooked, but because the transition reveals a clear discrepancy. The new curriculum's structure can be evaluated right away, while its outcomes will only be evident four years later. As a result, the report must juxtapose design evidence from the current curriculum with outcome evidence from the previous one. This transitional report makes explicit what quality assurance documentation typically leaves implicit.

Two questions guide the analysis. First, how does the report present evidence of outcome achievement, and at what level of the system does that evidence reside? Second, is that

evidence sufficient to distinguish genuine pedagogical reform from ceremonial compliance? The second question admits a positive answer. If the documentary record contained evidence that only genuine reform could produce, the framework's evidentiary requirements would be vindicated.

The analysis reveals a comprehensive, internally traceable alignment architecture in which every element is consistently linked to both reforms that affected the classroom and those that appeared only in documents. Additionally, the report provides outcome indicators describing groups of students who were taught under a curriculum that is no longer in use. This article has three significant contributions. First, the methodological approach demonstrates that a self-assessment report can be analysed as a research object, an artifact whose claims can be scrutinised rather than being viewed merely as a source of information about a program. Second, it conceptually differentiates between documentary maturity and outcome maturity. The distinction sets this phenomenon apart from traditional decoupling theories. It also demonstrates how transitional reporting periods expose limitations of outcome-based quality assurance that steady-state reporting hides. Section 2 develops the conceptual framework, Section 3 covers the case study, Section 4 discusses the document analysis method and its limits, Section 5 presents findings, and Section 6 explores implications for framework design and assessor practices.

2. Conceptual Framework

2.1 Outcome-based education and the assessability requirement

Outcomes-Based Education (OBE) reverses the traditional approach to curriculum design. Instead of starting with content and then inferring what students will learn, OBE begins by clearly defining what graduates should be able to do. It then works backward to identify the evidence needed to demonstrate that students have achieved these capabilities, followed by determining the teaching methods that will cultivate these skills (Spady, 1994; Wiggins & McTighe, 2005).

This reversal introduces a straightforward yet challenging requirement: every stated outcome must be assessable. An outcome that cannot be measured is not merely ineffective; it is superficial, and including it in curriculum documents represents a promise the program cannot fulfil. This requirement is particularly challenging when a national qualifications framework specifies outcome domains that are difficult to assess, such as dispositional, attitudinal, and character-related domains (Maneerat et al., 2015; Potgieter et al., 2025). When faced with such a mandate, a program has three options: develop assessment instruments, declare outcomes

unmeasurable, or limit its outcomes to those existing instruments can evaluate. The second and third options are merely administrative solutions to a pedagogical issue and are not reflected in a curriculum map.

This matters for the argument that follows because it establishes that OBE generates two separable artifacts, the specification of outcomes and the evidence of their achievement, which can exist independently of each other. The remainder of this framework concerns what happens when the two come apart.

2.2 Constructive alignment as a testable claim

Constructive alignment provides the framework for how Outcome-Based Education (OBE) is intended to transform learning, rather than just altering documentation (Biggs, 1996; Biggs & Tang, 2011). Students create meaning through the activities they engage in. When the intended outcomes, learning activities, and assessment tasks use the same verbs at the same cognitive level, student effort naturally shifts toward these outcomes because the assessment reinforces the alignment. Conversely, misalignment not only results in disorganized documentation but also signals to students that the stated outcomes are not the true expectations they need to meet.

The theory's value lies in its locatable claim that alignment is a property of individual courses rather than a programme-level matrix. It can be observed through the verbs in course learning outcomes, student activities, and the assessment criteria. A curriculum map might suggest alignment that courses do not actually achieve, while a course can be well aligned despite not appearing so in a matrix.

This yields the study's first analytical requirement: examine claims of alignment where alignment resides, not where it is declared. It also yields a caution that applies to this study itself. When the only available record of course-level practice is the programme's own account, the examination is conducted on descriptions of teaching, not on teaching.

2.3 Two readings of compliance

The literature on quality assurance in higher education has two well-developed and incompatible readings of what a programme is doing when it produces quality assurance documentation.

Institutional theory suggests that organizations under pressure for external legitimacy adopt formal structures while protecting their core activities from disruptions. This results in a loose

coupling between formal structure and operational activities, leading to ceremonial compliance (Meyer & Rowan, 1977; DiMaggio & Powell, 1983). In the aspect of higher education, quality assurance efforts are seen as labor-intensive and sincere but largely disconnected from actual classroom practices (Newton, 2000; Pham & Nguyen, 2024).

The second reading stated that the institutional learning emphasises the importance of specifying outcomes and assessments to enhance curricular reasoning. Documentation reflects genuine deliberation rather than serving as a mere substitute (Almuhaideb & Saeed, 2020; Uchiyama & Radin, 2009). Both readings have empirical support and address different cases effectively.

Both readings are supported by empirical evidence, and each accounts for cases that the other explains less adequately. Despite their disagreement, however, the two readings share a common assumption: that the distinction between genuine reform and ceremonial compliance is empirically recoverable, such that sufficiently close examination would allow any given programme to be assigned to one reading or the other. The debate in the literature has therefore centered on which reading applies more frequently, rather than on whether the question can be answered at all.

2.4 What assurance frameworks measure

Harvey and Green's (1993) typology distinguish quality as exceptional, as perfection, as fitness for purpose, as value for money, and as transformation. The distinction most relevant here is between fitness for purpose and transformation.

AUN-QA's stated rationale is transformative: the framework exists to improve what graduates can do. Its procedures, however, concern fitness for purpose. A programme declares its outcomes and is assessed on whether its documented processes are adequate to what it has declared. A programme can therefore score well by showing that its processes are fit for its declared purposes, without making any claim about whether its students have been transformed.

This is less a criticism of the framework's design than a description of it. It carries, however, an implication it does not pursue. If the procedures measure fitness for purpose, the evidence they generate shows correspondence between process and declaration, and this correspondence is precisely what both readings in Section 2.3 predict. A programme engaged in institutional learning produces documented alignment; a programme engaged in ceremonial compliance also produces documented alignment. The evidentiary output is identical because the framework was never designed to distinguish between the two.

2.5 Documentary maturity and outcome maturity

The two properties of a programme can be distinguished as follows:

Documentary maturity is the degree to which a programme's declared alignment architecture is complete, internally consistent, and traceable from stakeholder evidence through outcomes and assessment to teaching. It can be verified by inspection and can be achieved within a single planning cycle.

Outcome maturity is the degree to which students demonstrably achieve the declared outcomes and reach the ends the programme exists to serve. It can be verified only by observing graduates, and it cannot be verified in less time than the length of the programme.

This distinction is not merely a restatement of the institutional-theory division between formal structure and technical activity. Two differ in the role they assign to intent. Decoupling is a motivational account, organizations buffer their technical core because buffering serves them, and the gap between structure and activity results from organizational strategy. If that strategy is removed, for instance by supposing an organization that reforms in complete good faith and implements every documented change, the decoupling account predicts that the gap will close.

The gap identified here persists even when strategy is removed. A programme reformed in complete sincerity, in which every documented pedagogical change is fully implemented in every classroom, still cannot evidence outcome maturity for four years, because its first cohort has not yet graduated. The gap is a matter of time, not intent. For that reason, it is present in both the sincere and the ceremonial case, which is why the documentary record cannot distinguish between them.

2.6 Analytic consequences

According to the study, three consequences follow for the analysis in Sections 4 and 5, including:

First, the focus of the analysis is on the claims made in the report, not on the actual practices of the programme Since the record consists solely of the program's self-representation, we don't have access to information about what the program truly does. Instead, we can assess what the report claims and examine the internal consistency of those claims.

Second, the study's central question can have a negative answer. If the documentary evidence fails to differentiate between two interpretations, this indicates a limitation in the framework's evidentiary requirements, not a flaw in the analysis itself.

Third, the analysis must apply its own standards to itself. If a study criticizes a quality assurance framework for evaluating programs based on documents while it simultaneously judges a program through documents, it either needs to acknowledge this inconsistency or address it by equating the analyst's perspective with that of the assessor and asking what conclusions can be drawn by either party.

3. The Case

3.1 Institutional setting

The site is a private higher education institution located in a major city in Thailand. It has operated a formal quality assurance framework since 2001 and adopted AUN-QA for program-level self-assessment in 2021. Each program must prepare an annual self-assessment report, which a committee of one external assessor and two internal assessors evaluates. The institution is identified by its sector, size, and regulatory environment rather than by name, as the analysis focuses on characteristics it shares with similar institutions rather than on features unique to it.

The institution's status as a private entity is significant for this analysis. In Thailand, private higher education institutions rely primarily on tuition fees for revenue and compete for a limited pool of domestic students, a situation made more challenging by demographic decline and the expansion of public-sector capacity (Scott & Guan, 2023). Consequently, enrollment volume is not a typical performance indicator but a financial condition. This implication recurs in Section 5. Indicators such as enrollment against plan, attrition, and graduation rates, which publicly funded institutions treat as quality signals, carry a second, financial meaning in this context, and the quality assurance framework records only the first.

3.2 The programme

The programme studied is a bachelor's degree in English for Business Communication, established in the early 2000s and subject to AUN-QA reporting since the institution adopted the framework in 2021. It requires 123 credits, covering general education, four groups of core courses, major courses, cooperative education, and free electives, and includes a mandatory sixteen-week work placement in the final year.

The programme is small. It has eight full-time academic staff, three of whom hold doctorates and one of whom holds the rank of assistant professor. Annual intake across the nine recorded cohorts ranged from 30 to 73 students, averaging approximately 47, against a planned intake of 80, which was not reached in any year in the dataset.

3.3 Two curricula in parallel

In the academic year under analysis, the programme operated two curricula simultaneously. The previous curriculum, structured according to the model prescribed by the earlier national qualifications' framework, applies to students admitted up to the transition year and remains in force until those students' graduate. The revised curriculum, introduced following the revision of the national framework, adopts an outcome-based design and organizes its outcomes according to the domains mandated by the revised framework.

No cohort had yet graduated under the revised curriculum. At the time the report was prepared, the most advanced students in the revised curriculum were in their second year.

This configuration is the reason the case was selected, and its structure should be stated precisely. It produces three distinct populations within a single report: students whose entire education took place under the previous curriculum, whose outcomes are fully observable; students who transitioned partway through, whose experience combines both curricula; and students admitted under the revised curriculum, for whom only course-level evidence exists. The framework requires all three to be reported under a single set of Criterion 8 indicators and provides no field for distinguishing the provenance of each.

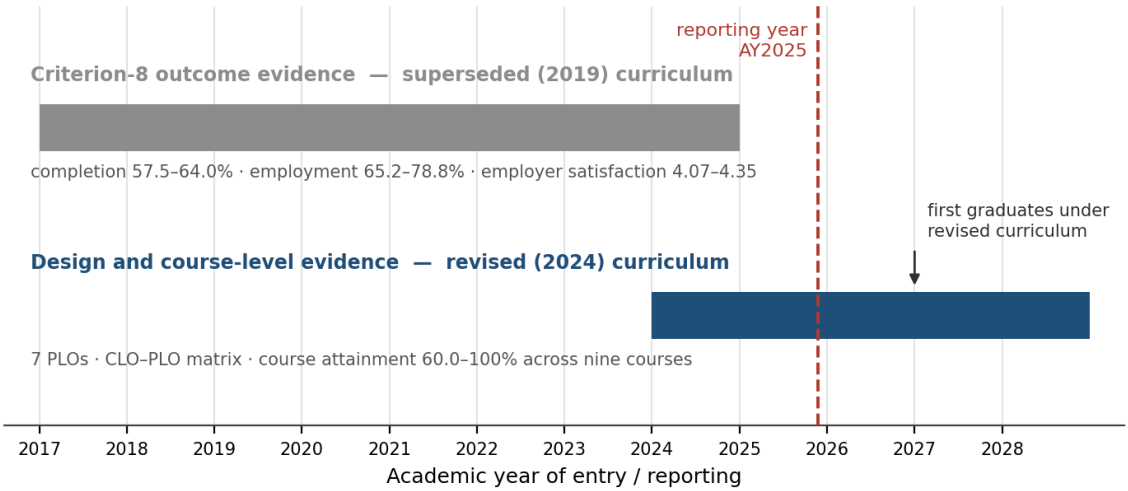


Figure 1: Sources of the two types of evidence presented under a single set of criteria. The lower bar shows evidence of curriculum design, while the upper bar shows evidence of curriculum outcomes.

3.4 Why this case

The case was selected on theoretical rather than representative grounds (Eisenhardt, 1989; Flyvbjerg, 2006; Siggelkow, 2007). No claim is made that the programme is representative of its sector, and no attempt is made to generalize from it to that population.

The analytical value of the case lies in a property that programmes in a steady state do not display. When a programme is not in transition, design evidence and outcome evidence describe the same curriculum, and the relationship between them does not arise as a question. Outcome indicators can be read, however loosely, as evidence about the design that produced them. A programme in transition severs that relationship. Its design evidence describes one curriculum, its outcome evidence describes another, and the framework reports both under a single set of criteria without marking the difference.

The transition therefore functions as a natural disclosure. What the case makes visible is not a deficiency of this programme but a property of the framework's evidentiary architecture, one ordinarily concealed by the coincidence that design, and outcomes usually refer to the same object.

3.5 The document

The unit of analysis is the programme's 358-page self-assessment report under the AUN-QA Version 4.0 criteria for the year under study. It comprises an executive summary, institutional

information, narratives and evidence for each of the eight criteria, the self-assessment results, and appendices containing national standards compliance tables, a common data set, and a register of evidence sources.

The report was prepared by the programme for programme-level quality assessment. In the terms set out in Section 2.6, it is an artifact whose claims are the object of analysis, not a source of verified facts about the programme. Section 4 explains what this permits and what it forecloses.

4. Method

4.1 Design and unit of analysis

This is a documentary study of a single artifact. The unit of analysis is the self-assessment report described in Section 3.5, not the programme the report describes.

The distinction is consequential and is maintained throughout. The programme is an ongoing arrangement of people, practices, and resources; the report is a text the programme produced for an external audience in a prescribed format. Only the latter is open to examination. Statements in Section 5 therefore concern what the report asserts, records, or omits, and are phrased accordingly. Where an inference about practice is unavoidable, it is identified as an inference.

This is not a reluctantly conceded limitation but a design choice, and it reflects the evidentiary position the framework itself establishes. AUN-QA assessors evaluate programmes primarily through self-assessment documentation, supplemented by a brief site visit. A study that examines what such documentation can and cannot establish is therefore studying the assessor's epistemic situation, not working at a disadvantage relative to the assessor.

4.2 The document as evidence

Documentary sources are not transparent windows onto the activities they describe (Atkinson & Coffey, 2011; Prior, 2003; Scott, 1990). Three properties of this document govern how it is read.

First, the document was produced for quality assessment. Its rhetorical function is to demonstrate compliance with eight criteria. That function shapes its selection, framing, and emphasis, which are therefore analysable material, not noise to be filtered out.

Second, much of its content is mandated. The framework specifies what must be reported, including indicators unfavourable to the programme. This forecloses an inference commonly drawn from self-authored sources: that negative content is credible because a persuasive document has no reason to include it. Here it has every reason. The framework requires it, and negative content presented within an explanatory frame is more persuasive than an omission. Negative figures in this report are therefore treated with the same caution as positive ones.

Third, its quantitative content cannot be independently verified. The reported cohort, graduate-tracking, and course-level figures derive from institutional systems to which this study had no access. They are analysed as reported figures: claims about numbers, whose internal consistency can be checked but whose accuracy cannot. Where recalculation from the report's own tables conflicts with its narrative summaries, both are presented, and the discrepancy is treated as a feature of the document.

4.3 What the design can and cannot establish

Stating this in advance disciplines the analysis, which is why it is placed here rather than deferred to a section on limitations.

The design can establish what claims the report makes, whether its evidence supports its own conclusions, whether its components are internally consistent, how it constructs justifications for its self-assessment ratings, and what the framework's evidentiary requirements permit and do not permit an assessor to conclude.

The design cannot establish whether the documented pedagogical changes occurred, whether the reported figures are accurate, whether staff or students experienced the transition as described, or, most centrally, whether the reform is genuine or ceremonial. This last point is not a failure of execution. Section 2.4 anticipates it: if both readings generate identical documentary output, no analysis confined to that output can decide between them. The study's central finding follows from its design, not from a flaw in it.

4.4 Analytic procedure

The analysis proceeded in four phases as follows:

Structural mapping. The report was indexed against the eight criteria and their sub-criteria to determine which claims are supported by evidence, which are merely asserted, and which sub-criteria are answered with unrelated material.

Deductive coding. Text was coded according to categories derived from Section 2. For alignment claims, the question was whether alignment is specified at the level at which it is observable (course verbs, learning activities, assessment criteria) or asserted only at the programme level. For outcome claims, the question was which of the three populations identified in Section 3.3 the evidence concerns. For justifications, the question was what the report offers as the basis for each self-assessment rating.

Inductive coding. Material that these categories could not accommodate was open-coded. Two claim-construction strategies emerged and are reported in Section 5: placing negative indicators alongside pre-emptive explanatory framing and substituting process evidence where outcome evidence is required.

Recalculation. All figures in Criterion 8 and the common data set were extracted and recalculated independently of the report's narrative interpretation, with attention to base populations, cohort provenance, and consistency between tables and text.

4.5 Reflexivity and countermeasures

The analyst holds a position within the institution. This provides contextual knowledge unavailable to an external reader, and it creates an interest in a favourable reading.

Disclosure does not neutralize this interest. Three countermeasures were adopted, and their limits are stated:

First, Independent counter-coding of a sample. A colleague with no involvement in the programme independently coded 75 pages using the same framework. The sample was selected purposively rather than randomly and comprised the sections densest in interpretive claims: the criterion on expected learning outcomes, the sub-criteria on the improvement cycle, the criterion on output and outcomes, and the self-assessment results table. Sampling by length would have weighted the sample toward the appendices and compliance tables, which require little interpretation. Section 5 reports disagreements rather than resolving them into consensus. This measure addresses coder bias but not bias in the framework that both coders applied.

Second, Recalculation against narrative. Where the report's tables and its interpretation of those tables diverge, the report notes the divergence. This is a check on the document, not on the analyst.

Third, Member reflections. The findings were returned to the programme, and points of disagreement are recorded in Section 5.4 without adjudication (Tracy, 2010; Smith & McGannon, 2018). Because the analyst occupies an asymmetric position relative to the respondents, this step elicits responses but cannot guarantee them, and the report reflects that.

4.6 Quality criteria

Conventional trustworthiness criteria are applied here only where the design supports them, and their limits are stated rather than asserted away.

Credibility rests on a complete reading of the single source, the independent counter-coding of a sample, and recalculation. It does not rest on data triangulation, which is unavailable with a single data source.

Dependability is supported by the coding framework set out in Section 4.4, which derives from Section 2, and an independent reader can be applied to the same document.

Confirmability is limited. The institution's underlying data cannot be verified, and this constrains every quantitative claim in Section 5.

Transferability is limited to programmes that share the structural characteristics described in Section 3: small programmes in tuition-dependent institutions that produce quality assurance documentation during a curriculum transition.

4.7 Ethics

The report is an institutional document. Written permission to analyse it and publish the findings was obtained from the programme and the faculty before the study began.

The institution is not named, but this affords only partial protection. In a small national sector, an English for Business Communication programme with eight academic staff, reporting under a named framework in a stated year, is identifiable to an informed reader. Two further measures were therefore adopted. First, individual staff members are identifiable in the report's appendices through their qualifications, workloads, and course evaluation records, so no

individual-level staff data are reproduced or analysed, and findings concerning staff are reported only in aggregate. Second, where an aggregate figure would itself identify individuals within a unit of eight, most clearly where research output is concentrated among a small number of staff, that figure is omitted, at little cost to the argument.

Students appear in this study only as aggregate cohort figures. They were not consulted, and their consent was not sought for using their outcome data, since those data had already been reported to the framework under the institution's data agreements. Section 7 considers what this exclusion means for the study's conclusions.

5. Findings

5.1 What the report claims about outcome specification

The report presents an outcome architecture comprising seven programme learning outcomes (PLOs), distributed across the four domains mandated by the revised national framework. Each PLO uses an action verb and a declared cognitive level, and each is broken down into knowledge, skill, and dispositional components.

The architecture is internally traceable. Every declared outcome map to at least one course, every course to a set of course learning outcomes (CLOs), and every CLO to a specified assessment instrument. The report includes a verification table confirming that each CLO's cognitive level matches the level declared for its parent PLO. This element is often absent from OBE documentation, and its presence suggests that the map was constructed rather than assembled from pre-existing syllabus text.

Two features of the outcome specification are analytically significant:

First, the report does not address the uneven distribution of declared cognitive levels. Three outcomes reach the Create level: PLO 4 (designing and presenting communication strategies), PLO 6 (self-development and adaptability), and PLO 7 (synthesis through cooperative education). Three reach the Evaluate level. One, PLO 2, declares a ceiling at Apply (Remember, Understand, Apply). That a business knowledge outcome should function as a knowledge base rather than an analytical capability is defensible in a communication programme. However, the report neither states nor defends this claim, and it sits uneasily alongside three things the report records elsewhere. The outcome statement itself reads "Apply fundamental business concepts and principles to analyse and resolve work-related challenges," so the verb analyse appears in the declared outcome but not in its declared cognitive level. The stakeholder needs analysis

records that employers and alumni require analytical thinking and problem-solving under time pressure. The attainment matrix records PLO 2 as only partially achieved across all stakeholder groups; the only PLO assessed. The report identifies this last point as a gap but does not connect it to the other two.

Table 1: Declared cognitive-level ceilings of the seven programme learning outcomes. PLO 2 is the only outcome whose declared cognitive level stops below Analyse, although the verb analyse appears in the outcome statement itself.

Programme learning outcome	**Declared Bloom levels**	**Ceiling**
1 Communicate in English and Thai in multicultural professional contexts	Apply · Analyse · Evaluate	Evaluate
2 Apply fundamental business concepts to analyze and solve workplace challenges	Remember · Understand · Apply	Apply
3 Select, evaluate, and use technology and AI tools	Understand · Apply · Evaluate	Evaluate
4 Design and present communication strategies	Apply · Analyse · Create	Create
5 Demonstrate professional and ethical conduct	Understand · Apply · Evaluate	Evaluate
6 Develop oneself, collaborate across roles, and adapt	Apply · Analyse · Evaluate · Create	Create
7 Synthesize knowledge, skills, and values through cooperative education	Apply · Analyse · Evaluate · Create	Create

Second, the dispositional domain is specified but not instrumented. Report Table 1.2-3 declares sixteen dispositional attributes, eight in the ethics domain (E1–E8) and eight in the character domain (C1–C8), and reproduces the same set verbatim in the row for each of the seven PLOs, including PLO 5, whose knowledge and skill cells are empty. The specification therefore asserts that every outcome develops every disposition equally, which cannot be assessed. When the document moves from declaration to instrument, only six of the sixteen attributes attach to any course (E1, E3, E6, C2, C3, and C7, in the three sample course specifications). The remaining ten do not appear in any course-level assessment label. E4 (patience) is not named in any rubric descriptor in either Report Table 1.5-A or Report Table 2.4-A, while those descriptors introduce "service mind," which is not among the eight declared ethics attributes. The attainment threshold is 80% of students meeting 80% of rubric criteria, which leaves unspecified which fifth of the criteria may go unmet; no individual attribute is therefore guaranteed. The report does not identify this gap. Its architecture is complete enough that the gap is apparent on inspection, which itself shows documentary maturity. A less developed specification would not reveal what it omits.

Table 2: Loss of the dispositional domain between declaration and instrument. Each successive layer is a strict subset of the layer above it, and the report acknowledges none of these reductions.

Layer of the specification	Attributes reached	Count
Declared in the outcomes table, repeated verbatim for every PLO	E1–E8, C1–C8	16 of 16
Named in program-level rubric descriptors	a subset varying by year level	partial
Attached to courses in the sample course specifications	E1, E3, E6, C2, C3, C7	6 of 16
Guaranteed for individual students under the stated pass criterion	none — 80% of students meeting 80% of criteria	0 of 16

5.2 What the report claims about design process

The report documents a design sequence consistent with backward design: analysis of stakeholder needs, consolidation into a graduate competency profile, derivation of programme learning outcomes, then course learning outcomes, then the assessments these require, and only then teaching activities.

This sequence, in which assessment is specified before activities, is the diagnostic signature of backward design as opposed to retrospective labelling, and the report maintains the ordering consistently. Traceability from stakeholder data to curriculum structure is observable at several points. A documented employer need for competence in the responsible use of generative AI appears as a core course with ethical use as an explicit learning outcome. A stakeholder need for third-language proficiency appears as a nine-credit elective sequence.

It cannot be established whether the sequence occurred as documented or was reconstructed retrospectively to meet the framework's expectations. Both scenarios produce identical documentation. The report offers dated working documents as evidence of the sequence. These are listed in the evidence register but were not available for examination.

5.3 Alignment where alignment can be observed

Section 2.2 established that claims of alignment must be examined at the course level. The report makes this possible for one course, for which course learning outcomes, teaching activities, assessment instruments, and the distribution of achievement are all reported together.

In that second-year business English course, the stated outcomes require students to produce polished, professional artifacts: business letters and professional emails, structured reports of

at least 250 words, and presentations of business information in visual and textual form. The reported teaching activities include lectures, guided discussion, and worksheet exercises. Assessment allocates 45% to the midterm and final examinations and 15% to the report itself. The reported distribution of achievement shows 56.26% of students at grade C or below, with no failures.

This misalignment, predicted by constructive alignment, is evident in the distribution. Activities and assessments relate to comprehension, recall, and production outcomes, with student performance clustering at the intersection. The report cites an imbalance in which activities let students absorb content without producing work, yet still regards the course as improved, not misaligned. The remedies (real-world scenarios, simulated briefs, digital platforms) fix activity gaps but keep assessment weights unchanged.

This is the only course for which the report provides every component that a constructive-alignment check requires. For the other eight courses with reported achievement, activities and instruments are described at a level of generality that does not permit examination. The programme-level map asserts alignment for all nine.

5.4 What the report claims about outcomes

Table 3 reports course-level achievement for the nine courses taught under the revised curriculum. The proportion of students achieving grade C or above ranges from 60.0% to 100.0%, with a median class size of 25 students and the smallest class of 5.

Table 3: Course-level achievement in nine courses under the revised curriculum, academic year 2025. This is the only outcome evidence the report provides for the curriculum it documents.

Course	Term	n	≥ grade C (%)	CEFR outcome	Satisfaction
Smart English Conversation	1/2025	24	91.67	majority ≥ A2	—
English through Edutainment	1/2025	24	79.16	82.35% ≥ A2	4.54
Comprehensive English Grammar	1/2025	32	71.87	90.90% ≥ A2	4.37
Cross-cultural Communication	1/2025	22	77.27	not formally tested	4.11
Creative Writing	—	25	60.00	81.81% ≥ A2	4.21
English Business Presentation	1/2025	30	96.67	majority ≥ A2	—
Business English	—	32	65.63	59.25% ≥ B1	4.28
Digital Communication for PR	2/2025	30	76.66	95.00% ≥ A2	4.19
English for Customer Communication	3/2024	5	100.00	100% ≥ A2	4.60

Tables 4 and 5 report programme-level indicators. Graduation rates in the three cohorts that have reached their expected completion date range from 57.5% to 64.0%, against an implicit target of 100%. Positive employment within twelve months rose from 70.8% to a peak of 78.8%, fell to 66.7% in two consecutive years, and stood at 65.2% in the reporting year, against a target of 80%. Intake ranged from 30 to 73 students against a plan of 80, and no cohort met the plan.

Table 4: Cohort progression and graduation by entry year, with curriculum provenance added. Retention figures are percentages of intake. The final column appears in neither the report nor the framework's common data set; it is added here to make visible a distinction the reporting format does not accommodate.

Entry cohort	Intake	Y1	Y2	Y3	Y4	Graduated	Rate	Curriculum
2017	61	96.7	82.0	68.9	68.9	39	64.0	superseded
2018	73	93.2	76.7	68.5	68.5	42	57.5	superseded
2019	43	95.3	93.0	93.0	93.0	25	58.1	superseded
2020	37	91.9	91.9	75.7	75.7	15	40.5	superseded
2021	30	96.7	93.3	93.3	93.3	16	53.3	superseded
2022	48	93.8	93.8	93.8	—	3	6.2	transitional
2023	61	83.6	83.6	—	—	0	0.0	transitional
2024	36	97.2	—	—	—	0	0.0	revised
2025	31	93.5	—	—	—	0	0.0	revised

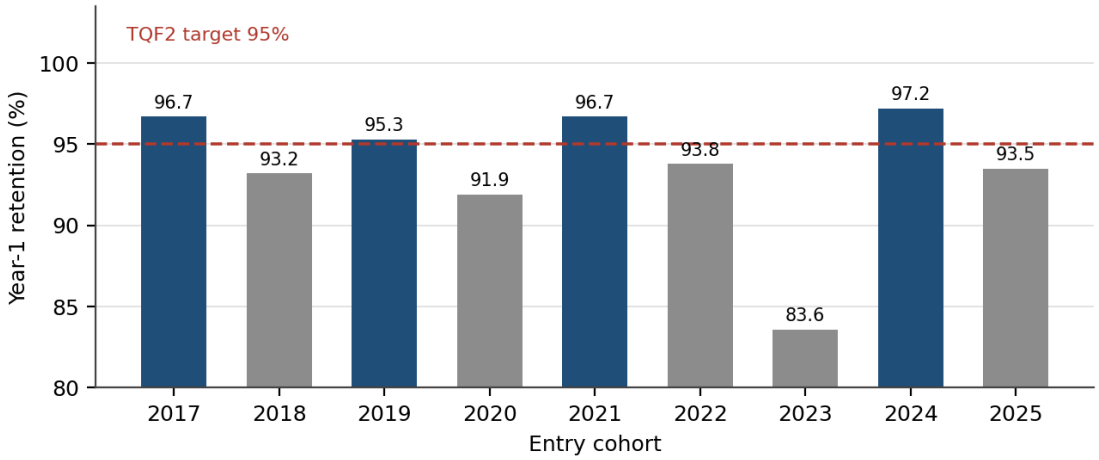


Figure 2: First-year retention by entry cohort against the 95% target. Four of the nine cohorts met the target. The report's narrative states four of eight and places one cohort in both the achieved and the not-achieved groups.

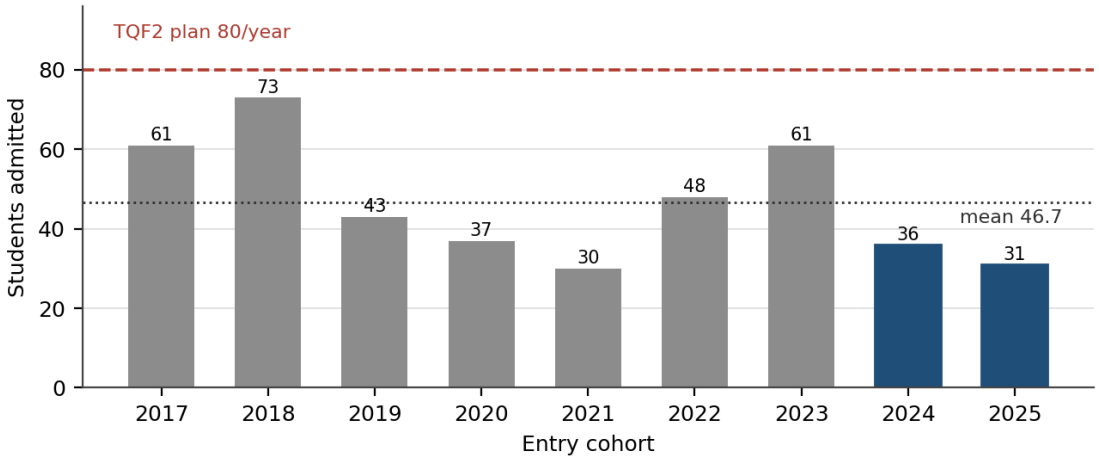


Figure 3: Annual intake against the planned intake of 80. No cohort met the plan. Cohorts admitted under the revised curriculum are shown in darker shading.

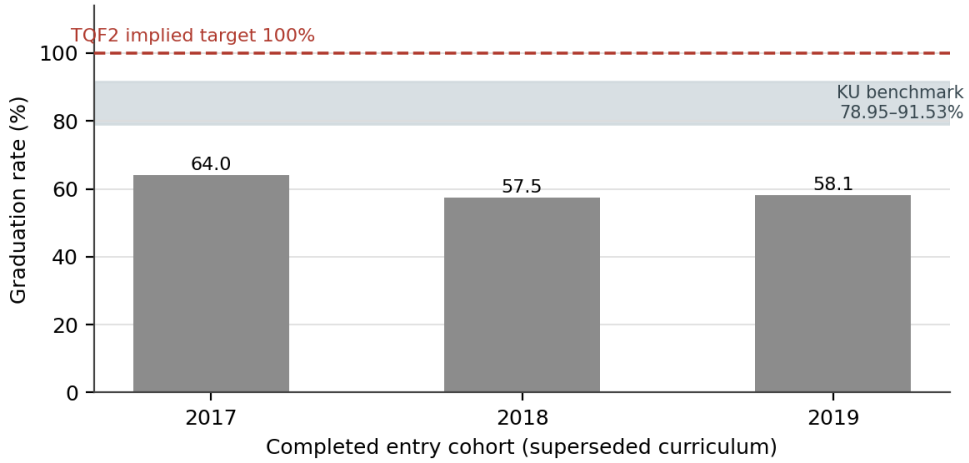


Figure 4: Graduation rates of the three cohorts that have reached their expected completion date, against the implicit target of 100% and external benchmarks.

Table 5: Programme-level indicators against stated targets and external benchmarks. This analysis adds the final column; neither the report's tables nor the framework's common data set contains an equivalent field.

Indicator	Reported	Target	Comparator	Provenance
Year-1 retention	83.6–97.2%	≥ 95%	—	both
Graduation, completed cohorts	57.5–64.0%	100% implied	78.95–91.53%	superseded
Cumulative non-completion	36.0–42.5%	—	8.47–21.05%	superseded

Positive destination ≤ 12 months	65.2–78.8%	≥ 80%	58.06–95.12%	superseded
Annual intake	30–73 (mean 46.7)	80 / year	33–66	both
Employer satisfaction (of 5.00)	4.07–4.35	≥ 4.00	not published	superseded
Course attainment ≥ grade C	60.0–100%	≥ 60% per CLO	—	revised

These tables describe different populations. Table 3 concerns students admitted under the revised curriculum, none of whom has yet graduated. Tables 4 and 5 concern cohorts whose entire education took place under the previous curriculum. The third population identified in Section 3.3, the students who transitioned partway through, namely the 2022 and 2023 entry cohorts, appears in no outcome table and is not reported separately anywhere in the document.

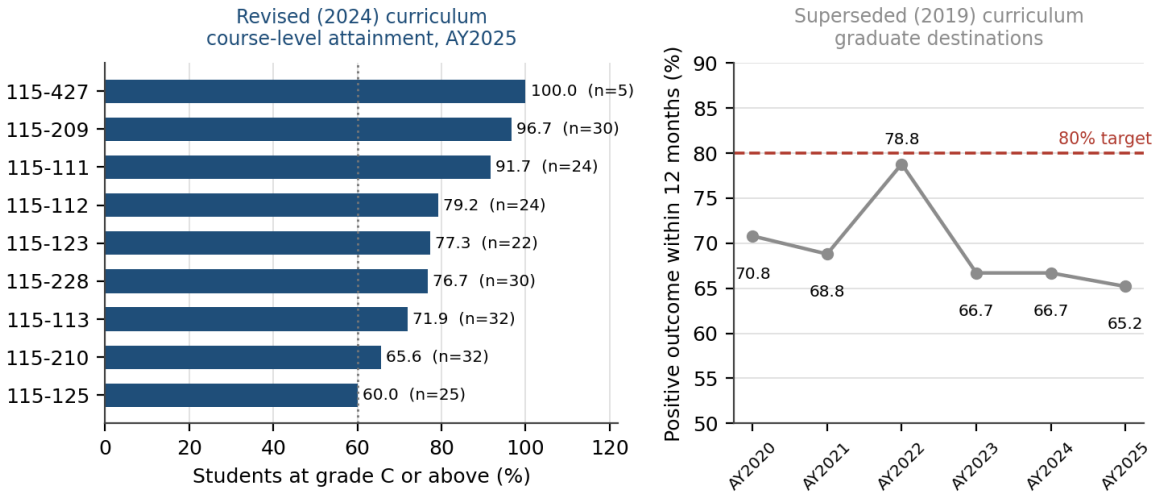


Figure 5: Two populations reported under a single criterion. Left: achievement of students admitted under the revised curriculum, none of whom has yet graduated. Right: employment outcomes of graduates who studied entirely under the previous curriculum. The framework requires both to be reported under Criterion 8 and identifies the provenance of neither.

The report does not mark this distinction in any table. It states elsewhere, in the Criterion 8 narrative, that the outcome data still derive from the previous curriculum, but the tables themselves lack a provenance field, and the framework's common data set specification does not provide one.

Recalculation from the report's own tables reveals four discrepancies between those tables and the narrative that interprets them, shown in Table 6. None works in the programme's favour, and none is material to the self-assessment ratings. All four fall within Criterion 8, and they are

reported here because of where they occur. A document that constructs a fully traceable outcome architecture does not reconcile its cohort counts in the criterion that its own framework treats as the culmination.

Table 6: Discrepancies between the report's tables and the narrative that interprets them. All fall within Criterion 8; none is material to the self-assessment ratings.

Location	Narrative states	Tables show
Criterion 8.1, retention trend	four of eight measurable cohorts met the 95% target	nine cohorts: four met, five did not
Criterion 8.1, retention trend	the 2017 cohort appears in both the meeting and the non-meeting group	2017 met at 96.7%; 2018 fell short at 93.2%
Criterion 8.1, benchmarking	"the eight measurable cohorts (2021–2024)"	a four-year span cannot contain eight cohorts
Employer satisfaction	4.37 under criterion 8.2; 4.27 under criterion 8.5 and in the executive summary	the 8.5 six-year series gives 4.27 for AY2025

5.5 How the report constructs its warrant

Two claim-construction strategies were identified inductively:

Negative indicators placed alongside pre-emptive explanatory framing. Every unfavourable figure in Criterion 8 is followed, within the same paragraph, by an explanation that locates its cause outside the assessment period: the previous curriculum, the absence of graduating cohorts, or sector-wide demographic conditions. Each explanation is accurate on its own terms. The cumulative effect is that no negative indicator in the document is left unexplained, producing a reading in which nothing the report records requires action within the year under assessment.

Process evidence is offered where outcome evidence is required. When a sub-criterion requires demonstrating that outcomes have been achieved, the report instead provides evidence that a process for monitoring achievement exists. This substitution is not concealed. It is visible in the evidence register, where most of the sources cited against outcome sub-criteria are procedural documents. The framework's wording permits this.

Neither strategy is evidence of bad faith, and both are available to a programme reporting sincerely. That is the point of recording them. They are properties of documents produced under this framework, not properties of this programme.

5.6 The self-rating

The report assigns a rating of 4, "adequate as expected," to every sub-criterion in all eight criteria, and a rating of 4 overall.

This uniformity is the finding. Criterion 1 is supported by an outcome architecture that is traceable, anchored in stakeholder input, and internally verified. Criterion 8 is supported by figures describing a curriculum that is no longer taught, showing graduation rates 36.0 to 42.5% below target and employment outcomes below the 80% threshold in every year of the dataset. The seven-point scale can distinguish between these evidentiary situations, but it is not used.

Section 2.5 anticipates this. A programme in the second year of a four-year transition, asked to rate criteria for which the evidence cannot yet exist, has three options: to rate low and appear to fail at what the reform was intended to fix, to rate high and misrepresent, or to rate at the midpoint of the scale, where the number conveys no information. The third is the only defensible option, and it is the one taken. The flat rating profile is not a claim about quality, but an artifact of an instrument asked a question its evidence base cannot answer.

5.7 The negative finding

Across the analysis, no element of the documentary record distinguishes a programme in which reform reached the classroom from one in which reform reached only the documents.

The alignment architecture (Section 5.1) could be produced by either. The design sequence (Section 5.2) could be produced by either, or its supporting evidence was not available for examination. The single observable alignment failure (Section 5.3) is equally consistent with a programme that diagnoses its own teaching and a programme that documents a diagnosis. The improvement records, staff development cycles, and closed-loop monitoring procedures are process artifacts, and both readings predict process artifacts.

The only type of evidence that could discriminate between the two, namely outcomes for students taught under the revised curriculum, cannot exist for another two years, and when it does, it will describe cohorts that themselves lived through the transition.

This is the study's principal result, and Section 4.3 anticipated it because of the design, not a failure of execution.

6. Discussion

6.1 What the case establishes

The analysis found a complete alignment architecture and no evidence that the architecture reached the classroom. What this does and does not show should be stated precisely.

It does not show that the reform is ceremonial. Nothing in the record supports that conclusion, and the record contains material that a purely ceremonial programme would have no reason to produce: a course-level diagnosis that locates an achievement problem in instructional design rather than in student deficiency.

Nor does it show that the reform is genuine. The same material could be produced by a programme documenting a diagnosis it did not act on, and the framework requires such documentation.

It shows that the evidence the framework requires cannot answer the question, and that this is a property of the evidence, not a deficiency of any report. Section 2.3 identified the assumption shared by both readings in the literature: that sufficiently close examination will assign a programme to one reading or the other. This case provides a counterexample. The examination here was as close as the documentary record permits, comprising a complete reading of the full report, recalculation of every reported figure, and independent counter-coding of a sample, and the assignment still could not be made.

6.2 Why the gap is temporal rather than motivational

The distinction proposed in Section 2.5 does its analytical work at this point, and its difference from decoupling can be specified against the evidence rather than in the abstract.

Decoupling is a motivational account. Formal structure departs from technical activity because the departure serves the organization: buffering protects the core from the disruption that compliance would cause. The account's explanatory power depends on that interest, and its predictions follow from it. A decoupled organization invests in what is visible and economizes on what is not, and the gap narrows when monitoring makes the invisible visible.

The gap in this case does not behave that way. Consider a programme identical to this one in every respect except intent: every documented change fully implemented, every rubric used as written, every improvement action carried into every classroom. That programme's self-assessment report would be indistinguishable from the one analyzed here, with the same architecture, the same Criterion 8 figures describing cohorts under the previous curriculum,

and the same midpoint self-assessment ratings. The gap persists even when the interest that decoupling requires is removed.

This has a consequence that decoupling does not predict, and one that is testable rather than merely definitional. Decoupling predicts that intensified monitoring narrows the gap: as external scrutiny reaches deeper into technical activity, buffering becomes more costly and compliance more substantive. The temporal account predicts the opposite for a programme in transition. Intensified monitoring during a period in which outcome evidence cannot yet exist generates more process documentation, not more outcome evidence, because process documentation is the only thing that can be produced. The self-assessment pattern in Section 5.6 is consistent with the second prediction: uniform midpoint ratings on a seven-point scale, arising from an instrument that compels a rating where evidence is absent, not from indifference.

The claim, then, is not that decoupling is wrong about this case, but that decoupling and the temporal account make different predictions about what monitoring does, and that this case is a site at which the difference becomes observable.

6.3 The framework measures what it was designed to measure

Section 2.4 observed that AUN-QA's rationale is transformative while its procedures assess fitness for purpose. The findings give this observation a sharper form.

The framework asks whether documented processes are adequate to declared outcomes. Both readings of compliance produce adequate documented processes. The framework's evidentiary output is therefore invariant across the distinction that the literature treats as central. This is not because the framework is poorly designed, but because it assesses the correspondence between process and declaration, and it does so accurately.

This reframes what a quality rating means. A rating of 4 on Criterion 8 does not certify that outcomes have been achieved; it certifies that the programme has processes adequate to monitor the outcomes it has declared. Reporting institutions and readers often read the two as equivalent, but the transitional case shows they are independent. Here, they refer to different curricula.

The practical implication is not that the framework should measure transformation. Measuring transformation within an annual cycle is impossible for a four-year programme, and no

redesign can change that. The implication is that the framework should stop producing ratings that will be read as claims it does not make.

6.4 What follows for framework design

Three changes follow directly from the findings. They are listed in ascending order of cost.

Provenance labelling. The common data set specification should require cohort provenance to be stated for each Criterion 8 indicator, that is, the curriculum under which the reported students studied. This is the addition of a single data field. It would make the population problem shown in Section 5.4 visible on the page rather than recoverable only through analysis, and it carries no implementation cost.

Suspension of ratings during a declared transition. When a programme declares a curriculum transition, Criterion 8 should be recorded as not yet assessable rather than rated. A midpoint rating on a seven-point scale is not a cautious estimate but an assertion of adequacy produced by an instrument that requires a value to be entered. Suspension is more honest, and more informative, than the number it replaces.

Separation of design assessment from outcome assessment. The two properties distinguished in Section 2.5 are assessed on incommensurable timescales and combining them in a single annual rating conceals which of the two a given score reflects. A framework that reported them separately would allow a programme to receive recognition for a well-constructed transition without certifying outcome achievement it cannot evidence. Conversely, it would prevent strong design documentation from obscuring outcomes that have not moved.

The recommendations have different addressees. The first two lie within the remit of the framework's custodians and could be implemented without renegotiating the framework's purpose. The third would change the assessment architecture and would require that renegotiation.

6.5 What follows for assessors

Assessors work within constraints the framework sets and cannot suspend ratings the framework requires. Two adjustments are nonetheless available within current practice.

The first is to treat a uniform rating profile as a prompt for inquiry rather than as a summary judgment. A programme that rates itself identically across eight criteria with differing

evidentiary situations is more likely to be reporting a problem with the instrument than a genuinely uniform quality profile, and the site visit is the appropriate place to establish which.

The second concerns the purpose of the site visit. If documentary evidence cannot distinguish genuine reform from ceremonial compliance, as Section 5.7 finds, the site visit is not a verification appended to the documentation. It is the only component of the assessment with access to evidence that the documentation cannot contain. Current practice, in which the site visit confirms documentary claims, inverts this relationship.

6.6 The students who are not in the evidence

One further implication follows from what the record omits rather than from what it contains.

In the three reported cohorts that have reached their expected completion date, between 36.0% and 42.5% of entrants did not graduate. They appear in this study as attrition figures in Table 4 and in the quality assurance record in the same way. Their reasons for leaving, the year in which they left, and their subsequent destinations are not recorded. The framework does not require this information; the program therefore does not report it, and no analysis of program documents can address it.

This is not a gap in the data in the ordinary sense, that is, an item that happened not to be collected. The record is detailed about the students who completed and the courses that were offered, but silent about those the programme did not retain. That asymmetry is a property of what the framework asks for, and it means that a quality assurance system organized around declared outcomes has no view of the students to whom those outcomes were never delivered.

This study reproduces that limitation and cannot remedy it. Recording it is the minimum obligation of an analysis conducted at this distance from the people whose education is at issue.

7. Conclusion

7.1 Summary

This study analysed a 358-page AUN-QA self-assessment report prepared by an undergraduate business English programme at a Thai private institution in the second year of its transition to an outcome-based curriculum. It asked how the report presents evidence of outcome achievement, at what level of the system that evidence resides, and whether that evidence is sufficient to distinguish genuine pedagogical reform from ceremonial compliance.

The report presents a complete and internally traceable alignment architecture. Course-level achievement figures for the revised curriculum range from 60.0% to 100.0% across nine courses. The programme-level indicators, graduation rates of 57.5% to 64.0% and positive employment rates of 65.2% to 78.8%, below target throughout, describe cohorts who studied entirely under the previous curriculum. The third population, students who transitioned partway through, appears in no dataset. The framework requires all of this to be reported under a single set of criteria and identifies the provenance of none of it. The programme rated itself uniformly at the midpoint of the scale across all eight criteria.

The principal result is negative. No element of the documentary record distinguishes a programme in which reform reached the classroom from one in which reform reached only the documents, because both produce the same evidence. The design anticipated this, rather than discovering it as a deficiency. If the framework assesses the correspondence between process and declaration, and both readings of compliance produce adequate correspondence, no analysis confined to that evidence can decide between them.

7.2 Contribution

The article contributes at three levels.

Methodologically, it treats a quality assurance self-assessment report as an object of research, an artifact whose construction of claims can be analyzed, rather than as a source of facts about the programme it describes. This places the analyst where the assessor stands, so that what the analysis cannot establish is evidence of what the assessment cannot establish.

Conceptually, it distinguishes documentary maturity from outcome maturity and locates the gap between them in time rather than intent. The distinction is not a restatement of decoupling: the gap persists even when the organizational interest that decoupling requires is removed, and the two accounts make different predictions about the effect of intensified monitoring during a transition.

Empirically, it shows that transitional reporting periods expose a limit of outcome-based quality assurance that steady-state reporting conceals. The limit becomes visible not because this programme is deficient, but because the transition severs a coincidence that ordinarily holds that design evidence and outcome evidence describe the same curriculum.

7.3 Limitations

The study observes documentary claims, not practice. The reported figures cannot be independently verified and are analyzed as claims about numbers. A single document was examined by a single analyst, with independent counter-coding of a sample and member reflections as partial countermeasures whose limits are stated in Section 4.5.

The analyst's position within the institution provides contextual knowledge and creates an interest in a favorable reading. Disclosure does not neutralize this interest.

Most consequentially, the students whose outcomes are aggregated in the indicators, including the 36.0% to 42.5% of entrants in cohorts that have reached their expected completion date who did not graduate, have no voice in this evidence base. They were not consulted, their reasons are not recorded, and no analysis of this document could supply them. Conclusions about programme quality drawn from a record that omits those the programme did not retain are conclusions of a specific and limited kind and should be read as such.

7.4 Further research

Three directions follow directly.

The first is longitudinal. The cohorts admitted under the revised curriculum will begin to graduate in two years, and the figures reported here provide the baseline against which to assess the transition. Whether the outcome indicators move, and whether any movement can be attributed to curriculum design rather than to cohort composition, can be answered then, and not before.

The second is comparative. Whether the asymmetry documented here is general or specific to this case requires examining quality assurance documentation across programmes at different stages of transition and across frameworks with different evidentiary requirements. The prediction implied by Section 6.2, that programmes in transition cluster at midpoint self-assessment ratings, can be tested against documentation that already exists.

The third addresses what this study could not do. Quality assurance documentation cannot recover why students left, or when. Establishing these things requires the students themselves, and a study that begins with them rather than with the record would answer questions that this design cannot pose.

7.5 Closing

Quality assurance frameworks generate documents, and those documents are read as evidence about programmes. This study examined what one such document can establish and found the answer narrower than the uses to which such documents are put.

The finding is not that quality assurance is theatre. The programme examined here produced a curriculum architecture more elaborate than a merely ceremonial programme would have reason to build, and a course-level diagnosis that locates a learning problem in instructional design rather than in student deficiency. Something was done. The record cannot establish how far it reached into the classroom.

That limit is not a deficiency of this report or of this framework. It follows from what documentary evidence is, and it is worth stating plainly, because the alternative, treating documentary ratings as claims about student learning, is a reading the evidence does not support, and the framework does not make.

References

Almuhaideb, A. M., & Saeed, S. (2020). Fostering sustainable quality assurance practices in outcome-based education: Lessons learned from ABET accreditation process of computing programs. *Sustainability*, *12*(20), Article 8380. https://doi.org/10.3390/su12208380

Anderson, L. W., & Krathwohl, D. R. (Eds.). (2001). *A taxonomy for learning, teaching, and assessing: A revision of Bloom's taxonomy of educational objectives*. Longman.

ASEAN University Network. (2020). *Guide to AUN-QA assessment at programme level* (Version 4.0). ASEAN University Network.

Atkinson, P., & Coffey, A. (2011). Analysing documentary realities. In D. Silverman (Ed.), *Qualitative research: Issues of theory, method and practice* (3rd ed., pp. 77–92). SAGE.

Biggs, J. (1996). Enhancing teaching through constructive alignment. *Higher Education, 32*(3), 347–364. https://doi.org/10.1007/BF00138871

Biggs, J., & Tang, C. (2011). *Teaching for quality learning at university* (4th ed.). Open University Press.

Bowen, G. A. (2009). Document analysis as a qualitative research method. *Qualitative Research Journal, 9*(2), 27–40. https://doi.org/10.3316/QRJ0902027

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Council of Europe. (2001). *Common European framework of reference for languages: Learning, teaching, assessment*. Cambridge University Press.

DiMaggio, P. J., & Powell, W. W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review, 48*(2), 147–160. https://doi.org/10.2307/2095101

Eisenhardt, K. M. (1989). Building theories from case study research. *Academy of Management Review, 14*(4), 532–550. https://doi.org/10.2307/258557

Eisenhardt, K. M., & Graebner, M. E. (2007). Theory building from cases: Opportunities and challenges. *Academy of Management Journal, 50*(1), 25–32. https://doi.org/10.5465/amj.2007.24160888

Flyvbjerg, B. (2006). Five misunderstandings about case-study research. *Qualitative Inquiry, 12*(2), 219–245. https://doi.org/10.1177/1077800405284363

Harvey, L., & Green, D. (1993). Defining quality. *Assessment & Evaluation in Higher Education, 18*(1), 9–34. https://doi.org/10.1080/0260293930180102

Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry*. SAGE.

Maneerat, P., Malaivongs, K., & Khlaisang, J. (2015). The comparison of Thai qualification framework for higher education and capability maturity model integration for service. *Procedia – Social and Behavioral Sciences, 182*, 225–231. https://doi.org/10.1016/j.sbspro.2015.04.759

Meyer, J. W., & Rowan, B. (1977). Institutionalized organizations: Formal structure as myth and ceremony. *American Journal of Sociology, 83*(2), 340–363. https://doi.org/10.1086/226550

Mitchell, J. C. (1983). Case and situation analysis. *The Sociological Review, 31*(2), 187–211. https://doi.org/10.1111/j.1467-954X.1983.tb00387.x

Newton, J. (2000). Feeding the beast or improving quality? Academics' perceptions of quality assurance and quality monitoring. *Quality in Higher Education, 6*(2), 153–163. https://doi.org/10.1080/713692740

Oware, E. N., & Mokoena, S. (2026). Navigating institutional audit: A new institutional theory perspective on quality assurance in Ghanaian universities. *Frontiers in Education, 11*, Article 1872529. https://doi.org/10.3389/feduc.2026.1872529

Pham, H. T., & Nguyen, P. V. (2024). ASEAN quality assurance scheme and Vietnamese higher education: A shift to outcomes-based education? *Quality in Higher Education, 30*(2), 285–312. https://doi.org/10.1080/13538322.2023.2261974

Potgieter, M. L., Filmalter, C., & Maree, C. (2025). Teaching, learning and assessment of the affective domain of undergraduate students: A scoping review. *Nurse Education in Practice, 86*, Article 104417. https://doi.org/10.1016/j.nepr.2025.104417

Prior, L. (2003). *Using documents in social research*. SAGE.

Scott, J. (1990). *A matter of record: Documentary sources in social research*. Polity Press.

Scott, T., & Guan, W. (2023). Challenges facing Thai higher education institutions financial stability and perceived institutional education quality. *Power and Education, 15*(3), 326–340. https://doi.org/10.1177/17577438221140014

Siggelkow, N. (2007). Persuasion with case studies. *Academy of Management Journal, 50*(1), 20–24. https://doi.org/10.5465/amj.2007.24160882

Smith, B., & McGannon, K. R. (2018). Developing rigor in qualitative research: Problems and opportunities within sport and exercise psychology. *International Review of Sport and Exercise Psychology, 11*(1), 101–121. https://doi.org/10.1080/1750984X.2017.1317357

Spady, W. G. (1994). *Outcome-based education: Critical issues and answers*. American Association of School Administrators.

Stake, R. E. (1995). *The art of case study research*. SAGE.

Tracy, S. J. (2010). Qualitative quality: Eight "big-tent" criteria for excellent qualitative research. *Qualitative Inquiry, 16*(10), 837–851. https://doi.org/10.1177/1077800410383121

Uchiyama, K. P., & Radin, J. L. (2009). Curriculum mapping in higher education: A vehicle for collaboration. *Innovative Higher Education, 33*(4), 271–280. https://doi.org/10.1007/s10755-008-9078-8

Wiggins, G., & McTighe, J. (2005). *Understanding by design* (2nd ed.). Association for Supervision and Curriculum Development.

Yin, R. K. (2018). *Case study research and applications: Design and methods* (6th ed.). SAGE.

RCG-JF South Korea -1

International Student Recruitment and Retention in South Korean Higher Education: A Comparative IR Analysis of Gachon University and Keimyung University

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ABSTRACT

South Korean higher education faces simultaneous pressures from a rapidly declining college-age population, regional concentration, and growing institutional dependence on international student enrolment. This study compares the recruitment structures, educational and living support environments, and retention outcomes of Gachon University, a metropolitan institution, and Keimyung University, a non-metropolitan institution. A purposive comparative case-study design was employed using standardized institutional research data disclosed through the Higher Education in Korea information system for 2023-2025, supplemented by official university webpages, admissions materials, and institutional reports. Astin's Input-Environment-Outcome framework was not used as a causal or longitudinal model; rather, its basic categories were adapted as a heuristic classification scheme. Input was operationalized as the scale and composition of international student enrolment and publicly reported Korean-language readiness; environment as university-provided housing, administrative, academic, and settlement support; and outcome as nationality-specific dropout rates. Both universities expanded international enrolment rapidly, but their structures differed. Gachon University developed a degree-oriented, large-scale recruitment pattern supported mainly by administrative services, mentoring, and nationality-specific staffing. Keimyung University displayed a larger non-degree share and stronger housing and regional-settlement support. Korean-language proficiency rates remained below one-half at both institutions, and both were increasingly concentrated in Vietnamese enrolment. Retention outcomes varied more by nationality than by institution: Vietnamese students recorded relatively low dropout rates, while selected smaller nationality groups showed substantially higher rates. The findings indicate that sustainable internationalization requires alignment between student composition and institutional support capacity rather than numerical expansion alone. The study also demonstrates the value and limitations of public IR data for institutional comparison and recommends cohort-level, student-level, and longitudinal analysis in future research.

Keywords: International Students, Institutional Research, Student Retention, Support Environment, South Korean Higher Education

Introduction

South Korean higher education is undergoing a structural transition driven by demographic decline and regional imbalance. The national school-age population is projected to continue decreasing, while enrolment demand and educational resources remain concentrated in the Seoul metropolitan area (Statistics Korea, 2023). For many universities, particularly private and non-metropolitan institutions, student recruitment has therefore become closely connected to financial sustainability and institutional survival. In this context, international student recruitment is no longer a marginal internationalization activity; it has become a central institutional strategy for securing enrolment, strengthening global visibility, and maintaining educational capacity.

The government has reinforced this policy direction through the Study Korea 300K Project, which aims to attract 300,000 international students by 2027 (Ministry of Education, Republic of Korea, 2023). Numerical expansion, however, does not automatically produce sustainable internationalization. Rapid recruitment can be accompanied by inadequate Korean-language preparation, unstable housing, academic adjustment difficulties, dropout, and visa-related problems. The institutional challenge is therefore not simply to recruit more students, but to build support systems that enable students to remain enrolled, progress academically, and establish stable lives in Korea.

Regional location adds another layer to this challenge. Metropolitan universities generally benefit from accessibility, employment opportunities, cultural amenities, and stronger brand recognition. Non-metropolitan universities often operate under less favorable recruitment and settlement conditions, but some have compensated through institutional networks, housing provision, language education, and local-government partnerships. Comparing successful institutions in different regional contexts can therefore reveal how similar enrolment growth is produced through different combinations of student composition and institutional support.

This study examines Gachon University (G University), located in the Seoul metropolitan area, and Keimyung University (K University), located in Daegu. In 2025, G University enrolled approximately 5,000 international students, while K University enrolled more than 3,000. Both institutions recorded rapid growth between 2023 and 2025 despite their different locations and recruitment conditions. The comparison addresses three questions: (1) How do the two universities differ in international student inflow and academic-readiness characteristics? (2) How are their educational and living support environments organized? and (3) What differences appear in nationality-specific retention outcomes?

The contribution of the study is twofold. Empirically, it uses standardized institutional research data to compare enrolment structure, language-readiness indicators, housing capacity, support arrangements, and dropout rates across two institutions. Conceptually, it shifts attention from recruitment totals to the fit between the composition of international students and the support capacity of the receiving institution. Because the data are aggregated and not longitudinal, the study does not estimate causal effects. It instead offers a structured, descriptive comparison that can inform institutional benchmarking and the design of more sustainable international student policies.

Literature Review

The internationalization of higher education has increasingly influenced university organization, student services, and national competitiveness. In South Korea, earlier policies emphasized the numerical expansion of international student enrolment, whereas recent research and policy debates have placed greater emphasis on educational quality, adjustment, employment, and long-term settlement (Byeon & Eom, 2012; Kim, 2025; Son, 2025). This shift reflects recognition that international students are not a homogeneous enrolment category. Their academic preparation, linguistic resources, social networks, financial conditions, and post-graduation intentions vary substantially.

Research on international student adjustment consistently identifies language as a central resource. Language proficiency supports classroom participation, interaction with domestic students, use of institutional services, and psychological adaptation (Church, 1982). Inability to communicate effectively in the host-country language may be associated with academic, social, and emotional difficulties (Sam et al., 2015). School support can moderate the negative relationship between acculturative stress and college-life satisfaction, suggesting that institutional services matter even when students enter with unequal levels of preparation (Kim, 2025).

Institutional support extends beyond academic instruction. Administrative guidance, housing, mentoring, visa assistance, health services, career support, and local community connections shape the conditions under which students study and live. These supports may be especially important for non-metropolitan universities, where regional settlement and employment linkages are increasingly incorporated into international student policy (Lee, 2025). At the same time, universities require comparable data for benchmarking and institutional improvement. Ko and Yoo (2010) argued that institutional information systems should support comparison across universities and inform internal development strategies. Nevertheless, few comparative studies integrate enrolment composition, language readiness, living infrastructure, and retention indicators at the institutional level.

The present study responds to this gap through a comparative IR approach. It does not treat metropolitan location as automatically advantageous or non-metropolitan location as uniformly disadvantageous. Instead, it examines how two universities with high growth rates combine different inflow structures and support arrangements, and whether retention outcomes display consistent institutional patterns or more differentiated nationality-specific patterns.

Methodology

Research Design and Data

This research is a purposive comparative case study of two private universities. G University was selected as a rapidly expanding metropolitan case with strong access to Seoul and a large degree-seeking international student population. K University was selected as a major non-metropolitan case that has achieved substantial international enrolment despite regional recruitment constraints. The objective is analytical comparison rather than statistical generalization.

The primary data source is the Higher Education in Korea disclosure system operated by the Korean Council for University Education. Standardized indicators were collected for 2023-2025, including total international enrolment, degree and non-degree enrolment, nationality composition, compliance with publicly reported Korean-language proficiency criteria among degree students, and international student dormitory capacity. Nationality-specific dropout rates were available mainly for 2023 and 2024 because of the disclosure schedule. Official university webpages, admissions information, press releases, and institutional project descriptions were used as supplementary sources for identifying formal support programs. Program availability is interpreted as an institutional provision, not as evidence that all students participated or benefited.

Analytical Framework

Astin's Input-Environment-Outcome (I-E-O) model distinguishes the characteristics students bring to college, the environments they experience during enrolment, and subsequent educational outcomes (Astin, 1985). The present study does not apply the model to estimate educational effects or trace individual change. Instead, the categories are adapted as a heuristic classification framework for organizing heterogeneous public indicators. The adaptation is necessary because the available data are institution-level aggregates rather than student-level longitudinal records.

Input is therefore defined as the observable scale and composition of the international student population and its publicly reported academic-readiness profile. Environment refers to university-provided educational, administrative, housing, and settlement supports rather than each student's verified exposure to those supports. Outcome is limited to academic retention as measured by nationality-specific dropout rates. The framework supports parallel description and cross-case comparison, but it does not establish temporal or causal relationships among the three domains.

Table 1: Research Questions and Adapted Analytical Framework

Domain	Research Question	Operational Indicators
Input	How do the universities differ in international student inflow and academic-readiness characteristics?	Total enrolment and growth; degree/non-degree composition; nationality composition; Korean-language proficiency compliance
Environment	How are educational and living support environments organized at each university?	Dormitory capacity; administrative and multilingual services; mentoring; academic, living, and settlement programs
Outcome	How do nationality-specific academic retention outcomes differ between the universities?	Nationality-specific dropout rates and year-to-year change

Results

G University: Metropolitan Large-Scale Recruitment

G University's international student enrolment increased from 2,743 in 2023 to 4,996 in 2025, an increase of 82.1%. Degree enrolment grew by 49.9%, whereas non-degree enrolment grew by 316.9% from a much smaller base. Despite the rapid expansion of the non-degree sector, degree students still accounted for 72.4% of international enrolment in 2025. The institution can therefore be characterized as degree-oriented, while simultaneously expanding a non-degree recruitment pipeline.

The nationality profile also changed rapidly. Vietnamese enrolment rose from 634 to 2,106 between 2023 and 2025, while Chinese enrolment declined from 1,443 to 1,250. Mongolian enrolment increased from 303 to 707. By 2025, Vietnamese students represented 42.2% of all international students, Chinese students 25.0%, and Mongolian students 14.1%. The shift indicates diversification away from a previously China-centered structure, but it also creates increasing dependence on Vietnamese recruitment.

The publicly reported Korean-language proficiency compliance rate among degree students improved from 31.3% in 2023 to 38.1% in 2025. Nevertheless, 61.9% of degree students did not meet the reported benchmark in 2025. This figure should not be interpreted as a direct

measure of individual academic failure, because the disclosure indicator is measured at the reporting date and may not represent proficiency at entry. It does, however, indicate a substantial need for ongoing Korean-language and discipline-specific academic support.

Table 2: International Student Inflow and Academic-Readiness Indicators at G University

Indicator	2023	2024	2025	Change/Share
Total international students	2,743	3,749	4,996	+82.1%
Degree students	2,412	3,045	3,616	+49.9%; 72.4% in 2025
Non-degree students	331	704	1,380	+316.9%; 27.6% in 2025
Vietnamese students	634	1,151	2,106	+232.2%; 42.2% in 2025
Chinese students	1,443	1,573	1,250	-13.4%; 25.0% in 2025
Mongolian students	303	509	707	+133.3%; 14.1% in 2025
Korean proficiency compliance	31.3%	32.0%	38.1%	+6.8 percentage points

G University's support environment is characterized by strong administrative and adjustment services but limited university-provided housing. In 2025, the university accommodated 275 international students in dormitories, equivalent to 5.5% of the total international population. The rate was 2.5% for degree students and 13.4% for non-degree students. Most international students therefore lived outside university housing, which may increase exposure to private rental costs and reduce the institution's direct capacity to monitor living conditions.

The university supplements its limited housing capacity with a one-stop international student support center, assistance with immigration and administrative procedures, multilingual information, mentoring between domestic and international students, and Vietnamese-speaking staff. It has also announced a dedicated college for international students. These arrangements show an effort to manage large-scale enrolment through centralized administration and targeted adaptation support. The available data, however, do not measure participation rates or the effects of these services.

Retention outcomes differed by nationality. Vietnamese dropout decreased from 3.3% in 2023 to 2.9% in 2024, while the Chinese rate declined from 4.8% to 4.5%. The Mongolian rate increased from 5.9% to 7.9%. Thus, the largest and fastest-growing group displayed a relatively low dropout rate, whereas a smaller group experienced a notable deterioration. This pattern cautions against evaluating retention solely through university-wide averages.

Table 3: Support Environment and Retention Indicators at G University

Area	Indicator	Result
Housing	Overall international student dormitory rate (2025)	5.5% (degree 2.5%; non-degree 13.4%)
Formal supports	Institutional provisions	One-stop administrative service; multilingual information; mentoring; Vietnamese-speaking staff; international student college
Retention	Vietnamese dropout rate	3.3% (2023) -> 2.9% (2024)
Retention	Chinese dropout rate	4.8% (2023) -> 4.5% (2024)
Retention	Mongolian dropout rate	5.9% (2023) -> 7.9% (2024)

K University: Non-Metropolitan Recruitment and Settlement Support

K University's international enrolment rose from 1,719 in 2023 to 3,044 in 2025, representing growth of 77.1%. Degree enrolment increased by 31.6%, while non-degree enrolment increased by 151.6%. In 2025, non-degree students constituted 53.8% of the international student population. This differs substantially from the degree-oriented structure at G University and suggests that language training and other non-degree programs occupy a larger position in K University's recruitment portfolio. The aggregate data do not allow individual transitions from language study to degree programs to be traced.

Vietnamese students accounted for 57.3% of international enrolment in 2025, increasing from 744 in 2023 to 1,744 in 2025. Chinese enrolment decreased from 469 to 365, whereas Mongolian enrolment increased from 101 to 379. K University therefore achieved both rapid growth and some expansion into Mongolia, but its enrolment structure remained highly concentrated in Vietnam. Such concentration can improve recruitment efficiency through established networks, while increasing vulnerability to changes in demand, visa conditions, or sending-country policy.

The Korean-language proficiency compliance rate among degree students was 45.3% in 2023, 48.5% in 2024, and 44.8% in 2025. The 2025 rate exceeded G University's by 6.7 percentage points, but still remained below one-half. The higher rate is consistent with the institution's substantial non-degree sector and Korean-language training infrastructure, although the data cannot demonstrate that non-degree participation caused higher proficiency among degree students.

Table 4: International Student Inflow and Academic-Readiness Indicators at K University

Indicator	2023	2024	2025	Change/Share
Total international students	1,719	2,154	3,044	+77.1%
Degree students	1,068	1,118	1,406	+31.6%; 46.2% in 2025

Indicator	2023	2024	2025	Change/Share
Non-degree students	651	1,036	1,638	+151.6%; 53.8% in 2025
Vietnamese students	744	1,208	1,744	+134.4%; 57.3% in 2025
Chinese students	469	374	365	-22.2%; 12.0% in 2025
Mongolian students	101	137	379	+275.2%; 12.5% in 2025
Korean proficiency compliance	45.3%	48.5%	44.8%	-0.5 percentage points from 2023

K University's most visible environmental advantage is university-provided housing. In 2025, 798 international students were accommodated in dormitories, equivalent to 26.2% of international enrolment. The rate was 16.6% among degree students and 34.4% among non-degree students. The higher provision for non-degree students is compatible with an emphasis on early-stage adaptation, although the available data do not show whether residence directly improved academic outcomes.

The institution also operates selective recruitment interviews, partnerships with Korean Education Centers, the Bridge to Keimyung experience program, an English-medium college, dual-degree arrangements, and a foreign-language dormitory. More recently, local RISE initiatives have supported a full-cycle system linking recruitment, study, employment, and regional settlement. Taken together, these provisions indicate a broader institutional orientation toward housing, transition, and local integration rather than administration alone.

Nationality-specific dropout rates again show differentiated patterns. Vietnamese dropout declined from 2.0% in 2023 to 1.2% in 2024, and Chinese dropout fell from 7.7% to 5.6%. Mongolian dropout increased from 3.0% to 4.4%. The highest rate was observed among Uzbek students, rising from 14.8% to 17.5%. K University's support structure therefore coexisted with relatively strong retention among the dominant Vietnamese group and significant vulnerability among a smaller nationality group.

Table 5: Support Environment and Retention Indicators at K University

Area	Indicator	Result
Housing	Overall international student dormitory rate (2025)	26.2% (degree 16.6%; non-degree 34.4%)
Formal supports	Institutional provisions	Full-cycle support; foreign-language dormitory; English-medium college; dual degrees; regional settlement and employment linkage
Retention	Vietnamese dropout rate	2.0% (2023) -> 1.2% (2024)
Retention	Chinese dropout rate	7.7% (2023) -> 5.6% (2024)
Retention	Mongolian dropout rate	3.0% (2023) -> 4.4% (2024)
Retention	Uzbek dropout rate	14.8% (2023) -> 17.5% (2024)

Cross-Case Comparison

The two universities achieved similar rates of numerical expansion through different enrolment structures. G University was larger and remained predominantly degree-oriented, whereas K University enrolled a larger proportion of non-degree students. This difference matters because degree and non-degree students may have different language, housing, administrative, and academic support needs. The comparison therefore suggests that growth rates alone are insufficient for institutional benchmarking; the composition of growth must also be examined.
The support environments also differed in emphasis. G University combined limited dormitory capacity with centralized administrative services, mentoring, multilingual communication, and nationality-specific staffing. K University combined higher dormitory provision with language-related programs, foreign-language residential arrangements, and local settlement and employment initiatives. These patterns can be described as a degree-oriented, large-scale inflow and administrative-support model at G University and a non-degree-intensive, early-adjustment and settlement-support model at K University. The labels are descriptive rather than evaluative, and neither model can be considered superior on the basis of the available data.
The retention comparison provides the strongest reason to avoid simple institutional ranking. K University had a lower Vietnamese and Mongolian dropout rate in 2024, while G University had a lower Chinese rate. K University also recorded a very high Uzbek dropout rate, and G University recorded a rising Mongolian rate. Retention appears to be shaped by heterogeneity within each university, including nationality, program type, recruitment channel, language background, and access to support. University-wide strategies should therefore be combined with targeted monitoring of smaller groups that may not benefit equally from systems designed around the largest nationality group.

Table 6: Cross-Case Comparison of International Student Recruitment and Retention

Domain	G University	K University	Comparative Interpretation
Input	4,996 students; 72.4% degree; Vietnamese share 42.2%; proficiency 38.1%	3,044 students; 53.8% non-degree; Vietnamese share 57.3%; proficiency 44.8%	G: degree-oriented large-scale inflow; K: non-degree-intensive inflow and stronger nationality concentration
Environment	Dormitory 5.5%; one-stop administration; mentoring; Vietnamese-speaking staff	Dormitory 26.2%; full-cycle support; foreign-language housing; regional settlement and employment linkage	G emphasizes administrative and adjustment services; K emphasizes housing, transition, and settlement
Outcome	2024 dropout: Vietnam 2.9%; China 4.5%; Mongolia 7.9%	2024 dropout: Vietnam 1.2%; China 5.6%; Mongolia 4.4%; Uzbekistan 17.5%	No consistent institutional advantage; substantial nationality-specific variation

Domain	G University	K University	Comparative Interpretation
Primary challenge	Housing capacity, language support, rising Mongolian dropout	Vietnamese concentration and high dropout among selected smaller groups	Both require diversified recruitment and group-sensitive retention systems

Conclusion and Implications

This study compared two rapidly growing South Korean universities using an adapted I-E-O classification framework. Both institutions expanded international enrolment by more than three-quarters between 2023 and 2025, but the composition and institutional management of that growth differed. G University combined a predominantly degree-seeking population with centralized administrative and adaptation support. K University had a larger non-degree share and placed greater emphasis on housing, transition, and regional settlement. These differences reflect institutional responses to student composition and regional context rather than a clear hierarchy of effectiveness.

Three implications follow. First, internationalization policy should evaluate the structure of enrolment, not only its scale. Degree and non-degree students require different forms and timing of support, and rapid growth can create capacity gaps even when overall dropout remains moderate. Second, language readiness should be treated as a continuing institutional responsibility. Because fewer than half of degree students met the reported proficiency benchmark at either university in 2025, academic Korean, discipline-specific language support, tutoring, and early diagnostic assessment should be integrated with recruitment. Third, retention monitoring should be disaggregated. The comparatively low dropout rates of the largest Vietnamese groups could conceal serious problems among smaller nationality groups. IR systems should routinely connect nationality, program type, entry pathway, residence, service participation, academic progression, and dropout.

For metropolitan universities, expansion of housing partnerships and off-campus residential support may be as important as increasing university-owned dormitory capacity. For non-metropolitan universities, regional settlement initiatives should be paired with diversified recruitment so that institutional enrolment is not excessively dependent on a single sending country. At the national level, performance assessment should move beyond headline enrolment totals toward a balanced set of indicators covering readiness, participation in support, persistence, graduation, employment, and settlement.

The study has important limitations. It relies on university-level aggregated disclosure data and secondary institutional documents, and it cannot determine which students used particular services. The Korean-language indicator reflects the disclosure date rather than a consistent entry measure. The main input and environmental indicators are reported for 2025, whereas the

most recent dropout rates are from 2024, preventing temporal ordering. Dropout is also only one dimension of educational outcome. Finally, two purposively selected cases cannot represent all metropolitan and non-metropolitan universities. Future research should use entry cohorts, student-level records, service-use data, interviews, and longitudinal designs to test how particular environments are associated with retention, graduation, employment, and regional settlement.

Within these limits, the study shows that public IR data can support meaningful cross-institutional diagnosis when claims are kept proportional to the evidence. Sustainable international student policy depends not on a single recruitment model, but on the fit among the students recruited, the institutional environment provided, and the differentiated risks visible in retention data.

References

Astin, A. W. (1985). *Achieving educational excellence*. Jossey-Bass.

Baek, S. Y. (2024, July 4). Temporary migrants are not a population solution: They need pathways to settlement [In Korean]. *Multicultural Education Portal*. https://www.edu4mc.or.kr/guide/news/view.html?newsitemid=01100611.20240705180723001

Byeon, G. Y., & Eom, S. H. (2012). Regionalization of higher education in Northeast Asia [In Korean]. *Comparative Education Review*, *22*(3), 1-30.

Church, A. T. (1982). Sojourner adjustment. *Psychological Bulletin, 91*(3), 540-572. https://doi.org/10.1037/0033-2909.91.3.540

Gachon University Office of International Affairs. (n.d.). *International student mentoring program* [In Korean]. http://oia.gachon.ac.kr/international/a/m/counselingPro.do

Gachon University Office of International Affairs. (2023, May 10). *Check-in with Quynh, a Vietnamese international student* [Video, in Korean]. YouTube. https://www.youtube.com/watch?v=RzQt76UFEfE

Keimyung University Office of External Relations. (2025, April 22). *Keimyung University selected for Daegu RISE project and strengthens international student settlement support* [In Korean]. https://www.kmu.ac.kr/uni/kmupr/page.jsp?cmd=2&mnu_uid=285&parm_bod_uid=252805

Kim, H. S. (2025). The effect of acculturative stress on international students' satisfaction with college life: The moderating effect of school support [In Korean]. *Journal of Learner-Centered Curriculum and Instruction, 25*(2), 195-208.

Ko, J. W., & Yoo, H. S. (2010). Policy implications from an analysis of higher education information disclosure and use in the United States [In Korean]. *Journal of Politics of Education, 17*(4), 7-37.

Korean Council for University Education. (n.d.-a). *Higher Education in Korea disclosure data* [Data set, in Korean]. https://www.academyinfo.go.kr/pubinfo/pubinfo0360/selectListLink.do

Korean Council for University Education. (n.d.-b). *Definitions and calculation formulas for higher education disclosure indicators* [In Korean]. https://aims.kcue.or.kr/EgovPageLink.do?subMenu=5020000

Lee, E. C. (2025). Problems and improvement directions of local ordinances supporting migrants in depopulation areas: International students participating in regional-specialized visa programs in four counties of Jeollanam-do [In Korean]. *Journal of Legislation Research, 68*, 281-322.

Lee, G. Y. (2022). A study on the recruitment and management of international students [In Korean]. *Asian Studies, 25*(1), 375-396.

Ministry of Education, Republic of Korea. (2023*). Study Korea 300K Project: Entering the world's top ten study destinations by 2027* [Press release].

Sam, D. L., Tetteh, D. K., & Amponsah, B. (2015). Satisfaction with life and psychological symptoms among international students in Ghana and their correlates. *International Journal of Intercultural Relations, 49*, 156-167.

Son, Y. H. (2025). *Employment conditions and issues among international students* [In Korean]. Proceedings of the Korean Association for Immigration Policy, 284-296.

Statistics Korea. (2023). *Population projections for Korea: 2022-2072* [In Korean]. https://www.kostat.go.kr/board.es?act=view&bid=207&list_no=428476&mid=a10301020600

RCG-JF South Korea -2

A Systematic Review of AI Governance in Higher Education: Current Trends and Future Challenges

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ABSTRACT

The rapid integration of generative AI into higher education has created governance challenges related to ethics, accountability, academic integrity, data protection, and institutional regulation. While AI applications in education have been widely studied, research on AI governance in higher education remains fragmented. This study conducts a systematic literature review to examine publication characteristics, major themes, and future challenges in this field. A search of the Web of Science database was conducted on 4 May 2026, covering journal articles published between 2021 and 2025. Following predefined criteria and the PRISMA 2020 framework, 50 studies were included. The findings show a sharp increase in publications from 2023 to 2025, uneven regional distribution, and a dominance of qualitative approaches. Four major themes were identified: institutional governance frameworks, academic integrity and assessment governance, AI literacy and capacity building, and data governance, privacy, and risk management. The review also highlights four future challenges: policy fragmentation, policy implementation, AI literacy development, and information governance. This study contributes a systematic overview of AI governance research in higher education and suggests that future governance should move beyond fragmented and reactive responses towards integrated, evidence-based, and context-sensitive systems.

Keywords: AI Governance, Higher Education, Systematic Literature Review

Introduction

While AI offers substantial benefits for higher education, it also raises significant ethical concerns, particularly regarding academic integrity, research ethics, data privacy, fairness, and institutional accountability. These challenges require clear institutional policies and governance mechanisms to ensure responsible AI use in academic contexts (Güneş & Liman Kaban, 2025). In this context, the central issue facing higher education institutions has shifted

from whether to use AI to how AI can be governed responsibly.

UNESCO (2023) argues that the rapid emergence of generative AI in education and research has challenged both national regulatory frameworks and the preparedness of educational institutions. It therefore calls for long-term policy planning, data privacy protection, and human capacity development to guide GenAI toward a human-centred vision of education. Similarly, existing studies suggest that AI governance in higher education involves multiple concerns, including ethical guidelines, algorithmic fairness, stakeholder collaboration, curriculum integration, political bias, discrimination, and the digital divide (Kumi-Yeboah et al., 2023; Atenas et al., 2023; Rozado, 2023; Temper et al., 2025). However, despite growing attention to responsible AI principles, current research remains largely focused on high-level guidelines and ethical considerations, while paying insufficient attention to concrete governance mechanisms and implementation processes (Butcher & Beridze, 2019; Schiff et al., 2021).

Therefore, the key limitation of current research does not lie in whether the importance of responsible AI use has been recognised, but in the lack of systematic explanation of how AI governance concerns can be concretised, institutionalised, and implemented within higher education contexts. Existing studies have not yet sufficiently addressed what should be governed, who should be responsible for governance, how governance should be carried out, and what gaps remain between governance principles and real-world practice. To address this gap, this study adopts a systematic literature review approach to identify the core themes, governance contents, and existing challenges of AI governance in higher education.

This study contributes to the literature in three ways. First, it examines the annual and regional distribution of research on AI governance in higher education and summarises the research methods employed in existing studies. Second, it systematically identifies the major themes and contents of AI governance in higher education. Third, it reveals current limitations and challenges in this field and proposes recommendations for more systematic and effective AI governance in higher education. Based on these objectives, this study proposes the following research questions:

RQ1: What are the annual and regional distributions of the literature on AI governance in higher education, and what research methods are mainly employed?

RQ2: What are the main themes and contents of the current literature on AI governance in higher education?

RQ3: What challenges exist for the future development of AI governance in higher education?

Literature review

AI in Higher Education

Artificial intelligence (AI) has developed rapidly in higher education in recent years (Chu et al., 2022). Existing studies show that AI is increasingly embedded in teaching, learning, assessment, student support, and institutional management. Zawacki-Richter et al. (2019) identified four main areas of AI applications in higher education: profiling and prediction, assessment and evaluation, adaptive systems and personalisation, and intelligent tutoring systems. This framework provides an early foundation for understanding the major functions of AI in higher education.

Crompton and Burke (2023) further classified AI uses into assessment/evaluation, predicting, AI assistant, intelligent tutoring system, and managing student learning. These studies indicate that AI has moved beyond personalised learning and tutoring to wider institutional and academic practices. However, the expansion of AI has also generated significant ethical and governance concerns. Castillo-Martínez et al. (2024) found that key challenges include ethics, plagiarism risks, and lack of transparency. Bittle and El-Gayar (2025) similarly highlighted the impact of generative AI on academic integrity, including academic dishonesty, pedagogical change, ethical use, and student learning. They argue that higher education institutions need ethical guidelines and regulatory frameworks to ensure transparency, accountability, and fairness. Therefore, AI in higher education should not be viewed only as a technological innovation, but also as an institutional governance issue requiring systematic oversight.

AI Governance

The risks associated with AI have promoted increasing attention to AI governance. Early discussions mainly focused on AI ethics principles. Jobin et al. (2019) reviewed global AI ethics guidelines and found broad agreement on principles such as transparency, justice and fairness, non-maleficence, responsibility, and privacy. However, they also noted that consensus on general principles does not necessarily lead to agreement on implementation.

Mittelstadt (2019) further argues that principles alone cannot ensure ethical AI, because AI ethics lacks shared professional norms, clear responsibilities, practical implementation methods, and strong accountability mechanisms. This critique reveals the limitation of principle-based approaches: values such as fairness, transparency, privacy, and accountability may remain abstract without institutional structures and enforceable procedures.

AI governance therefore serves as a bridge between ethical principles and practical implementation. Papagiannidis et al. (2025) distinguish responsible AI principles from responsible AI governance. While principles provide normative goals, governance refers to organisational practices that operationalise these goals across the AI lifecycle, including responsibility allocation, risk monitoring, procedural design, and stakeholder participation. Batool, Zowghi, and Bano (2023) similarly examine AI governance through the questions of who governs, what is governed, when governance occurs, and how it is implemented. Their findings show that few studies fully address these questions, indicating that AI governance remains an emerging field. Overall, AI governance shifts attention from what responsible AI should be to how responsible AI can be achieved, implemented, and sustained.

AI Governance in Higher Education

As AI, especially generative AI, becomes widely used in higher education, AI governance has become increasingly important. Universities face distinctive challenges because AI affects teaching quality, assessment validity, academic integrity, research practice, data privacy, and institutional decision-making. Thus, AI governance in higher education must address both general AI risks and academic-specific concerns.

Existing studies show that universities have begun to respond through institutional policies and governance frameworks. Dabis and Csáki (2024) found that early institutional responses to generative AI addressed accountability, human oversight, transparency, and inclusiveness. This suggests that universities have recognised the ethical risks of AI and started to provide formal guidance. However, policy statements alone are insufficient for effective governance.

Recent research has therefore paid more attention to governance structures and implementation. Wu, Zhang, and Carroll (2024) identified multi-unit governance, role-specific governance, and academic-context governance as important features of AI governance in higher education. Their study shows that AI governance requires coordination among multiple institutional actors and must be adapted to academic contexts such as teaching, assessment, and academic integrity. Berba (2025), based on 65 institutional policies, found that universities have addressed data privacy, academic integrity, tool approval, and intellectual property, but also emphasised the need for clearer implementation, monitoring, and revision mechanisms.

Crompton et al. (2026) further proposed a governance framework for generative AI in higher education, covering academic integrity, ethical and responsible use, privacy and protection, equitable access, AI literacy, human oversight and accountability, and institutional support. This framework highlights that governance should be an ongoing process involving policy

review, stakeholder engagement, professional development, and impact evaluation.

Overall, the literature shows a shift from general AI ethics to more practical AI governance in higher education. Nevertheless, important gaps remain. Existing studies often focus on broad principles, policy responses, or separate issues such as academic integrity and privacy. Less attention has been paid to how governance mechanisms are operationalised within universities and how different components interact as an integrated institutional process. Therefore, further research is needed to examine AI governance in higher education through governance mechanisms, stakeholder responsibilities, implementation practices, and contextual adaptation.

Methods

This study employs a systematic literature review (SLR) to synthesise existing research on AI governance in higher education. SLR is a transparent, replicable, and rigorous approach that applies predefined search strategies and inclusion and exclusion criteria to identify, select, and critically analyse relevant studies, enabling researchers to answer specific research questions (Gough, Thomas, & Oliver, 2017).A systematic literature search was conducted in the Web of Science (WoS) database. As one of the most widely used international bibliographic databases, WoS is recognised as a major source for journal selection, research evaluation, and bibliometric analysis (Pranckutė, 2021; Li et al., 2018). The following search string was applied to the Topic (TS) field, covering the title, abstract, and keywords:

TS=(("artificial intelligence" OR "generative AI" OR "large language model*" OR ChatGPT) AND ("AI governance" OR regulation OR policy OR "AI ethics" OR "data governance" OR accountability) AND ("higher education"))

The search was conducted on 4 May 2026 and covered all publications published between 2021 and 2025. The search strategy was developed by combining the core terminology related to AI governance with concepts specific to the higher education context to achieve an appropriate balance between the comprehensiveness and precision of the search results.

Inclusion and Exclusion Criteria

To ensure the relevance and methodological quality of the included studies, a predefined set of inclusion and exclusion criteria was applied throughout the screening process. The specific criteria are as follows: (1)Studies published between 2021 and 2025; (2)English publications; (3)Journal publications; (4)Studies addressing both Artificial Intelligence (AI) governance and higher education as the primary research domains; (5)Studies in which AI governance

constitutes the primary research focus rather than serving as background information or a secondary topic; (6)Studies conducted within the context of higher education; (7)Studies focusing on governance-related issues, such as institutional policies, governance frameworks, ethical principles, accountability, and data governance.

Study Selection Process

The study selection process followed the four-stage framework recommended by the PRISMA 2020 Statement (Page et al., 2021), comprising identification, screening, eligibility assessment, and inclusion. Figure 1. presents the PRISMA flow diagram illustrating the flow of records through each stage of the study selection process. The screening process was conducted independently by two reviewers to ensure the objectivity and consistency of the study selection.

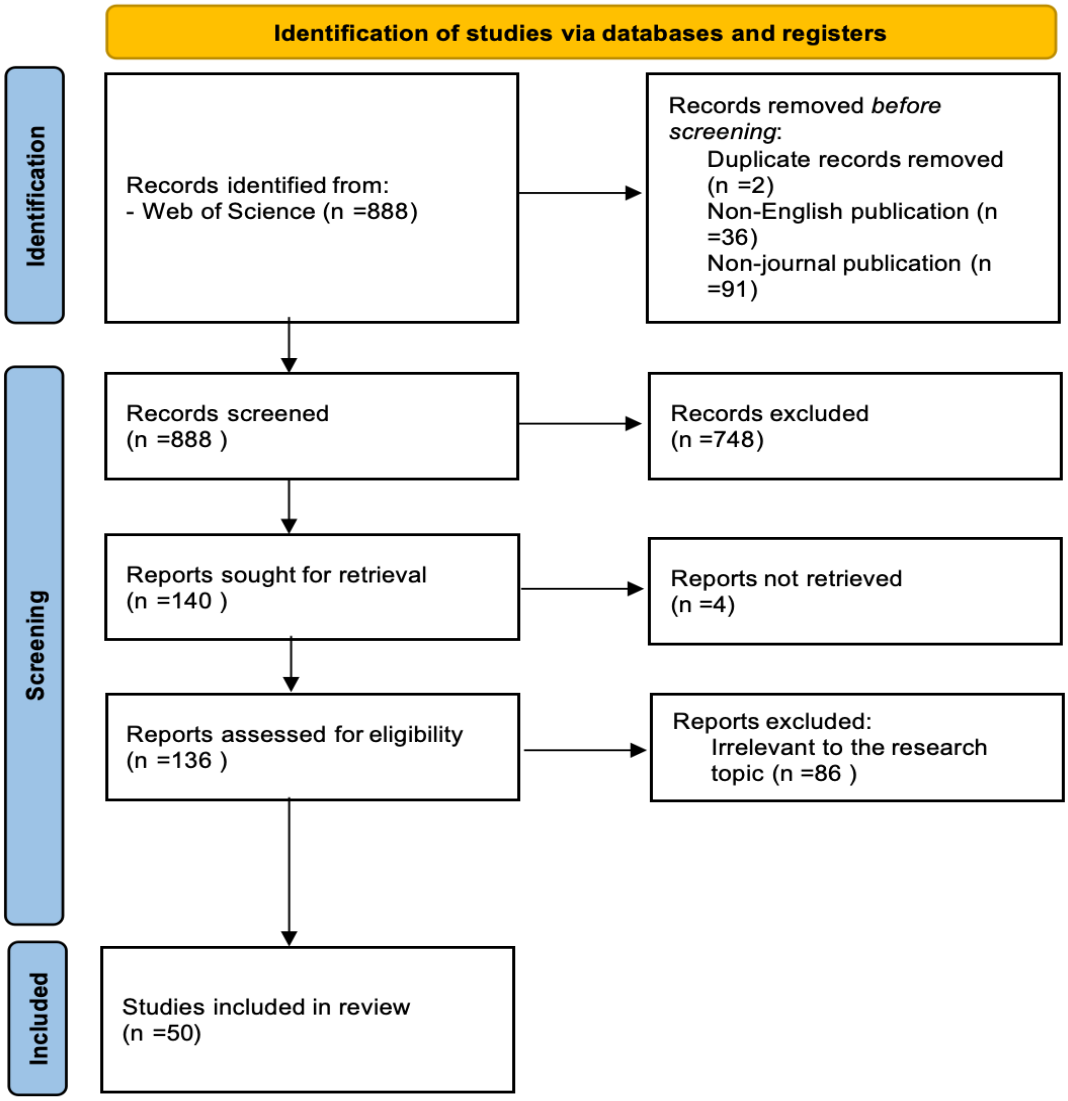


Figure 1: PRISMA flow diagram

Findings

Based on the analysis of the 50 included studies, it answers the three research questions on the publication characteristics, major research themes, and future challenges of AI governance in higher education.

RQ1: What are the annual and regional distributions of the literature on AI governance in higher education, and what research methods are mainly employed?'

Annual Distribution. The annual distribution of the 50 included studies shows a clear pattern of rapid growth in AI governance research in higher education. Only 3 studies (6.0%) were published in 2023, increasing to 12 studies (24.0%) in 2024 and 35 studies (70.0%) in 2025. The limited number of studies published in 2023 is consistent with the time lag between the public release of ChatGPT in late 2022 and the subsequent development of academic research and institutional policy responses. The increase in publications in 2024 suggests that higher education institutions and researchers began to respond more systematically to the governance implications of generative AI. The sharp rise in 2025 further indicates that AI governance has become a major research focus in higher education, reflecting the growing need for institutional and policy responses worldwide.

Regional Distribution. The included studies cover six geographical regions, reflecting the global interest in AI governance in higher education. Europe contributed the largest number of studies (n = 14), followed by global and cross-national studies (n = 13), North America (n = 9), and the Asia-Pacific region (n = 6). In contrast, relatively few studies originated from the Middle East (n = 2), Africa (n = 2), and Latin America (n = 1). This distribution suggests that current research is concentrated in developed higher education systems, while evidence from developing regions remains limited, highlighting the need for broader geographical representation in future research.

Research Method Distribution. Qualitative research was the dominant methodological approach, accounting for 35 studies, reflecting the policy-oriented nature of AI governance research in higher education. These studies primarily employed policy analysis, thematic analysis, case studies, and interviews to examine institutional AI policies and governance practices. Eight studies adopted mixed-methods approaches, combining policy analysis with questionnaire surveys to explore both policy content and stakeholder perspectives. Five studies were conceptual or theoretical in nature, focusing on the development of governance frameworks, whereas only 2 studies employed quantitative methods. Overall, the findings indicate that current research remains largely descriptive and conceptual, with relatively

limited empirical evidence.

RQ2: What are the main themes and contents of the current literature on AI governance in higher education?

Based on the analysis of the 50 included studies, four major themes were identified: (1) AI governance frameworks and institutional policies (n = 50), (2) academic integrity and assessment governance (n = 33), (3) AI literacy and capacity building (n = 27), and (4) data governance, privacy and risk management (n = 17).

AI governance frameworks and institutional policies constitute the most frequently discussed theme. The reviewed studies show that higher education institutions regulate generative AI through policies, guidelines, governance frameworks, and institutional procedures covering teaching, learning, assessment, research, and administration (Dabis & Csáki, 2024; Wu et al., 2024). Core governance principles include transparency, accountability, responsible AI use, and human oversight (Dabis & Csáki, 2024). Universities mainly rely on institutional policies and disclosure requirements, although governance approaches vary across regions, with Europe emphasising legal accountability and data protection, North America institution-specific guidance, and Asia–Oceania policy adaptation (Tabacu, 2025; Wu et al., 2024; Dai et al., 2025). Overall, AI governance is becoming increasingly institutionalised through formal policies and governance principles.

Academic integrity and assessment governance is the second most frequently identified theme. Research focuses on plagiarism, unauthorised assistance, originality, authorship, contract cheating, and assessment validity (Moya & Eaton, 2024; Rasul et al., 2024). Universities respond through disclosure requirements, AI detection tools, plagiarism detection systems, and misconduct procedures (Ullah et al., 2024; Evangelista, 2025). However, detection alone is insufficient, leading to increasing emphasis on assessment redesign, authentic assessment, oral assessment, project-based learning, reflective writing, and higher-order thinking (Furze et al., 2024). The AI Assessment Scale further supports the alignment of AI use with learning outcomes. Overall, research shows a shift from plagiarism detection towards broader assessment governance.

AI literacy and capacity building emerged as the third major theme. The reviewed studies emphasise that effective AI governance depends on developing stakeholders' competencies to use generative AI responsibly and critically (Chan, 2023; Nartey, 2024). AI literacy includes technical understanding, ethical awareness, prompt use, and critical evaluation of AI-generated outputs. Capacity-building initiatives focus on staff development, teacher training, and

institutional support, while student AI literacy emphasises responsible AI use, academic writing, and source evaluation (Michalak et al., 2025; Alduais et al., 2025). Overall, AI literacy serves as a bridge between policy and practice.

Data governance, privacy and risk management represent the fourth major theme. The reviewed studies focus on data protection, privacy, information governance, algorithmic bias, copyright, misinformation, deepfake technologies, and AI-related risks (Symeou et al., 2025; Lin et al., 2025). Major concerns include the protection of sensitive information, compliance with GDPR, and responsible information governance in AI-supported environments (Tabacu, 2025; Erhardt et al., 2025). The literature also highlights institutional trust, privacy protection, algorithmic bias, misinformation, deepfake-style AI tutors, and digital safety as key governance issues (Sharif et al., 2025). Overall, AI governance has expanded beyond academic conduct to broader technological and informational governance.

RQ3: What challenges exist for the future development of AI governance in higher education?'

Based on the thematic synthesis of the reviewed studies, four major future challenges were identified: Policy Fragmentation, Policy Implementation, AI Literacy and Capacity Building, and Information Governance. Policy Fragmentation remains a major challenge because substantial differences persist in governance scope, policy content, stakeholder coverage, and implementation mechanisms across institutions and regions, while many policies lack international alignment and evidence-based practices, resulting in inconsistent governance approaches (Dai et al., 2025). Policy Implementation is equally challenging, as universities have introduced policies and guidelines but continue to experience considerable variation in institutional support, organisational coordination, and formal governance structures, leaving a gap between policy development and institutional practice (Erhardt et al., 2025). In addition, AI Literacy and Capacity Building remain essential for effective governance, as current institutional guidance provides limited support for developing competencies such as understanding AI systems, prompt design, critical evaluation of AI-generated outputs, and responsible disclosure practices, while faculty members often lack sufficient professional development opportunities (Ullah et al., 2024; Labrague, 2026). Finally, Information Governance is emerging as an increasingly important challenge as AI governance expands beyond academic integrity to encompass information management, digital safety, privacy protection, and AI-related risks, including AI-generated misinformation, deepfake-style AI tutors, algorithmic bias, and institutional trust (Erhardt et al., 2025; Sharif et al., 2025). Overall, these findings suggest that future AI governance in higher education will require a more integrated governance approach that combines institutional policy, organisational practice,

stakeholder capability, and responsible information management.

Discussion and Conclusion

This study systematically reviewed 50 studies on AI governance in higher education, focusing on its development trajectory, thematic structure, and future challenges. The findings show that AI governance has rapidly shifted from a marginal and reactive concern to a central issue in institutional policy, academic practice, and educational governance. This transformation reflects both the disruptive impact of generative AI and the need for higher education institutions to reconstruct governance mechanisms under technological uncertainty.

The publication trend increased markedly from 2023 to 2025, indicating that the diffusion of generative AI has accelerated scholarly attention to issues such as academic integrity, assessment, data protection, and responsible AI use. However, the literature remains regionally uneven, with studies mainly concentrated in Europe, North America, and cross-national contexts. Research from Africa, Latin America, the Middle East, and parts of the Asia-Pacific region is still limited, suggesting that current knowledge is largely shaped by developed higher education systems and does not fully reflect diverse institutional, cultural, regulatory, and resource conditions. Methodologically, the field is dominated by qualitative research, including policy analysis, thematic analysis, case studies, and interviews. While appropriate for an emerging field, the limited use of quantitative, longitudinal, and comparative designs indicates that current research remains more descriptive and interpretive than explanatory or evaluative.

The thematic synthesis identifies four interrelated dimensions: institutional governance frameworks, academic integrity and assessment governance, AI literacy and capacity building, and data governance, privacy, and risk management. Institutional policies form the foundation of current research, as universities seek to formalise AI use through guidelines, principles, procedures, and accountability mechanisms. Academic integrity remains a key concern, but the literature shows a gradual shift from detection-oriented control to assessment redesign and pedagogical adaptation. This suggests that AI governance should not be limited to misconduct prevention, but should be embedded in curriculum design, learning outcomes, and quality assurance. AI literacy is also essential, since policies cannot be effectively implemented without sufficient capacity among students, teachers, and administrators. Meanwhile, increasing attention to privacy, misinformation, algorithmic bias, copyright, and institutional trust shows that AI governance has expanded beyond classroom management to become a broader issue of educational information governance.

Several challenges remain unresolved. Policy fragmentation continues to limit coherent institutional responses, while many universities lack operational procedures, governance

structures, and sustainable support systems for implementation. AI literacy remains insufficient, particularly in critical evaluation, ethical judgement, prompt design, and responsible disclosure. Information governance is also becoming more urgent as AI-related risks extend to misinformation, privacy breaches, synthetic educational content, and algorithmic discrimination.

The significance of this study lies in clarifying the current state and developmental logic of AI governance in higher education. It demonstrates that AI governance should not be understood merely as a technical or compliance issue, but as a structural transformation of higher education governance. Effective governance requires the integration of policy design, institutional capacity, pedagogical reform, ethical responsibility, and information risk management. Future governance should therefore move beyond fragmented and reactive responses toward evidence-based, context-sensitive, and participatory systems. Future research should further strengthen empirical, comparative, and longitudinal inquiry, especially in underrepresented regions, to build a more inclusive and globally relevant knowledge base for AI governance in higher education.

References

Alduais, A., Qadhi, S., Chaaban, Y., & Khraisheh, M. (2025). The ETHICAL protocol for responsible use of generative AI for research purposes in higher education. *AI Magazine, 46*(4), Article e70047. https://doi.org/10.1002/aaai.70047

Atenas, J., Havemann, L., Rodés, V., & Podetti, M. (2023). Critical data literacy in praxis: An open education approach for academic development. *Edutec. Revista Electrónica de Tecnología Educativa, 85*, 49–67. https://doi.org/10.21556/edutec.2023.85.2851

Batool, A., Zowghi, D., & Bano, M. (2024). Responsible AI governance: A systematic literature review. arXiv. https://doi.org/10.48550/arXiv.2401.10896

Berba, E. M. (2025). Navigating the landscape of generative AI in higher education: Institutional policies, workforce readiness, and ethical guidelines. In F. Lumban Gaol et al. (Eds.), Management Science and Industrial Engineering: Proceedings of the 7th International Conference (MSIE 2025), Bali Island, Indonesia, 24–26 April 2025 (Advances in Transdisciplinary Engineering, Vol. 73, pp. 352–367). IOS Press. https://doi.org/10.3233/ATDE250550

Bittle, K., & El-Gayar, O. (2025). Generative AI and academic integrity in higher education: A systematic review and research agenda. *Information, 16*(4), Article 296. https://doi.org/10.3390/info16040296

Butcher, J., & Beridze, I. (2019). What is the state of artificial intelligence governance globally? *The RUSI Journal, 164*(5–6), 88–96. https://doi.org/10.1080/03071847.2019.1694260

Castillo-Martínez, I. M., Flores-Bueno, D., Gómez-Puente, S. M., & Vite-León, V. O. (2024). AI in higher education: A systematic literature review. *Frontiers in Education, 9*, Article 1391485. https://doi.org/10.3389/feduc.2024.1391485

Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education, 20*, Article 38. https://doi.org/10.1186/s41239-023-00408-3

Chu, H.-C., Hwang, G.-H., Tu, Y.-F., & Yang, K.-H. (2022). Roles and research trends of artificial intelligence in higher education: A systematic review of the top 50 most-cited articles. *Australasian Journal of Educational Technology, 38*(3), 22–42. https://doi.org/10.14742/ajet.7526

Crompton, H., & Burke, D. (2023). Artificial intelligence in higher education: The state of the field. *International Journal of Educational Technology in Higher Education, 20*, Article 22. https://doi.org/10.1186/s41239-023-00392-8

Crompton, H., Burke, D., Nickel, C., Bozkurt, A., Singh, L., Eaton, L., Xiao, J., Velander, J., Kim, J., Bellas, F., Rajalakshmi, R., de Bem Machado, A., Palalas, A., Yu, S., & others. (2026). Governing generative AI in higher education: A global Delphi study on policy and practice. *International Journal of Educational Technology in Higher Education, 23*, Article 21. https://doi.org/10.1186/s41239-026-00602-z

Dabis, A., & Csáki, C. (2024). AI and ethics: Investigating the first policy responses of higher education institutions to the challenge of generative AI. *Humanities and Social Sciences Communications, 11*, Article 1006. https://doi.org/10.1057/s41599-024-03526-z

Dai, Y., Lai, S., Lim, C. P., & Liu, A. (2025). University policies on generative AI in Asia: Promising practices, gaps, and future directions. *Journal of Asian Public Policy, 18*(2), 260–281. https://doi.org/10.1080/17516234.2024.2379070

Erhardt, C., Kullenberg, H., Grigoriadis, A., Kumar, A., Christidis, N., & Christidis, M. (2025). From policy to practice: The regulation and implementation of generative AI in Swedish higher education institutes. *International Journal for Educational Integrity, 21*, Article 21. https://doi.org/10.1007/s40979-025-00195-6

Evangelista, E. D. L. (2025). Ensuring academic integrity in the age of ChatGPT: Rethinking exam design, assessment strategies, and ethical AI policies in higher education. *Contemporary Educational Technology, 17*(1), Article ep559. https://doi.org/10.30935/cedtech/15775

Furze, L., Perkins, M., Roe, J., & MacVaugh, J. (2024). The AI Assessment Scale (AIAS) in action: A pilot implementation of GenAI-supported assessment. *Australasian Journal of Educational Technology, 40*(4), 38–55. https://doi.org/10.14742/ajet.9434

Gough, D., Oliver, S., & Thomas, J. (Eds.). (2017). An introduction to systematic reviews (2nd ed.). SAGE Publications. https://collegepublishing.sagepub.com/products/an-introduction-to-systematic-reviews-2-245742

Güneş, A., & Liman Kaban, A. (2025). A Delphi study on ethical challenges and ensuring academic integrity regarding AI research in higher education. *Higher Education Quarterly, 79*(4), Article e70057. https://doi.org/10.1111/hequ.70057

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. *Nature Machine Intelligence, 1*, 389–399. https://doi.org/10.1038/s42256-019-0088-2

Kumi-Yeboah, A., Kim, Y., Yankson, B., Aikins, S., & Dadson, Y. A. (2023). Diverse students' perspectives on privacy and technology integration in higher education. *British Journal of Educational Technology, 54*(6), 1671–1692. https://doi.org/10.1111/bjet.13386

Li, K., Rollins, J., & Yan, E. (2018). Web of Science use in published research and review papers 1997–2017: A selective, dynamic, cross-domain, content-based analysis. *Scientometrics, 115*(1), 1–20. https://doi.org/10.1007/s11192-017-2622-5

Lin, L. S. F., Mekonnen, G. T., Zecevic, M., Motsi-Omoijiade, I., Aslett, D., & Allan, D. M. C. (2025). Reducing AI-generated misinformation in Australian higher education: A qualitative analysis of institutional responses to AI-generated misinformation and implications for cybercrime prevention. *Informatics, 12*(4), Article 132. https://doi.org/10.3390/informatics12040132

Miao, F., & Holmes, W. (2023). Guidance for generative AI in education and research. UNESCO. https://unesdoc.unesco.org/ark:/48223/pf0000386693

Michalak, R., Tzoc, E., & Lewis, J. D. (2025). Practical considerations for adopting generative AI tools in academic libraries. *Journal of Library Administration, 65*(5), 596–615. https://doi.org/10.1080/01930826.2025.2506151

Mittelstadt, B. (2019). Principles alone cannot guarantee ethical AI. *Nature Machine Intelligence, 1*, 501–507. https://doi.org/10.1038/s42256-019-0114-4

Moya, B. A., & Eaton, S. E. (2024). Academic integrity policy analysis of Chilean universities. *Journal of Academic Ethics, 22*(4), 639–663. https://doi.org/10.1007/s10805-024-09515-w

Nartey, E. K. (2024). Guiding principles of generative AI for employability and learning in UK universities. *Cogent Education, 11*(1), Article 2357898. https://doi.org/10.1080/2331186X.2024.2357898

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., McGuinness, L. A., … Moher, D. (2021). *The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372*, Article n71. https://doi.org/10.1136/bmj.n71

Papagiannidis, E., Mikalef, P., & Conboy, K. (2025). Responsible artificial intelligence governance: A review and research framework. *The Journal of Strategic Information Systems, 34*(2), Article 101885. https://doi.org/10.1016/j.jsis.2024.101885

Pranckutė, R. (2021). Web of Science (WoS) and Scopus: The titans of bibliographic information in today's academic world. *Publications, 9*(1), Article 12. https://doi.org/10.3390/publications9010012

Rizki, I. A., & Daoud, R. (2026). Generative artificial intelligence in higher education: Review of institutional policies and practices across New Zealand. *New Zealand Journal of Educational Studies, 61*(1), 233–255. https://doi.org/10.1007/s40841-025-00417-y

Rozado, D. (2023). The political biases of ChatGPT. *Social Sciences, 12*(3), Article 148. https://doi.org/10.3390/socsci12030148

Schiff, D., Rakova, B., Ayesh, A., Fanti, A., & Lennon, M. (2021). Explaining the principles to practices gap in AI. *IEEE Technology and Society Magazine, 40*(2), 81–94. https://doi.org/10.1109/MTS.2021.3056286

Sharif, H., Atif, A., & Nagra, A. A. (2025). Deepfake-style AI tutors in higher education: A mixed-methods review and governance framework for sustainable digital education. *Sustainability, 17*(21), Article 9793. https://doi.org/10.3390/su17219793

Symeou, L., Louca, L., Kavadella, A., Mackay, J., Danidou, Y., & Raffay, V. (2025). Development of evidence-based guidelines for the integration of generative AI in university education through a multidisciplinary, consensus-based approach. *European Journal of Dental Education, 29*(2), 285–303. https://doi.org/10.1111/eje.13069

Tabacu, A. E. (2025). Marco normativo del uso de la inteligencia artificial en la educación superior europea. *Jurídicas CUC, 21*(1), 124–152. https://doi.org/10.17981/juridcuc.21.1.2025.07

Temper, M., Tjoa, S., & David, L. (2025). Higher Education Act for AI (HEAT-AI): A framework to regulate the usage of AI in higher education institutions. *Frontiers in Education, 10*, Article 1505370. https://doi.org/10.3389/feduc.2025.1505370

Ullah, M., Bin Naeem, S., & Kamel Boulos, M. N. (2024). Assessing the guidelines on the use of generative artificial intelligence tools in universities: A survey of the world's top 50 universities. *Big Data and Cognitive Computing, 8*(12), Article 194. https://doi.org/10.3390/bdcc8120194

Wang, H., Dang, A., Wu, Z., & Mac, S. (2024). Generative AI in higher education: Seeing ChatGPT through universities' policies, resources, and guidelines. Computers and Education: Artificial Intelligence, 7, Article 100326. https://doi.org/10.1016/j.caeai.2024.100326

Wu, C., Zhang, H., & Carroll, J. M. (2024). AI governance in higher education: Case studies of guidance at Big Ten universities. *Future Internet, 16*(10), Article 354. https://doi.org/10.3390/fi16100354

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the

educators? *International Journal of Educational Technology in Higher Education, 16*, Article 39. https://doi.org/10.1186/s41239-019-0171-0

RCG-JF South Korea -3

Mapping the Evolution of Data-Driven Quality Assurance in Higher Education: A BERTopic Analysis of Assessment and Accreditation Research (2010–2025)

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ABSTRACT

This study aims to examine the thematic development of data-driven quality assurance research in higher education, with a focus on assessment and accreditation. The dataset consists of publications retrieved from the Web of Science database covering the period from 2010 to 2025. To identify the thematic structure of the field and trace its changes over time, the study uses BERTopic modeling. The study is guided by three questions: what the main themes are in higher education quality assurance research related to assessment and accreditation, how these themes evolve from 2010 to 2025, and which emerging themes reflect the data-driven transformation of quality assurance. The analysis focuses on mapping major research clusters and tracing shifts in scholarly attention across the field. By outlining the intellectual landscape of this field, the study provides a clearer understanding of the development and direction of data-driven quality assurance research in higher education.

Keywords: Data-driven quality assurance; Higher education; Assessment; Accreditation; BERTopic modeling

Introduction

Quality assurance has become an important issue in higher education governance as universities are increasingly expected to demonstrate educational quality, institutional accountability, and continuous improvement. Harvey and Green (1993) argued that quality in higher education can be understood in different ways, including excellence, consistency, fitness for purpose, value for money, and transformation. This multidimensional understanding of quality has shaped quality assurance as a field concerned not only with external accountability but also with institutional improvement. In this field, assessment, evaluation, accreditation, and audit have been widely discussed as mechanisms through which higher education institutions define, monitor, and demonstrate quality (Shah, 2012; Steinhardt et al., 2017).

Assessment and accreditation are particularly important in quality assurance because they connect evidence, standards, and institutional judgment. In higher education assessment, evidence about student learning, teaching, programs, and institutional performance is used to understand whether educational goals are being achieved and how improvement can be supported (Banta & Palomba, 2015; Suskie, 2018). Accreditation and external quality assurance, by contrast, are commonly associated with review processes in which institutions or programs are judged against established standards, often for the purposes of accountability, public trust, and institutional legitimacy (Shah, 2012; Elken & Stensaker, 2023). Steinhardt et al. (2017) further showed that quality assurance research related to teaching and learning has developed into a recognizable research area with its own thematic structure, including assessment, evaluation, quality management, and teaching quality.

The scope of quality assurance research has expanded over time. Earlier studies of external quality assurance and audit emphasized formal review, accountability, and the evaluation of quality assurance effectiveness (Shah, 2012). More recent studies have examined how quality assurance is connected to internal quality systems, institutional decision-making, and quality culture. Cardoso et al. (2019) showed that internal quality assurance can support institutional improvement, but it may also increase documentation work and administrative procedures when implemented mainly to satisfy external requirements. Krooi et al. (2024) reviewed internal quality assurance in higher education and proposed a conceptual model that emphasizes purpose, people, and process. Elken and Stensaker (2023) also argued that quality assurance agencies in Europe have moved beyond traditional evaluation functions and have become more closely involved in broader governance processes.

At the same time, higher education has become increasingly data-intensive. Daniel (2015) argued that big data and analytics create opportunities for higher education institutions to improve decision-making, although they also raise challenges related to data quality, interpretation, and institutional capacity. Learning analytics research has similarly shown growing interest in using student data to support learning, retention, engagement, and institutional decision-making (Viberg et al., 2018). Foster and Francis (2020) found that data analytics in higher education has been used to improve student outcomes, particularly through the analysis of academic performance, retention, and learning behavior. Tsai et al. (2020) further showed that learning analytics has become an important development in European higher education, while its institutional implementation still faces challenges related to strategy, infrastructure, ethics, and stakeholder engagement.

These studies indicate that quality assurance, accreditation, internal quality systems, and data analytics have each been examined in higher education research. However, existing studies have tended to focus on different aspects of the field. Studies on quality assurance have mapped assessment, evaluation, quality management, and teaching quality as major themes (Steinhardt

et al., 2017), while studies on learning analytics and data analytics have mainly focused on student performance, retention, engagement, and decision-making (Foster & Francis, 2020; Tsai et al., 2020; Viberg et al., 2018). Therefore, the connection between assessment- and accreditation-related quality assurance research and data-driven developments remains insufficiently mapped at the thematic level. In particular, it remains unclear how data-driven themes have appeared within this research area over time and whether they represent a limited technological application or a broader shift in how quality is evidenced, monitored, and improved.

To address this gap, this study examines the thematic development of data-driven quality assurance research in higher education, with a focus on assessment and accreditation. The dataset consists of publications retrieved from the Web of Science database covering the period from 2010 to 2025. Methodologically, this study applies BERTopic modeling to identify the thematic structure of the field and trace changes in scholarly attention over time. BERTopic uses transformer-based embeddings to capture semantic relationships among documents and class-based TF-IDF to generate interpretable topic representations (Grootendorst, 2022). Benz et al. (2025) emphasized that topic modeling can provide useful insights into the semantic structure of scientific fields when combined with substantive knowledge of the research object.

The study is guided by the following research questions:

RQ1. What thematic structures characterize research on assessment- and accreditation-related quality assurance in higher education from 2010 to 2025?

RQ2. How have the prominence and content of these themes evolved during this period?

RQ3. Which emerging themes reflect the data-driven transformation of quality assurance in higher education?

By answering these questions, this study aims to identify the major themes of assessment- and accreditation-related quality assurance research, trace their evolution from 2010 to 2025, and examine how data-driven themes have emerged within this field.

Literature Review

Research on higher education quality assurance has shown that formal review systems do not automatically lead to educational improvement. Newton (2000) found that quality assurance procedures may be perceived by academics as external monitoring when they are mainly associated with reporting, documentation, and compliance. Stensaker (2008) similarly argued that studies of quality assurance outcomes should examine not only whether formal systems exist, but also what kinds of institutional knowledge, practices, and changes are produced

through these systems. These studies suggest that the effects of quality assurance depend on how external requirements are interpreted and incorporated into institutional practices.

A related body of research has examined how quality assurance becomes embedded in institutional management and organizational routines. Manatos et al. (2017) reviewed the integration of quality management in higher education institutions and found that quality management is connected to leadership, strategy, stakeholder involvement, and continuous improvement. Bendermacher et al. (2017) further showed that quality culture depends on both formal structures and cultural conditions, including shared values, communication, staff participation, and leadership support. These studies move the discussion beyond the existence of accreditation or assessment procedures and emphasize how institutions use quality-related information within their internal governance processes.

This institutional perspective is important for understanding the changing role of evidence in quality assurance. When quality assurance is treated primarily as an external requirement, institutions may focus on producing documents for review rather than using evidence to improve educational practice (Newton, 2000). When it is integrated into institutional routines, assessment results, student feedback, program review, and performance information can become part of continuous improvement (Manatos et al., 2017). Therefore, the literature suggests a shift from isolated review activities toward more continuous and institutionally embedded uses of quality-related evidence.

The increasing availability of digital data has extended this discussion. Macfadyen and Dawson (2010) showed that learning management system data can be used to identify students at academic risk and support early warning interventions. Siemens (2013) described learning analytics as an emerging field that uses educational data to understand and improve learning environments. Gašević et al. (2015) further argued that learning analytics should remain connected to learning theory and educational practice rather than being treated only as a technical or predictive activity. These studies are relevant to quality assurance because they show how digital traces of learning can become new forms of evidence for monitoring learning processes, identifying risks, and supporting educational improvement.

Learning analytics research has also examined how data-informed practices are used in higher education institutions. Ifenthaler and Yau (2020) reviewed the use of learning analytics to support study success and found that analytics can contribute to interventions related to retention, performance, and student support, although its effects depend on research design, implementation context, and institutional use. This finding is important for data-driven quality assurance because it suggests that the value of data does not lie only in data collection or prediction. It depends on whether institutions are able to interpret analytics results and connect them to meaningful educational decisions.

At the same time, the use of student data raises ethical and governance concerns. Slade and Prinsloo (2013) argued that learning analytics involves responsibility, transparency, student agency, and institutional power. Pardo and Siemens (2014) emphasized the need for ethical and privacy principles when institutions collect, analyze, and report student data. Ifenthaler and Schumacher (2016) also showed that students' perceptions of privacy are important for the implementation of learning analytics in higher education. These studies indicate that data-driven quality assurance should be examined not only as a technical development, but also as a governance issue involving consent, privacy, transparency, and institutional responsibility.

Taken together, previous studies provide two important foundations for the present research. Studies of quality assurance and quality management explain how external requirements become internal practices and how institutions use quality-related evidence for governance and improvement (Bendermacher et al., 2017; Manatos et al., 2017; Newton, 2000; Stensaker, 2008). Studies of learning analytics and data ethics explain how digital data can support student success, early warning, and educational decision-making, while also raising ethical and governance issues (Gašević et al., 2015; Ifenthaler & Schumacher, 2016; Ifenthaler & Yau, 2020; Macfadyen & Dawson, 2010; Pardo & Siemens, 2014; Siemens, 2013; Slade & Prinsloo, 2013). However, these studies have mainly developed as separate research lines. They have not fully shown how institutional quality assurance, assessment-related evidence, accreditation-related requirements, learning analytics, and data ethics are connected within the same thematic field, nor how these connections have changed over time. This study therefore examines the thematic structure and temporal evolution of assessment- and accreditation-related quality assurance research and identifies emerging themes that reflect the data-driven development of higher education quality assurance.

Data collection

Following the PRISMA 2020 framework (Page et al., 2021), records were retrieved from the Web of Science Core Collection. The search string combined terms for quality assurance practices, higher education contexts, and evaluation mechanisms ("quality assurance" OR "quality enhancement" OR "internal quality assurance" OR "external quality assurance") AND ("higher education" OR universit* OR college* OR "tertiary education" OR HEI OR HEIs) AND (accredit* OR assess* OR evaluat* OR audit* OR review OR "learning outcomes" OR "program review" OR "institutional review"). The search was limited to journal articles published between January 2010 and December 2025 in the Web of Science category of Education and Educational Research. 2010 was chosen as the baseline, as outcomes-based accreditation frameworks became established in the early 2010s (Ewell, 2010; Harvey & Williams, 2010). After removing duplicates (n = 2), incomplete records (n = 15), and non-

English publications (n = 34), 535 of the initial 586 records were retained after title and abstract screening.

Data analysis

The corpus was analyzed using BERTopic, which integrates contextual embeddings, dimensionality reduction, density-based clustering, and class-based TF-IDF (Grootendorst, 2022). Its contextual embeddings capture domain-specific meaning more reliably than co-occurrence methods such as LDA, while reducing the subjectivity of manual coding (Blei et al., 2003; Janssens et al., 2025).

For each article, the title, abstract, author keywords, and Keywords Plus were concatenated. Preprocessing involved lowercasing, symbol removal, and consolidation of variant terms (Gomes et al., 2023); country and regional names were excluded so that themes, rather than geography, drove clustering. Embeddings were generated with the all-MiniLM-L6-v2 model (Reimers & Gurevych, 2019); UMAP reduced dimensionality (n_neighbors = 15, n_components = 5, min_dist = 0.0, metric = cosine); HDBSCAN identified clusters (min_cluster_size = 10, min_samples = 2, metric = euclidean, cluster_selection_method = eom); and class-based TF-IDF with a CountVectorizer (ngram_range = (1, 2), min_df = 3) extracted representative terms. Parameters were finalized through iterative testing guided by topic coherence, topic count, and the outlier proportion.

The model yielded 14 valid topics and one outlier category (Topic −1; 103 documents, 19.25%), which was excluded. Topics with substantial keyword overlap and adjacent placement in the agglomerative hierarchy were consolidated into six final themes, informed by the intertopic distance map and annual publication trends.

Result

Figure 1 presents the topic word scores for the six groups identified through BERTopic. Research on quality assurance in higher education is organized around quality assurance in professional education, accreditation and quality governance, policy reform and resource allocation, digital learning environments, learning outcomes assessment, and external accountability. Because the scores indicate term salience rather than topic frequency, the interpretation focuses on weighted terms and their semantic relations.

Topic Group 0 centers on medical education, quality management, quality culture, accreditation, and health professions education, indicating a focus on quality assurance in medical and health professions education. Its association with professional accreditation, clinical competence, qualification, and public responsibility distinguishes it from general institutional approaches, reflecting the specific relationship among quality standards, professional competence, and social responsibility (Blouin et al., 2018; Amaral et al., 2023). The co-occurrence of accreditation, quality management, and quality culture indicates that accreditation is connected not only to certification and compliance, but also to internal improvement and the organizational enactment of quality.

Topic Group 1 comprises accreditation, policy governance, quality agencies, internal quality assurance, and external quality assurance. It focuses on accreditation systems and governance structures, especially how quality assurance is organized through standards, agencies, and external evaluation. The pairing of quality agencies and policy governance reflects the role of agencies in both systemic improvement and indirect state steering (Elken & Stensaker, 2018; Hörlesberger et al., 2022). The joint presence of internal and external quality assurance further indicates concern with how external frameworks shape institutional mechanisms.

Topic Group 2 is structured around policy governance, partnerships, participation, reform, and funding, focusing on policy reform, stakeholder participation, and resource allocation. It emphasizes how quality assurance becomes embedded in broader reform processes shaped by multiple actors, policy goals, and resource conditions. The co-occurrence of partnerships and participation highlights stakeholder involvement, which can broaden evaluation and enhance legitimacy, though its effects depend on institutional design, capacity, and authority distribution (Beerkens & Udam, 2017; Leisyte & Westerheijden, 2021). The pairing of reform and funding links quality assurance reform to resource allocation, with financial support and performance-based incentives influencing how institutions implement these arrangements.

Topic Group 3 consists of online learning, distance learning, instructional design, blended learning, and open education, indicating a focus on quality assurance in technology-supported environments. It shifts attention from institutional and policy dimensions to teaching modes, extending the object of quality assurance to digital instructional design, learning support, and interaction. The co-occurrence of instructional design with online and blended learning suggests that quality assurance here concerns not merely technological delivery but whether course structures, activities, assessment, and support effectively promote learning. The presence of open education broadens the scope further. Given the post-2020 expansion of online teaching, this topic likely reflects the growing relevance of quality assurance in digital learning environments (Watermeyer et al., 2021).

Topic Group 4 comprises assessment, assessment standards, curriculum, learning outcomes, and feedback, pointing to a learning outcomes–oriented approach. It moves from institutional accreditation to the curriculum and teaching level, focusing on the relationship among curriculum goals, assessment standards, and student outcomes. The co-occurrence of learning outcomes and assessment indicates that measurable outcomes have become a key basis for judging quality (Biggs & Tang, 2011), while the pairing of assessment standards and curriculum raises the issue of alignment, and the contested problem of establishing comparable standards across disciplines and institutions (Boud et al., 2018). The presence of feedback shows the topic extends to how feedback supports teaching improvement.

Topic Group 5 includes teaching evaluation, external audit, external quality assurance, accountability, and feedback. It focuses on external monitoring and accountability. It concerns how external tools are used to evaluate and demonstrate institutional quality and performance. The co-occurrence of external audit and teaching evaluation links external monitoring with teaching improvement, although strong accountability pressures may shift attention toward documentation rather than substantive change (Seyfried & Pohlenz, 2018; Stensaker et al., 2021). The presence of feedback suggests that external evaluation may support improvement when institutions have sufficient internal response capacity.

Overall, the six groups show a multi-layered structure. Topic Groups 1, 2, and 5 address governance, reform, and accountability; Topic Groups 3 and 4 focus on digital learning environments, curriculum, assessment, and outcomes; and Topic Group 0 highlights the distinctive role of professional education. This structure suggests that the field has moved beyond external accreditation and institutional review toward broader concerns with governance, policy reform, teaching practice, and student learning.

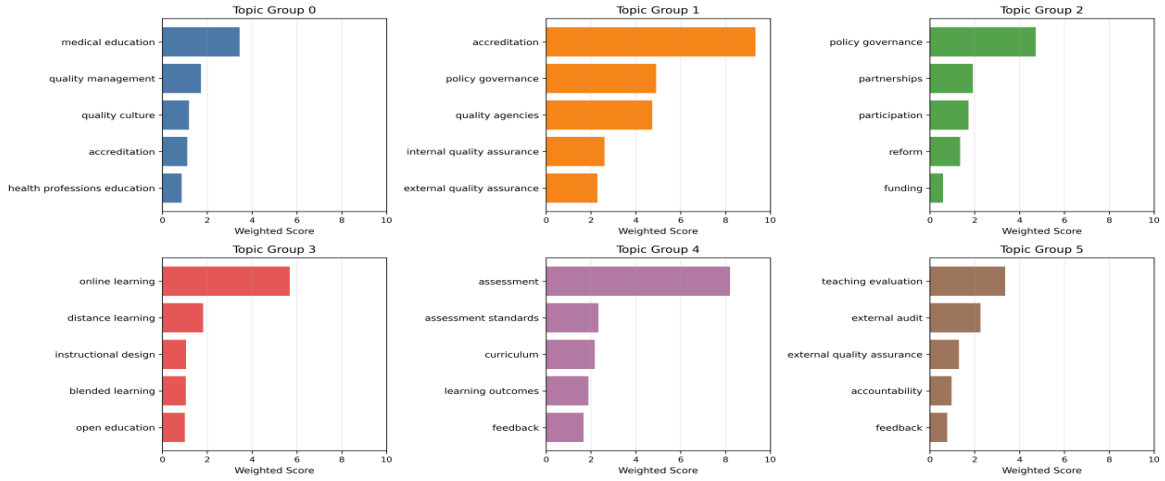


Figure 1. Topic Word Scores of the Six Topic Groups Identified by BERTopic

Annual trend analysis

Figure 2 shows that the six topic groups developed unevenly between 2010 and 2025. From 2010 to 2019, publication counts were generally low and stable. Topic Group 4 (learning outcomes, curriculum, and assessment standards), which concerns learning outcomes, curriculum, and assessment standards, was comparatively more active between 2013 and 2018, suggesting that outcomes-oriented assessment formed an early and continuing foundation of the field.

After 2020, several groups expanded more visibly. Topic Group 3 (online and distance education) increased after 2021, reflecting the post-pandemic growth of online and distance education and the related need to assure instructional design and learning support (Watermeyer et al., 2021). Topic Group 1 (accreditation systems and quality governance) peaked in 2022, while Topic Group 0 (medical and health professions education) also rose after 2021, suggesting renewed attention to accreditation governance and professional education under changing teaching and workforce conditions. Topic Group 2(policy reform, participation, and resource governance) grew more clearly after 2024, indicating recent interest in policy reform, participation, and resource governance.

Topic Group 5(external audit, teaching evaluation, and accountability) remained relatively low and stable, which suggests that external audit and teaching evaluation did not expand as rapidly as digital learning, outcomes assessment, or accreditation governance. Overall, the trend is cumulative rather than substitutive: newer concerns such as digital learning and policy reform were layered onto established themes of outcomes assessment, accreditation, and accountability. This pattern indicates a broadening thematic boundary while the core concern with evaluating, governing, and improving educational quality remained continuous.

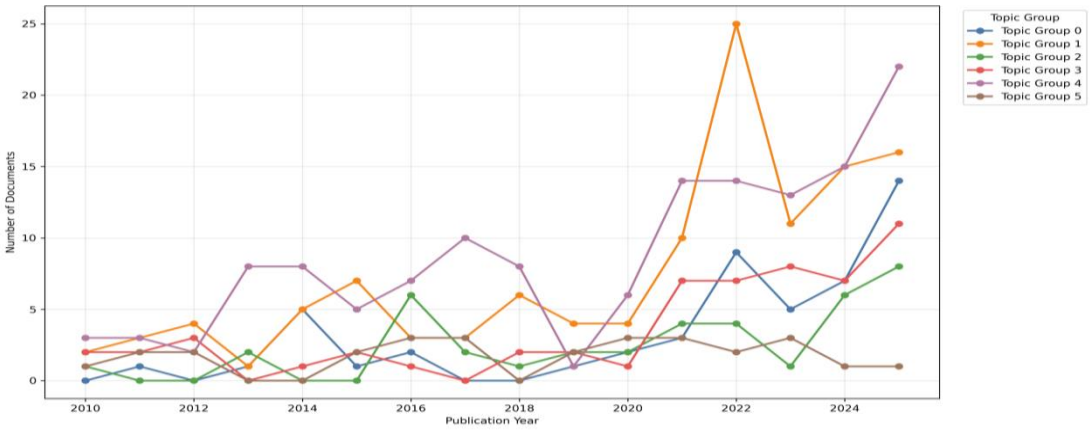


Figure 2. Annual Trends of the Six Topic Groups(2010–2025)

Conclusion

This study examined the thematic development of assessment- and accreditation-related quality assurance research in higher education from 2010 to 2025 using BERTopic modeling. The analysis identified six major topic groups: quality assurance in professional education, accreditation and quality governance, policy reform and resource allocation, digital learning environments, learning outcomes assessment, and external accountability. These themes show that quality assurance research has developed as a multi-layered field, linking institutional governance, policy reform, teaching and learning practices, and professional education.

The findings suggest that the field has not moved away from traditional concerns with accreditation, standards, and accountability. Instead, these concerns have been extended through new forms of evidence, digital learning environments, and outcomes-oriented assessment. Topic Group 4 indicates that learning outcomes, curriculum, assessment standards, and feedback have remained an important foundation of the field. Topic Group 3 shows that online and blended learning have become more visible after 2020, reflecting the growing need to assure quality in technology-supported education. Topic Groups 1, 2, and 5 further show that accreditation, policy governance, stakeholder participation, funding, and external accountability remain central to how quality assurance is organized and implemented.

Overall, the results indicate a cumulative rather than substitutive pattern of thematic development. Emerging topics such as digital learning and resource governance have been layered onto established themes of accreditation, assessment, and accountability. In this sense, the data-driven transformation of quality assurance does not appear only as a technical shift toward analytics or digital tools. It is also reflected in the broader use of evidence to monitor learning, support institutional decision-making, and connect external requirements with internal improvement.

This study contributes to the literature by mapping the thematic structure and temporal evolution of data-driven quality assurance research in higher education. However, the analysis is limited to English-language journal articles indexed in the Web of Science Core Collection, and topic modeling results depend on corpus construction and model parameters. Future research may compare multiple databases, include full-text analysis, or examine how specific quality assurance systems use data in institutional practice.

References

Amaral, A., Tavares, O., & Santos, C. (2023). Quality assurance in health professions education: Role of accreditation and licensure. *Medical Education, 57*(1), 45–53.

Banta, T. W., & Palomba, C. A. (2015). *Assessment essentials: Planning, implementing, and improving assessment in higher education* (2nd ed.). Jossey-Bass.

Beerkens, M., & Udam, M. (2017). Stakeholders in higher education quality assurance: Richness in diversity? *Higher Education Policy, 30*(3), 341–359.

Bendermacher, G. W. G., oude Egbrink, M. G. A., Wolfhagen, I. H. A. P., & Dolmans, D. H. J. M. (2017). Unravelling quality culture in higher education: A realist review. *Higher Education, 73*(1), 39–60.

Benz, P., Pradier, C., Kozlowski, D., Shokida, N. S., & Larivière, V. (2025). Mapping the unseen in practice: Comparing latent Dirichlet allocation and BERTopic for navigating topic spaces. *Scientometrics, 130*, 3839–3870.

Biggs, J., & Tang, C. (2011). *Teaching for quality learning at university* (4th ed.). McGraw-Hill/Society for Research into Higher Education & Open University Press.

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research, 3*, 993–1022.

Blouin, D., Tekian, A., Kamin, C., & Harris, I. B. (2018). The impact of accreditation on medical schools' processes. *Medical Education, 52*(2), 182–191.

Boud, D., Dawson, P., Bearman, M., Bennett, S., Joughin, G., & Molloy, E. (2018). Reframing assessment research: Through a practice perspective. *Studies in Higher Education, 43*(7), 1107–1118.

Cardoso, S., Rosa, M. J., Videira, P., & Amaral, A. (2019). Internal quality assurance: A new culture or added bureaucracy? *Assessment & Evaluation in Higher Education, 44*(2), 249–262.

Daniel, B. (2015). Big data and analytics in higher education: Opportunities and challenges. *British Journal of Educational Technology, 46*(5), 904–920.

Elken, M., & Stensaker, B. (2018). Conceptualising quality work in higher education. *Quality in Higher Education, 24*(3), 189–202.

Elken, M., & Stensaker, B. (2023). Bounded innovation or agency drift? Developments in European higher education quality assurance. *Assessment & Evaluation in Higher Education, 48*(3), 321–332.

Foster, C., & Francis, P. (2020). A systematic review on the deployment and effectiveness of data analytics in higher education to improve student outcomes. *Assessment & Evaluation in Higher Education, 45*(6), 822–841.

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends, 59*(1), 64–71.

Gomes, J., Rodrigues, F., & Castelo-Branco, M. (2023). Research trends in quality assurance in higher education: A bibliometric analysis. *Quality in Higher Education, 29*(1), 1–22.

Grootendorst, M. (2022). BERTopic: Neural topic modeling with a class-based TF-IDF procedure. *arXiv*.

Harvey, L., & Green, D. (1993). Defining quality. *Assessment & Evaluation in Higher Education, 18*(1), 9–34.

Hörlesberger, M., Gorraiz, J., & Gumpenberger, C. (2022). Quality assurance agencies and their role in European higher education. *European Journal of Education, 57*(2), 234–248.

Ifenthaler, D., & Schumacher, C. (2016). Student perceptions of privacy principles for learning analytics. *Educational Technology Research and Development, 64*(5), 923–938.

Ifenthaler, D., & Yau, J. Y.-K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development, 68*(4), 1961–1990.

Janssens, F., Zhang, L., De Moor, B., & Glänzel, W. (2025). Topic modeling in research evaluation. *Scientometrics, 130*(1), 1–24.

Krooi, M., Whittingham, J., & Beausaert, S. (2024). Introducing the 3P conceptual model of internal quality assurance in higher education: A systematic literature review. *Studies in Educational Evaluation, 82*.

Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers & Education, 54*(2), 588–599.

Manatos, M. J., Sarrico, C. S., & Rosa, M. J. (2017). The integration of quality management in higher education institutions: A systematic literature review. *Total Quality Management & Business Excellence, 28*(1–2), 159–175.

Newton, J. (2000). Feeding the beast or improving quality? Academics' perceptions of quality assurance and quality monitoring. *Quality in Higher Education, 6*(2), 153–163.

OECD. (2022). *Digital higher education: Emerging quality standards*. OECD Publishing.

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Gluud, C., Mayo-Wilson, E., McDonald, S., McGuinness, L. A., Stewart, L. A., Thomas, J., Tricco, A. C., Welch, V. A., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*, Article n71.

Pardo, A., & Siemens, G. (2014). Ethical and privacy principles for learning analytics. *British Journal of Educational Technology, 45*(3), 438–450.

Reimers, N., & Gurevych, I. (2019). Sentence-BERT: Sentence embeddings using Siamese BERT-networks. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing* (pp. 3982–3992). Association for Computational Linguistics.

Seyfried, M., & Pohlenz, P. (2018). Assessing quality assurance in higher education: Quality managers' perceptions of effectiveness. *European Journal of Higher Education, 8*(3), 258–271.

Shah, M. (2012). Ten years of external quality audit in Australia: Evaluating its effectiveness and success. *Assessment & Evaluation in Higher Education, 37*(6), 761–772.

Siemens, G. (2013). Learning analytics: The emergence of a discipline. *American Behavioral Scientist, 57*(10), 1380–1400.

Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist, 57*(10), 1510–1529.

Steinhardt, I., Schneijderberg, C., Götze, N., Baumann, J., & Krücken, G. (2017). Mapping the quality assurance of teaching and learning in higher education: The emergence of a specialty? *Higher Education, 74*(2), 221–237.

Stensaker, B. (2008). Outcomes of quality assurance: A discussion of knowledge, methodology and validity. *Quality in Higher Education, 14*(1), 3–13.

Stensaker, B., Frølich, N., Huisman, J., Waagene, E., Scordato, L., & Supported, E. (2021). Accountability, reform and university governance in Europe. *European Journal of Education, 56*(3), 322–336.

Suskie, L. (2018). *Assessing student learning: A common sense guide* (3rd ed.). Jossey-Bass.

Tsai, Y.-S., Rates, D., Moreno-Marcos, P. M., Muñoz-Merino, P. J., Jivet, I., Scheffel, M., Drachsler, H., Delgado Kloos, C., & Gašević, D. (2020). Learning analytics in European higher education: Trends and barriers. *Computers & Education, 155*, Article 103933.

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior, 89*, 98–110.

Watermeyer, R., Crick, T., Knight, C., & Goodall, J. (2021). COVID-19 and digital disruption in UK universities: Afflictions and affordances of emergency online migration. *Higher Education, 81*(3), 623–641.

RCG-JF Taiwan -1

Shifting Drivers of Faculty Teaching Engagement and Job Satisfaction in Taiwan: Longitudinal Insights into Policy-Driven Pedagogical Transformations

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ABSTRACT

This study investigates the longitudinal evolution of the relationship between university faculty members' teaching cognition and their actual physical teaching engagement within Taiwan's higher education sector, assessing how macro-level national policy interventions influence micro-level academic behaviors and professional fulfillment over time. Grounded in a comprehensive cognitive-behavioral and contextual framework of academic work, this study evaluates data from two waves of nationally representative faculty surveys: the 2012 Academic Profession in Asia (APA) survey and the 2019 Academic Profession in the Knowledge Society (APIKS) survey. Ordinary least squares regression, multi-group moderation, and structural path modeling were deployed to assess temporal reconfigurations. The empirical findings reveal a profound pedagogical paradigm shift across the decade. In 2012, faculty teaching engagement—operationalized as weekly instructional and advisory hours—was significantly predicted by a remedial, student-deficit orientation ($\beta = .078$, $p < .05$), reflecting a traditional paradigm where extra time allocation was reactive and focused on compensating for underprepared student backgrounds under the shadow of the research-centric Aim for the Top University Plan (ATUP). By 2019, this deficit-centered driver became non-significant, replaced entirely by a proactive, competency-based orientation emphasizing the transmission of practically oriented knowledge and market-relevant skills ($\beta = .071$, $p < .05$), a shift driven by the launch of the Higher Education Sprout Project (HESP) and the revolutionary Teaching Practice Research Program (TPRP) in 2018. Moderation analyses demonstrate that while junior faculty and lecture-centric modalities bore unequal instructional burdens under the deficit model in 2012 ($\beta = .121$ and $\beta = .226$, respectively), these systemic rank and modal disparities dissolved by 2019, with practice-based cognition translating smoothly into decentralized, high-impact active learning modalities (individualized instruction, lab-based practices, and intensive face-to-face out-of-class mentoring). Crucially, structural path modeling demonstrates that while weekly teaching hours had a non-significant association with global faculty job satisfaction in 2012 ($\beta = .056$, $p > .05$), a robust positive relationship emerged by 2019 ($\beta = .186$, $p < .05$). We interpret these structural shifts as a direct consequence of Taiwan's transition from macro-institutional funding models (TEP) to individualized, career-linked incentives (TPRP & Multi-track Academic Promotion Reforms), which successfully elevated the cultural and academic status of undergraduate instruction within deeply research-centric university environments. This study yields vital institutional research (IR) implications for higher education governance and the design of sustainable systemic capacity-building initiatives globally.

Keywords: Academic Profession in Asia (APA), Academic Profession in the Knowledge-Based Society (APIKS), Job Satisfaction, Taiwan, Teaching Engagement

1. Introduction

Over the past three decades, higher education systems across the globe have encountered a profound wave of structural transformation characterized by unprecedented massification, globalization, and the widespread adoption of neo-liberal governance models (Altbach et al., 2019; Marginson, 2016). Within East Asia, and specifically in Taiwan, this structural evolution has been particularly intense. Taiwan's higher education system experienced a rapid, state-managed expansion that transitioned the sector from an elite system into universal access within a remarkably condensed timeframe (Chiang, 2013). This transition was accompanied by extensive state deregulation, which dismantled traditional top-down administrative controls and replaced them with corporate-style accountability, institutional autonomy, and performance-driven, competitive funding mechanisms, frequently conceptualized under the paradigm of New Public Management (NPM).

While this market-oriented competitive funding model succeeded in stimulating institutional efficiency and administrative flexibility, it simultaneously generated severe, unintended systemic complications. Dominated by global university rankings and highly anxious to build "world-class" status, the Ministry of Education (MOE) and university administrations heavily prioritized quantifiable research outputs, primarily represented by the Science Citation Index (SCI) and Social Sciences Citation Index (SSCI) under the prestigious Aim for the Top University Plan (ATUP). This research-centric evaluation architecture led to pervasive institutional isomorphism across Taiwan's higher education landscape, forcing diverse institutions—including comprehensive universities, local colleges, and specialized vocational technical institutes—to converge around identical research-intensive benchmarks (Chou, 2015). Consequently, internal university cultures shifted dramatically; faculty members found themselves trapped in a "publish or perish" dilemma, resulting in a systemic devaluation of undergraduate instructional quality, curriculum innovation, and student stewardship (Mok, 2015).

To combat this problematic distortion and correct the structural imbalance between research and instruction, the Taiwanese government launched the Teaching Excellence Project (TEP), implemented from 2005 through 2017 (Hou & Hill, 2020). Operating via multi-year competitive grant cycles, the TEP acted as a financial and symbolic counterweight, establishing dedicated teaching-learning resource centers and outcome-based educational models (Dian-Fu & Yeh, 2012). However, a significant logical and chronological puzzle arises for higher education researchers: despite TEP being active since 2005, why did empirical data from 2012 still show that faculty teaching engagement remained heavily tied to reactive, deficit-oriented lecturing, and why did teaching workloads have no positive effect on faculty job satisfaction during that era?

This study argues that the resolution to this puzzle lies in the structural transition of policy mechanisms from macro-institutional subsidies to micro-individual incentives. In 2012, TEP was an institutional-level grant that was largely diluted by the overwhelming individual research pressure of ATUP. Individual faculty promotions, tenure, and academic prestige remained bound to traditional research output. The true paradigm shift occurred in 2018, when the MOE terminated the old plans and launched two revolutionary integrated policies: the Higher Education Sprout Project (HESP) and the Teaching Practice Research Program (TPRP). TPRP bypassed institutional bureaucracy by directly funding individual faculty members for

conducting systematic academic research on their own classroom practices, while simultaneously integrating these efforts into the national Academic Promotion Track. By treating pedagogical innovation as formal academic capital equivalent to traditional scientific research, this policy realigned individual motivators.

This study addresses this critical gap by conducting a rigorous, cohort-comparative longitudinal analysis across this transformative policy transition, evaluating data from two waves of nationally representative faculty datasets: the 2012 Academic Profession in Asia (APA) survey and the 2019 Academic Profession in the Knowledge Society (APIKS) survey. Grounded in a cognitive-behavioral and contextual framework of academic work (Meichenbaum, 2017), this inquiry aims to model the complex pathways through which the shift from institutional-level (TEP) to individual-level (TPRP) policy mechanisms has reshaped micro-level faculty engagement and professional fulfillment within Taiwan's higher education ecosystem. Evaluating data from the 2019 wave allows this study to capture faculty behavioral reconfigurations exactly one year following the implementation of this massive structural pivot. The framework comprises three main components—teaching cognition, teaching action, and individual background characteristics—as predictors of teaching engagement, with job satisfaction as a downstream outcome (Figure 1).

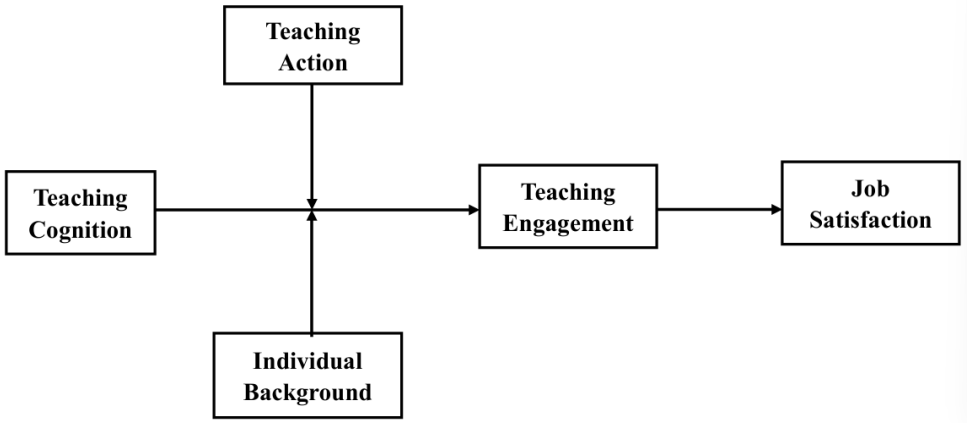


Figure 1: Conceptual framework-modeling teaching engagement and job satisfaction in higher education

2. Literature Review and Theoretical Framework

2.1. The Cognitive-Behavioral Architecture of Academic Work

To understand how faculty members allocate their time and emotional energy across competing institutional roles, it is necessary to examine the underlying cognitive-behavioral structures that govern academic labor. Grounded in cognitive-affective-behavioral frameworks (Meichenbaum, 2017), academic professionalism can be modeled as an interactive system where internal cognitive schemas—comprising values, epistemological beliefs, and instructional goals—serve as the primary interpretive lenses through which faculty perceive external institutional demands and choose specific behavioral actions. In the domain of higher education pedagogy, this internal cognitive landscape is defined as "teaching cognition" (Hora, 2014). Extensive scholarship on teaching paradigms establishes that an academic's approach to teaching typically oscillates between two major poles: A teacher-centered, content-oriented orientation, and a student-centered, learning-oriented orientation (Trigwell & Prosser, 2020).

Under a teacher-centered orientation, the academic views themselves as a primary transmitter of fixed information, often adopting a reactive or remedial perspective when encountering diverse student bodies. In contrast, under a student-centered orientation, the focus shifts entirely to the cultivation of competencies, autonomous problem-solving, and the co-construction of practically oriented skills that bridge the gap between academic knowledge and real-world execution (Wang et al., 2024).

Teaching cognition—faculty members' beliefs, assumptions, and values about teaching—has long been recognized as a key determinant of instructional behavior (Hora, 2014). In this study, teaching cognition is operationalized through three belief dimensions: ***Addressing Student Deficiencies***: This reflects a remedial, deficit-oriented mindset in which faculty spend more time helping students catch up on foundational knowledge. This traditional view may lead to more time-intensive teaching, particularly in lecture formats (Flake & Gabriel, 2023). ***Emphasizing Practically Oriented Knowledge and Skills***: Faculty who value the application of knowledge in real-world contexts often engage more in practice-based and project-based teaching approaches. These beliefs align with constructivist and experiential learning theories (Molderez & Fonseca, 2018). ***Emphasizing International Perspectives in Teaching***: Faculty with global outlooks may incorporate cross-cultural content, bilingual resources, or international case studies, leading to more diverse teaching engagements (Ma, 2024). Prior research has shown that faculty who adopt a learning-centered conception of teaching are more likely to use interactive and student-centered pedagogies (Wang et al., 2024). However, few studies have explored how the relationship between teaching cognition and engagement evolves over time in response to external policy interventions. This study aims to fill that gap by comparing data in 2012 and in 2018 through Taiwan's implementation of the Teaching Excellence Project (TEP). Recent scholarship has suggested that large-scale reforms can influence faculty teaching beliefs by institutionalizing new pedagogical norms. Thus, this question investigates whether Taiwan's shift from a remedial model of teaching to a competency-based, outcome-oriented approach is reflected in faculty engagement patterns over time. These beliefs are hypothesized to shape how faculty allocate time and resources to teaching, thereby influencing teaching engagement (Figure 2).

H1: The relationship between teaching cognition and teaching engagement change from 2012 to 2018.

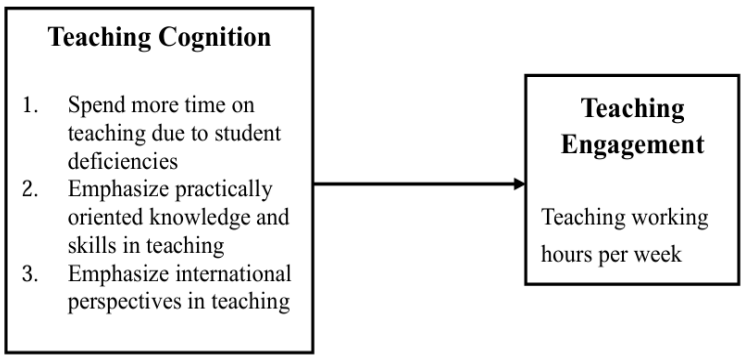


Figure 2: Conceptual framework- the relationship between teaching cognition and teaching engagement

2.2. Higher Education Accountability and National Policy Transition in Taiwan

National higher education policies act as powerful environmental factors that can reshape the internal cognitive schemas and external behavioral choices of the academic workforce. When governments utilize competitive, performance-based funding models, they introduce an "audit culture" that reshapes institutional values (Power, 1999). In research-centric environments, this audit culture often creates an intense tension between research and instruction, where faculty feel heavy pressure to maximize publication metrics while viewing undergraduate instruction as a routine, low-status obligation that incurs heavy role strain (Lin & Huang, 2021). To understand the longitudinal variations in faculty teaching behavior, one must contextualize the regulatory environment in which Taiwanese academics operated in 2012 compared to 2019. This transition represents a shift from "research supremacy with institutional teaching subsidies" to "integrated teaching innovation with individual academic validation."

2.2.1. The 2012 Policy Landscape: Peak ATUP and Institutional TEP: In 2012, Taiwan's higher education was dominated by the second phase of the Aim for the Top University Plan (ATUP), colloquially known as the "NT$50 Billion over 5 Years" project. ATUP pressured comprehensive universities to aggressively accumulate SCI and SSCI publication counts. Although the Teaching Excellence Project (TEP) was simultaneously active, its funding mechanism was strictly institutional. Subsidies were allocated to university administrations to establish macro-level infrastructures (such as building teaching centers, purchasing digital equipment, and organizing teaching workshops). However, because the individual promotion criteria and tenure review systems remained bound to ATUP's research metrics, the actual daily classroom experience of faculty was rarely affected. Teaching was structurally marginalized as a necessary but low-status chore. Faculty members adopted a reactive, deficit-oriented mindset, viewing teaching time as a remedial task to handle underprepared students within traditional, low-impact lecture formats (Flake & Gabriel, 2023; Lin & Huang, 2021).

2.2.2. The 2019 Policy Landscape: Reflection of HESP, TPRP, and Academic Promotion Reforms: Recognizing that institutional-level TEP grants failed to change individual faculty incentives, the MOE initiated a major reform in 2018. It consolidated ATUP, TEP, and vocational plans into the Higher Education Sprout Project (HESP), establishing "taking teaching as the core" as its primary pillar. To directly influence individual classrooms, the MOE introduced the Teaching Practice Research Program (TPRP). This was a critical policy shift: TPRP allowed individual faculty members to apply for competitive national research grants based on their own pedagogical design, student learning assessments, and classroom innovations (the Scholarship of Teaching and Learning, SoTL). Most importantly, TPRP was legally integrated into the Academic Promotion Track. When data collection for the APIKS survey commenced in 2019, university faculty had experienced a full year under this framework, allowing them to achieve tenure and promote to Associate or Full Professor based on their teaching practice research and pedagogical contributions, on par with traditional basic scientific research. This micro-level alignment of individual incentives transformed how faculty perceived instructional engagement, shifting it from a source of role strain into a validated path of academic capital and professional satisfaction (Chung & Hsu, 2023; Hou et al., 2022).

While teaching cognition serves as a cognitive driver of engagement, faculty engagement is also shaped by contextual factors such as teaching action and individual characteristics. Teaching action captures the pedagogical strategies and instructional modes that faculty employ. Based on the cognitive-affective-behavioral model of teaching (Meichenbaum, 2017), it is expected that faculty beliefs translate into observable practices that vary in intensity and time demand. Eight types of teaching actions are examined: ***Classroom Instruction/Lecturing*** – Typically associated with a teacher-centered, content-delivery model. ***Individualized***

Instruction – Includes mentoring and one-on-one tutoring. ***Project-Based Learning*** – Reflects a constructivist, student-centered pedagogy aligned with problem-solving. ***Practice Instruction/Laboratory Work*** – Common in applied fields; promotes skill acquisition and hands-on learning. ***ICT-Based/Computer-Assisted Learning*** – Reflects modern digital integration in teaching. ***Distance Education*** – Asynchronous or synchronous online teaching. ***Development of Course Materials*** – Indicative of engagement in curriculum design. ***Face-to-Face Interaction Outside Class*** – Includes office hours, informal advising, strongly associated with affective engagement and student development.

Faculty behavior and engagement are also influenced by personal and professional attributes, consistent with theories of role strain, career stage, and sociocultural expectations (Cheng et al., 2022). Four key demographic and structural variables are considered: ***Gender*** (male/ female), ***Academic Field*** (natural science/ social science), ***Academic Rank*** (Senior/ Junior), ***Marital Status*** (Married/ Single). At the same time, pedagogical actions are increasingly associated with deeper student learning and more meaningful faculty-student engagement (Chou, 2019). This question aims to examine whether such teaching actions or background factors reinforce or weaken the link between teaching cognition and engagement (Figure 3).

H2: Teaching actions and academic background characteristics moderate the relationship between teaching cognition and teaching engagement.

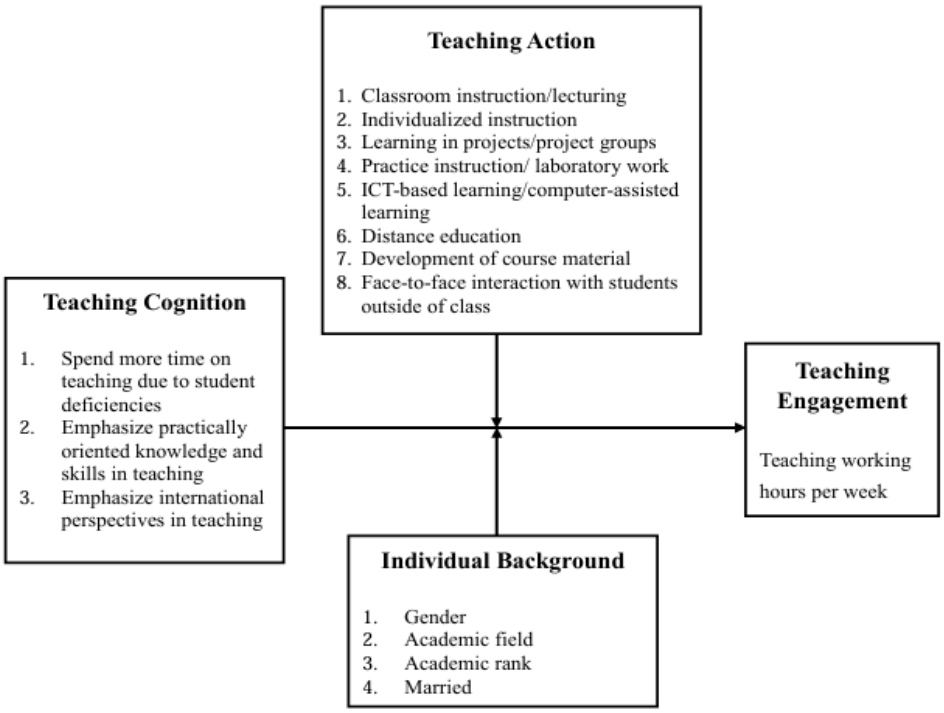


Figure 3: Conceptual framework- the moderation effect of teaching action and individual background on the relationship between teaching cognition and teaching engagement

2.3. Faculty Workloads and the Complexity of Job Satisfaction

The structural transition from TEP to HESP-TPRP represents a shift in state steering mechanisms from macro-bureaucratic steering to micro-individual professional alignment

(Hou et al., 2022; Lin & Huang, 2021). Under the old TEP framework, the funding was allocated directly to central university administrations, leading to superficial compliance and performance rituals without altering the core individual evaluation system (Power, 1999). Consequently, individual faculty behavior remained heavily locked into research supremacy due to the powerful rewards of ATUP (Chou, 2015). The introduction of HESP and TPRP in 2018 systematically resolved this decoupling by leveraging the Scholarship of Teaching and Learning (SoTL) paradigm. TPRP treats teaching not merely as a routine dissemination task, but as a legitimate field of academic inquiry where faculty generate formal research findings regarding student learning outcomes (Chung & Hsu, 2023). By legally integrating these SoTL outputs into the national multi-track promotion framework, the state converted pedagogical labor into formal academic capital (Hou et al., 2022). This structural alignment addresses Hackman and Oldham's Job Characteristics Model by enhancing task significance, autonomy, and feedback within the teaching role, transforming heavy teaching workloads from a primary source of role strain into an explicit driver of job satisfaction (McNaughtan et al., 2022; Njenga, 2023).

Faculty job satisfaction represents a vital indicator of an institution's operational health, directly affecting faculty retention, organizational commitment, and student learning success (McNaughtan et al., 2022). Grounded in Herzberg's Two-Factor Theory and Hackman and Oldham's Job Characteristics Model, professional satisfaction is driven by both hygiene factors (such as salary and baseline job security) and motivators (including autonomy, professional recognition, and a sense of meaningful alignment between personal work and institutional values). In higher education environments characterized by extreme research pressure, intensive teaching engagement is often experienced as a structural hygiene burden rather than a motivator, because the institutional reward system fails to recognize pedagogical labor (Lin, 2021).

Faculty job satisfaction has been linked to multiple dimensions of academic work, including autonomy, recognition, and alignment between personal values and institutional goals (McNaughtan et al., 2022). However, the relationship between teaching engagement and job satisfaction remains ambiguous, particularly in systems where research output is privileged over teaching contributions. Previous studies in East Asia have noted that faculty often experience a tension between teaching and research roles, with teaching sometimes perceived as a burden rather than a source of fulfillment (Lin, & Huang, 2021). Yet, as institutions begin to recognize and reward high-quality teaching—through initiatives like the TEP—this relationship may change. Teaching, when institutionally supported and professionally valued, can become a key driver of faculty satisfaction and professional identity (Hou, & Hill, 2020; Hou et al., 2022). This study utilizes longitudinal path modeling to examine whether the link between intensive teaching hours and global job satisfaction transformed from an initial non-significant correlation into a highly positive, statistically significant relationship as a result of structural policy adaptations. This question seeks to determine whether such a shift occurred in Taiwan between 2012 and 2018, offering insights into how policy reforms can influence the affective dimensions of academic work (Figure 4).

H3: The relationship between teaching engagement and job satisfaction evolve across the two survey waves.

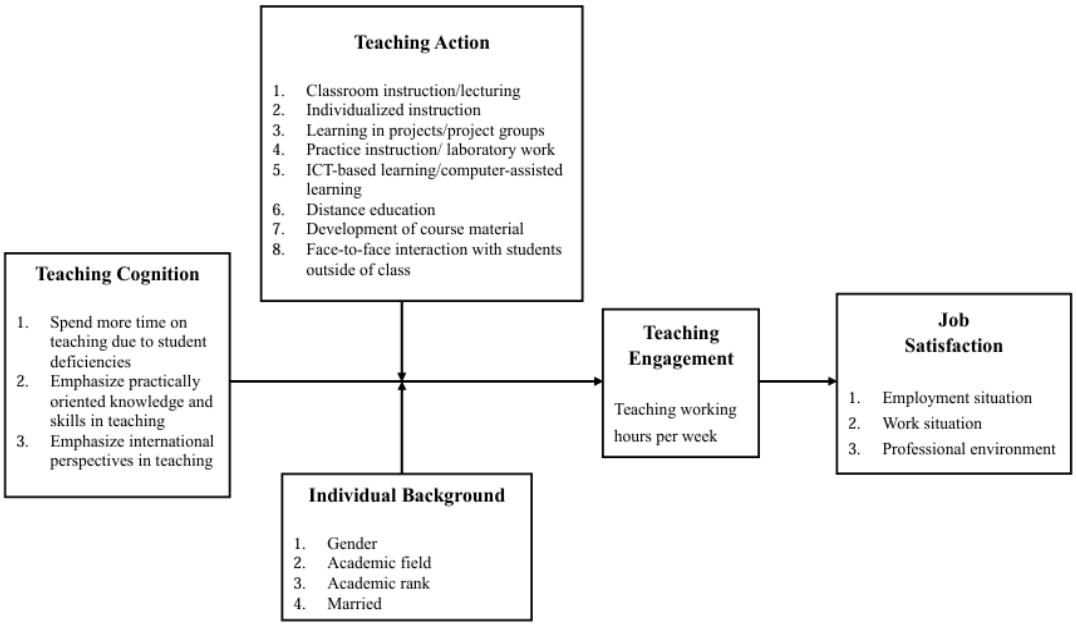


Figure 4: Conceptual framework- the relationship between teaching engagement and job satisfaction

Together, these three research hypotheses address a critical gap in the literature by linking cognitive, behavioral, and affective dimensions of academic engagement within a longitudinal and policy-sensitive framework. By examining changes across two time points in the context of Taiwan's national teaching reform, this study contributes not only to scholarship on teaching engagement but also to broader conversations on how institutional and policy environments shape the evolving nature of academic professionalism.

3. Methodology

3.1. Research Design

This study adopts a rigorous, quantitative, cohort-comparative longitudinal institutional research design to assess structural shifts in academic professionalism. By conducting a comparative analysis across two highly coordinated, nationally representative cross-sectional academic workforce surveys—the 2012 Academic Profession in Asia (APA) survey and the 2019 Academic Profession in the Knowledge Society (APIKS) survey—we effectively establish an empirical baseline and tracking frame spanning a crucial decade of higher education policy reform in Taiwan. Both instruments utilized identical, stringently validated core modules capturing time allocation, instructional values, and workplace perceptions, thereby guaranteeing strong conceptual equivalence and measurement reliability across the temporal cohorts.

3.2. Data Collection

Full-time academic staff of public and private universities in Taiwan were included in this study. Publicly available contact information was obtained from university websites to compile a comprehensive list of potential participants' email addresses. Eligible faculty members were then invited to participate via email and provided a detailed explanation of the research purpose,

assurances of confidentiality, and instructions for participation. This study drew upon two waves of nationally representative survey data from the Academic Profession in Asia (APA) survey conducted in 2012 and the Academic Profession in the Knowledge-Based Society (APIKS) survey conducted in 2019. These surveys were part of larger international comparative research initiatives designed to examine the working conditions, roles, and perceptions of university faculty across different countries.

The 2012 APA dataset included responses from 412 academic staff, while the 2019 APIKS dataset comprised 1,224 participants. Table 1 presents the demographic breakdown of both cohorts. In terms of gender, male respondents constituted a majority in both surveys—63.59% in 2012 and 64.79% in 2019—while female respondents made up 36.41% and 35.21%, respectively. Regarding academic field, faculty in the natural sciences dominated the 2012 sample (75.49%), though their proportion decreased in 2019 (61.19%), reflecting an increase in participation from social science faculty (24.51% in 2012 vs. 38.81% in 2019). With respect to academic rank, the 2012 sample included a larger proportion of senior faculty (associate and full professors), comprising 62.14%, while junior faculty (assistant professors and lecturers) made up 37.86%. In 2019, the distribution shifted slightly, with 57.35% senior faculty and 42.65% junior faculty. Finally, marital status data indicated that the majority of respondents in both waves were married—86.89% in 2012 and 84.72% in 2019—while 13.11% and 15.28% were single, respectively. These demographic profiles provide a foundational context for examining temporal changes in teaching cognition, teaching engagement, and job satisfaction among Taiwanese academics, particularly in relation to institutional and policy developments. The quantitative variables listed in Table 2 were used to address the research questions.

Table 1: Respondent Demographic Characteristics

Individual Factors	Demographics	APA (N = 412)		APIKS (N = 1,224)	
		Frequency	%	Frequency	%
Gender	Male	262	63.59%	793	64.79%
	Female	150	36.41%	431	35.21%
Academic field	Natural science	311	75.49%	749	61.19%
	Social science	101	24.51%	475	38.81%
Academic rank	Senior	256	62.14%	702	57.35%
	Junior	156	37.86%	522	42.65%
Married	Married	358	86.89%	1,037	84.72%
	Single	54	13.11%	187	15.28%

Table 2: Variables and Measures

Variables	Measurement
Gender	Male = 1; Female = 2
Academic filed	Natural science = 1; Social science = 2
Academic Rank	Senior = 1; Junior = 2
Married	Married = 1; Single = 2
Teaching Cognition	
1. Spend more time on teaching due to student deficiencies	5 Point Likert scale (1= strongly disagree to 5= strongly agree)
2. Emphasize practically oriented knowledge and skills in teaching	

Variables	Measurement
3. Emphasize international perspectives in teaching	
Teaching Action	
1. Classroom instruction/lecturing	Yes=1; No=0
2. Individualized instruction	
3. Learning in projects/project groups	
4. Practice instruction/ laboratory work	
5. ICT-based learning/computer-assisted learning	
6. Distance education	
7. Development of course material	
8. Face-to-face interaction with students outside of class	
Teaching engagement	
Teaching (preparation of instructional materials and lesson plans, classroom instruction, advising students, reading and evaluating student work, etc.)	Write the hours of these work engagements per week
Job satisfaction	
1. I am satisfied with current employment situation.	5 Point Likert scale (1= very low to 5= very high)
2. I am satisfied with my work situation.	
3. I am satisfied with the overall professional environment.	

3.3. Data Analysis

The data analysis was structured in three steps to test the hypotheses. First, Ordinary Least Squares (OLS) multiple linear regression models were executed separately across the 2012 and 2019 datasets to evaluate how the three dimensions of teaching cognition predict weekly teaching engagement hours (H1). Second, interaction models were built using centered continuous cognitive scores and the categorical blocks of teaching actions and backgrounds to calculate multi-group moderation effects (H2). Variance Inflation Factors (VIF) were cross-checked, confirming that multicollinearity remained well within acceptable limits (VIF < 2.1). Finally, structural path modeling was conducted using maximum likelihood estimation to analyze the direct longitudinal pathway connecting actual weekly teaching engagement hours to the global faculty job satisfaction metric (H3), controlling for structural demographics.

4. Results

4.1. The Influence of Teaching Cognition on Academics' Teaching Engagement: Evidence from the 2012 APA and 2019 APIKS Surveys

To investigate factors associated with teaching engagement, this study employed regression analyses to explore the relationship between academics' teaching cognition and their reported teaching working hours (Figure 2). Findings from the 2012 APA survey (Figure 5) suggest that teaching engagement was significantly associated with the time faculty spent addressing students' learning deficiencies (β = .078). In contrast, data from the 2019 APIKS survey (Figure 6) indicate that teaching engagement was more strongly linked to faculty emphasis on imparting practically oriented knowledge and skills (β = .071). These findings highlight a noteworthy shift in the determinants of teaching involvement over time—from a remedial and

student-deficit focus in 2012 to a more competency- and practice-oriented approach by 2018. This shift reflects the successful individualization of policy mechanisms via HESP and TPRP, which incentivized academics to design application-oriented courses rather than spending time on reactive remediation. These results confirm H1, illustrating a clear transition in academic professionalism away from reactive remediation toward active, competency-based education.

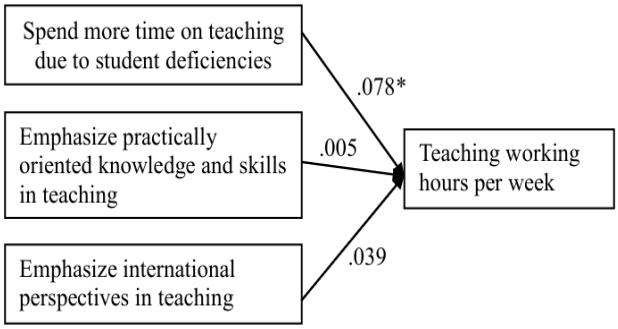


Figure 5: The influence of teaching cognition on academics' teaching engagement in 2012 APA surveys

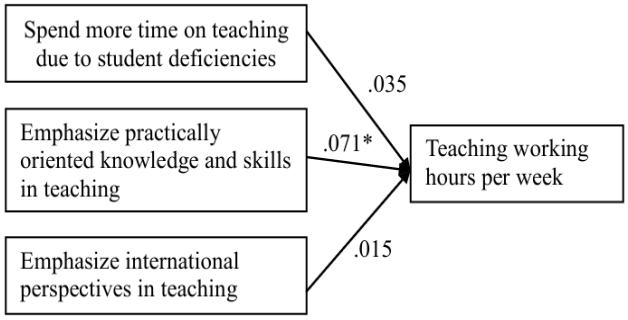


Figure 6: The influence of teaching cognition on academics' teaching engagement in 2018 APIKS surveys

4.2. Moderating Effects of Teaching Actions and Academic Background on the Relationship Between Teaching Cognition and Engagement

To empirically test the proposed research model grounded in teaching engagement theory, we employed multiple moderated regression analyses (Figure 3). These analyses examined the moderating roles of academics' teaching actions and individual background characteristics on the relationship between teaching cognition and teaching engagement.

Findings from the 2012 APA survey (Figure 7) indicate that faculty members who emphasized addressing student deficiencies tended to report higher weekly teaching hours, particularly through classroom instruction and lecturing (β = .121). Moreover, the analysis revealed that early-career (junior) academics were more likely to spend greater time on teaching-related activities compared to their senior counterparts (β = .226). In contrast, the 2019 APIKS survey results (Figure 8) suggest a shift in teaching practices. Faculty members who prioritized practically oriented knowledge and skill development reported spending more time on individualized instruction (β = .061), practice-based teaching (e.g., laboratory work) (β = .070), and face-to-face interactions with students outside of class (β = .066). However, no significant moderating effects were observed for other individual background variables, such as gender, academic field, academic rank, or marital status, in the 2019 data. This shift confirms

H2, showing a successful transition to active and experiential pedagogy across different academic ranks supported by TPRP grants.

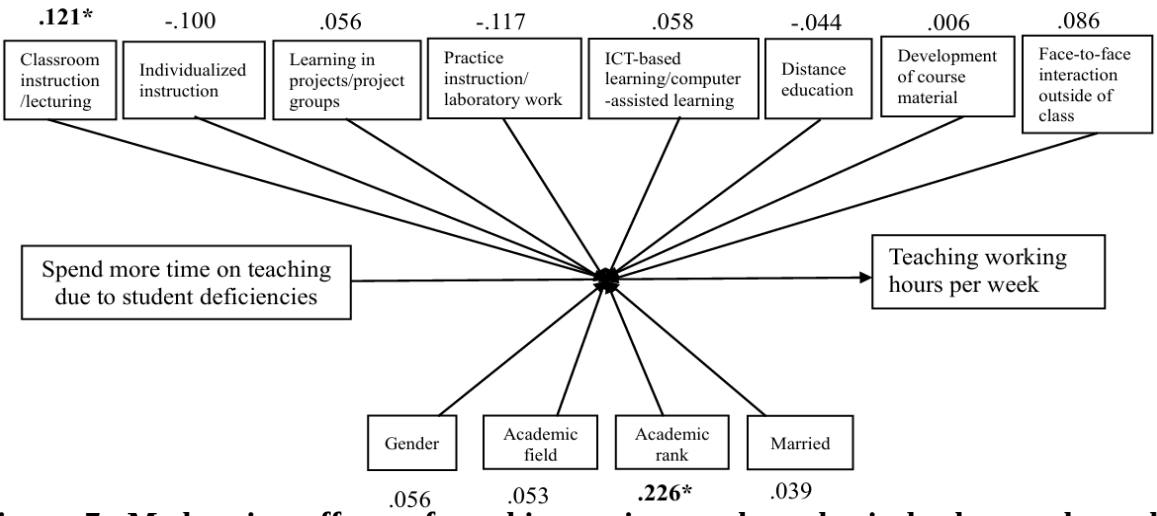


Figure 7: Moderating effects of teaching actions and academic background on the relationship between teaching cognition and engagement in 2012 APA surveys

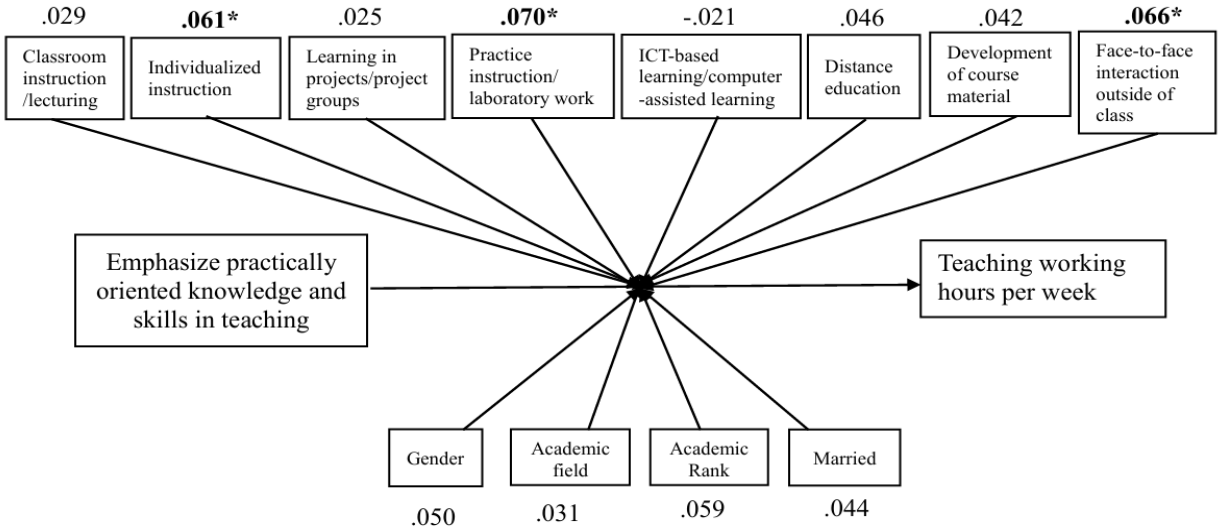


Figure 8: Moderating effects of teaching actions and academic background on the relationship between teaching cognition and engagement in 2018 APIKS surveys

4.3. Teaching Time and Job Satisfaction: Shifting Dynamics Between 2012 and 2018

Finally, this study further investigates the relationship between teaching engagement and job satisfaction among Taiwanese academics. Path analysis was conducted to assess whether the number of weekly teaching hours influenced faculty members' job satisfaction across the two survey waves (Figure 4).

Findings from the 2012 APA survey revealed no statistically significant association between teaching working hours and job satisfaction, suggesting that faculty time investment in teaching did not directly contribute to their perceived satisfaction at that time (Figure 9). In contrast, results from the 2019 APIKS survey demonstrated a significant and positive relationship between teaching hours and job satisfaction (Figure 10). This shift suggests that, by 2019, academics who devoted more time to teaching reported higher levels of job

satisfaction. This confirms H3, demonstrating that teaching engagement successfully transformed from an administrative burden into a key source of professional fulfillment when aligned with the TPRP and multi-track promotional reforms. Faculty were likely more willing to invest time in teaching when they perceived such efforts as valued and impactful, both in terms of personal fulfillment and student learning outcomes.

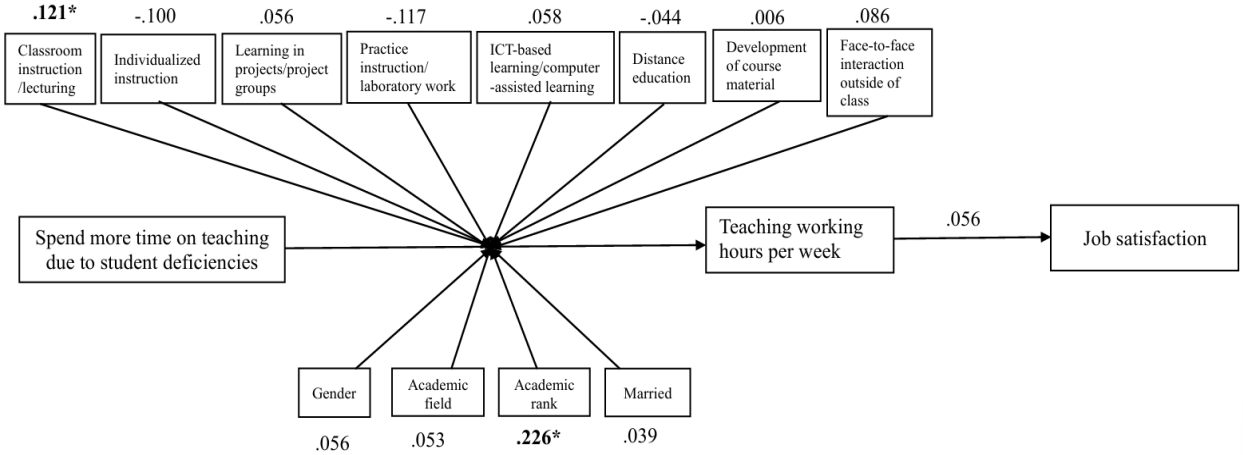


Figure 9: The influence of teaching engagement on academics' job satisfaction in 2012 APA surveys

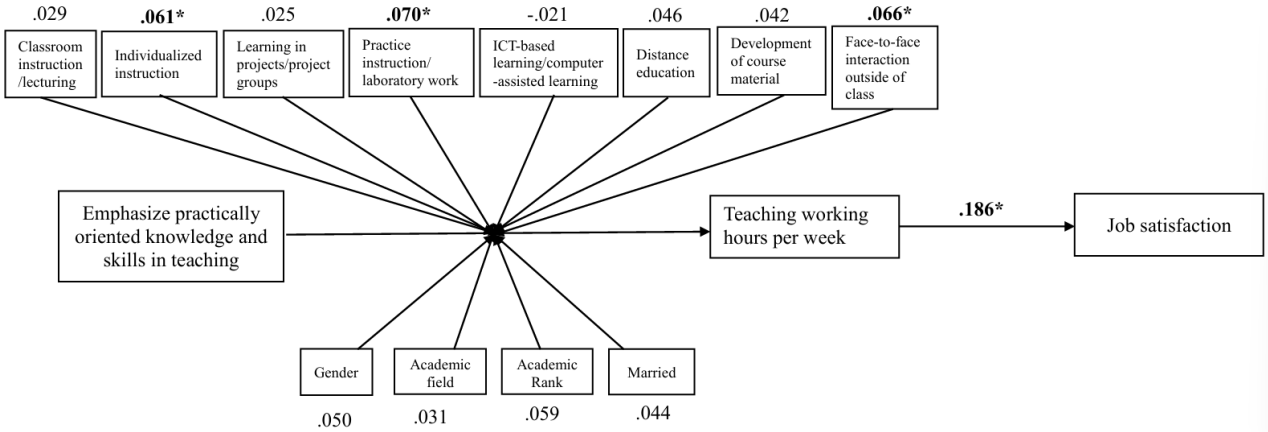


Figure 10: The influence of teaching engagement on academics' job satisfaction in 2018 APIKS surveys

5. Discussion

5.1. Resolving the Policy Mismatch: From Macro-Institutional Subsidies to Micro-Individual Incentives

The longitudinal findings of this study provide clear evidence of a significant paradigm shift within Taiwan's academic profession, revealing a clear transition from a reactive, remedial lecturing model in 2012 to a proactive, practice-oriented active-learning paradigm by 2019. This cognitive realignment addresses a critical chronological and logical mismatch in Taiwan's higher education policy history: if the Teaching Excellence Project (TEP) was launched as early as 2005, why did the 2012 baseline data still reveal a deficit-oriented, lecture-centric instructional model that failed to contribute positively to faculty job satisfaction? The explanation lies in the structural limitation of macro-level institutional funding models when

decoupled from individual career incentive systems (Hou & Hill, 2020; Power, 1999).

In 2012, the TEP operated primarily as an institutional-level subsidy. While university administrations utilized these funds to establish central teaching-learning resource centers and purchase digital hardware, the daily instructional assumptions of individual faculty members remained largely untouched (Dian-Fu & Yeh, 2012). Crucially, this period represented the peak of the Aim for the Top University Plan (ATUP), a high-stakes excellence initiative that pressured comprehensive universities to aggressively accumulate Science Citation Index (SCI) and Social Sciences Citation Index (SSCI) publication counts to capture global ranking prestige and state funding. Because institutional prestige and individual tenure promotion criteria remained tightly bound to traditional research outputs, undergraduate instruction was structurally marginalized as a low-status administrative chore (Chou, 2015; Mok, 2015). Faculty members thus adopted a reactive, student-deficit approach within rigid lecture formats, viewing extra instructional time as a zero-sum drain on their research survival (Flake & Gabriel, 2023; Lin & Huang, 2021).

The profound pedagogical realignment observed in the 2019 cohort highlights the long-term effectiveness of shifting state steering mechanisms from institutional-level funding to micro-individual incentives. In 2018, the Ministry of Education (MOE) terminated the old, fragmented plans and consolidated them into the Higher Education Sprout Project (HESP), establishing "taking teaching as the core" as its primary governance pillar (Hou et al., 2022). To directly influence the classroom level, the state introduced the revolutionary Teaching Practice Research Program (TPRP). By allowing individual faculty members to secure competitive national research grants based on classroom innovation and student learning assessments under the Scholarship of Teaching and Learning (SoTL) paradigm, and legally linking these achievements to the restructured national Academic Promotion Track, the state transformed pedagogical innovation into formal academic capital equivalent to traditional scientific research (Chung & Hsu, 2023; Hou et al., 2022). Experiencing a mature regulatory environment in 2019, faculty members were structurally incentivized to prioritize outcomes-based competencies and practical skill transmission, as these efforts now directly advanced their professional careers and institutional validation (Molderez & Fonseca, 2018).

5.2. Contextualizing Workload Dynamics: De-escalation of Rank Disparities and Lecture-Centric Constraints

The shifting interaction spaces and moderation patterns documented across the two survey waves offer important insights into how academics operationalize their core beliefs. The 2012 baseline context was characterized by severe role strain, where the translation of student-deficit orientations into increased teaching hours was heavily moderated by traditional classroom lecturing, particularly among early-career junior faculty. This finding aligns with historical critiques of East Asian higher education systems, where junior faculty members—vulnerable to the institutional pressures of ATUP's publication metrics—often face heavy introductory teaching loads and remedial duties within rigid, teacher-centered delivery models (Cheng et al., 2022; Lin & Huang, 2021).

By 2019, this unequal distribution of structural teaching burdens and modal constraints was completely eliminated. Assisted by individual TPRP grants and the institutionalization of multi-track promotion systems under HESP, the relationship between practice-oriented beliefs and actual teaching time was supported by decentralized, active learning modalities across all academic ranks (Chou, 2019; Hsieh, 2020). Faculty members who prioritized practical competencies effectively translated their beliefs into individualized instruction, hands-on laboratory work, and intensive face-to-face mentoring outside the official classroom schedule (Molderez & Fonseca, 2018).

From a theoretical standpoint, this evolution illustrates that teaching cognition is a context-sensitive construct that is structurally responsive to individual regulatory incentives (Trigwell & Prosser, 2020). By treating classroom-based research as a legitimate field of academic inquiry, the HESP and TPRP frameworks helped normalize collaborative and interactive pedagogies across different disciplines and academic ranks, successfully reducing the traditional rank-based disparities that previously isolated and burdened junior faculty (Chou, 2019; Wang et al., 2024).

5.3. **Structural Realignment of Teaching Labor and Global Faculty Job Satisfaction**

Perhaps the most notable finding for institutional research is the emergence of a robust, positive direct path coefficient between weekly teaching engagement hours and global faculty job satisfaction by 2019—a relationship that was entirely non-significant in 2012. Grounded in Hackman and Oldham's Job Characteristics Model and Herzberg's Two-Factor Theory, professional satisfaction depends heavily on task significance, autonomy, and a sense of alignment between personal effort and institutional recognition (McNaughtan et al., 2022; Njenga, 2023).

In the 2012 research-centric climate, intensive instructional allocation acted primarily as an exhausting hygiene factor. Because the institutional reward structure failed to validate pedagogical labor, the substantial time invested by faculty in lecturing acted as an administrative demand that detracted from research productivity, resulting in a neutral or negative impact on professional happiness (Lin & Huang, 2021). However, the structural realignments of 2019 successfully converted teaching from an exhausting obligation into an active motivator.

When national policy frameworks combine financial, symbolic, and professional incentives—such as national TPRP research grants, prestigious teaching awards, and clear academic promotion tracks—the affective nature of instructional labor changes (McNaughtan et al., 2022; Njenga, 2023). University faculty are more likely to view intensive teaching engagement as a worthwhile, professional, and personally fulfilling component of their academic identity when they perceive that their institutions actively value and support these contributions (Mok, 2015; Wang et al., 2024). This structural shift speaks to the broader international trend of repositioning teaching as a central pillar of academic work, demonstrating that state-level policy innovations can successfully realign faculty effort with institutional quality assurance to foster a highly committed and satisfied academic workforce (Altbach et al., 2019; Marginson, 2016).

6. Conclusions and Recommendations

6.1. Conclusions

This longitudinal study demonstrates that faculty teaching engagement is a dynamic, context-sensitive construct shaped by personal beliefs, institutional practices, and national policy initiatives. By comparing the 2012 APA and 2019 APIKS cohorts, we documented a transition from a reactive, remedial lecturing model in 2012 to a proactive, practice-oriented active-learning paradigm by 2019. This shift was accompanied by the reduction of rank-based disparities and the emergence of a positive relationship between teaching workloads and faculty job satisfaction. These findings demonstrate that national higher education policies are most effective when they shift from macro-institutional funding models to micro-individual incentives, successfully elevating the cultural and academic status of undergraduate instruction.

6.2. Institutional Research (IR) and Governance Recommendations

Based on the empirical findings, we offer three key recommendations for university administrators and higher education policy makers: First, ***Optimize and Expand Multi-Track Faculty Promotion Pathways***: To maintain the positive momentum of HESP and TPRP, university administrations must continue to expand and refine their specialized, multi-track promotion systems. Institutional research offices should design robust evaluation metrics that validate pedagogical innovation, curriculum design, and instructional leadership on par with traditional publication criteria, ensuring teaching remains a viable pathway for academic advancement. Second, ***Formally Recognize Out-of-Class Mentoring in Workload Calculations***: Because contemporary practice-oriented instruction relies heavily on high-impact practices like individualized instruction, project-based learning, and out-of-class mentoring, university workload models must look beyond traditional classroom hours. Academic departments should adjust their calculations to formally recognize and credit time spent on active, decentralized student advising, hands-on lab supervision, and collaborative experiential learning initiatives. Third, ***Build Sustainable Professional Support Infrastructures for TPRP***: Higher education policy must maintain continuous support for centralized teaching and learning resource centers. These institutional hubs should provide ongoing professional development, training in active learning pedagogies, digital learning integration, and outcomes-based assessment strategies, ensuring that faculty members possess the necessary tools to effectively translate their practice-oriented values into successful student learning outcomes. In conclusion, this study demonstrates that teaching engagement is a dynamic, context-sensitive construct influenced by cognition, institutional support, and policy frameworks.

References

Altbach, P. G., Reisberg, L., & de Wit, H. (2019). *Responding to massification: Differentiation in global higher education systems*. Routledge.

Cheng, T. M., Hou, H. Y., Chen, L. S., & Yu, S. P. (2022). Exploring the Inner Characteristics and External Competency of Excellent Teacher: The Case of a University of Technology in Taiwan. *Journal of Institutional Research South East Asia, 20*(2).41-63.

Chiang, C. H. (2013). Toward a universal higher education system: A case study of Taiwan. Quality & Quantity, 47(1), 411-420. https://doi.org/10.1007/s11135-011-9525-y

Chou, C. P. (2015). Higher education development in Taiwan. Mass higher education development in East Asia: Strategy, quality, and challenges, 89-103. https://doi.org/10.1007/978-3-319-12673-9_5

Chou, C. P. (2019). How Taiwan education pursues equity in excellence. Equity in Excellence: Experiences of East Asian High-Performing Education Systems, 43-54. https://doi.org/10.1007/978-981-13-2975-3_4

Chung, C. L., & Hsu, W. C. (2023). Characteristics and title keywords of Teaching Practice Research Projects driven by open data. *Journal of Educational Practice and Research, 36*(1), 121-162.

Dian-Fu, C., & Yeh, C. C. (2012). Teaching quality after the massification of higher education in Taiwan: A student perspective. Chinese Education & Society, 45(5-6), 31-44. https://doi.org/10.2753/CED1061-1932450503

Flake, S. M., & Gabriel, K. F. (2023). *Teaching unprepared students: Strategies for promoting success and retention in higher education*. Routledge.

Hora, M. T. (2014). Exploring faculty beliefs about student learning and their role in instructional decision-making. *The Review of Higher Education, 38*(1), 37-70.

Hou, A. Y. C., & Hill, C. (2020). What are the challenges for building world class universities in Taiwan? Assessing Taiwan's excellence initiatives since 2005. In *Higher Education in Taiwan: Global, Political and Social Challenges and Future Trends* (pp. 83-101). Singapore: Springer Singapore.

Hou, A. Y. C., Hill, C., Hu, Z., & Lin, L. (2022). What is driving Taiwan government for policy change in higher education after the year of 2016–in search of egalitarianism or pursuit of academic excellence? *Studies in Higher Education, 47*(2), 338-351. https://doi.org/10.1080/03075079.2020.1744126

Hsieh, C. C. (2020). Internationalization of higher education in the crucible: Linking national identity and policy in the age of globalization. *International Journal of Educational Development, 78*, 102245. https://doi.org/10.1016/j.ijedudev.2020.102245

Lin, T. B., & Huang, C. K. (2021). Taiwanese higher education in times of change: The implications of the new policy 2018. International Journal of Taiwan Studies, 5(1), 19-41. https://doi.org/10.1163/24688800-20211141

Ma, A. H. S. (2024). Faculty Members' Perspective on the Internationalization of Higher Education in Taiwan. Asia Pacific Education Review, 1-14. https://doi.org/10.1007/s12564-024-10016-z

Marginson, S. (2016). *The global higher education landscape: Shifting paradigms and emerging models*. Oxford University Press.

McNaughtan, J., Eicke, D., Thacker, R., & Freeman, S. (2022). Trust or self-determination: Understanding the role of tenured faculty empowerment and job satisfaction. The Journal of Higher Education, 93(1), 137-161. https://doi.org/10.1080/00221546.2021.1935601

Meichenbaum, D. (2017). Teaching thinking: A cognitive-behavioral perspective. In *The evolution of cognitive behavior therapy* (pp. 69-88). Routledge.

Molderez, I., & Fonseca, E. (2018). The efficacy of real-world experiences and service learning for fostering competences for sustainable development in higher education. *Journal of cleaner production, 172*, 4397-4410. https://doi.org/10.1016/j.jclepro.2017.04.062

Mok, K. H. (2015). Higher education transformations for global competitiveness: Policy responses, social consequences and impact on the academic profession in Asia. *Higher education policy, 28*(1), 1-15. https://doi.org/10.1057/hep.2014.27

Njenga, M. (2023). Teacher participation in continuing professional development: A theoretical framework. *Journal of Adult and Continuing Education, 29*(1), 69-85. https://doi.org/10.1177/14779714221123603

Power, M. (1999). *The audit society: Rituals of verification*. Oxford University Press.

Trigwell, K., & Prosser, M. (2020). *Qualitative manifestos of university educators: Approaches to teaching revisited*. Springer.

Wang, R. J., Chiang, Y. M., Hsueh, C. M., Shih, Y. H., & Wu, C. C. (2024). Empowering university students' learning in Taiwan's higher education: Pathways to overcome challenges. Edelweiss Applied Science and Technology, 8(6), 4261-4269. https://doi.org/10.55214/25768484.v8i6.2926

RCG-JF Taiwan -2

Between Excellence and Equity: Public Funding Concentration in Taiwanese Higher Education

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ABSTRACT

Balancing academic excellence and equitable resource distribution remains a central challenge in higher education funding policy. This study examines the concentration of government-funded project funding across Taiwanese higher education institutions from 2018 to 2024, with particular attention to the Higher Education SPROUT Project (HESP). It addresses three questions: how funding concentration differs between HESP and broader government-funded project funding, how concentration changes when institutional size is considered, and how these patterns evolve over time. Using institution-level data from Taiwan's Ministry of Education, the study employs the Gini coefficient and Herfindahl–Hirschman Index (HHI) to assess funding concentration based on institutional totals, funding per full-time faculty member, and funding per enrolled student. The results show that HESP funding was consistently less concentrated than broader government-funded project funding, although substantial institutional differences persisted. Concentration was considerably lower when funding was expressed relative to the numbers of full-time faculty members and enrolled students. While concentration in institutional funding totals remained relatively stable, size-adjusted concentration generally declined between 2018 and 2024, particularly for HESP. These findings highlight the importance of institutional scale and longitudinal patterns in evaluating funding distribution, demonstrating that broad institutional support can coexist with differentiated resource allocation.

Keywords: Higher education policy; Funding inequality; Gini coefficient; Resource allocation; Institutional size

1. Introduction

Public investment has long played a central role in the development of higher education. From a human capital perspective, education represents an investment that enhances individual knowledge and skills and generates economic returns over time (Becker, 1964). At the societal level, higher education contributes to knowledge production, innovation, economic development, and social progress, providing an important rationale for continued public investment in universities (OECD, 2008, 2025). Yet public funding involves not only how

much governments invest in higher education but also how limited resources are distributed across institutions. As governments seek to support teaching, research, educational opportunity, and international competitiveness, decisions about the allocation of public resources have become an increasingly important dimension of higher education policy.

This distributional question has become particularly salient with the expansion of excellence-oriented higher education policies. Over the past several decades, governments have increasingly used selective funding initiatives to strengthen universities considered capable of achieving research excellence and international competitiveness (Salmi, 2009; Shin, 2009; Hou et al., 2012). While concentrating resources in selected institutions can help build research capacity and strengthen international competitiveness, it also produces differentiated patterns of resource allocation across higher education systems. Funding concentration therefore provides a perspective on how public investment is distributed among institutions and how governments prioritize institutional development. This creates an important policy tension between concentrating resources to pursue excellence and maintaining a sufficiently broad distribution of public investment across the higher education system.

Taiwan provides a particularly relevant setting in which to examine this tension. Higher education, once accessible to only a relatively small proportion of the population, has become a common pathway for young people completing secondary education. Viewed through Trow's (2007) framework, Taiwan's higher education system has undergone a rapid transition from elite to mass and eventually universal participation, with the gross enrolment ratio reaching 85.3% and the net enrolment ratio 71.4% in 2025 (Ministry of Education [MOE], n.d.). At the same time, declining student populations and intensifying international competition have created new pressures over how public resources should be allocated across this large and diverse higher education sector (Hou, 2023; MOE, n.d.). As higher education participation has expanded, attention to the distribution of public resources among institutions has become increasingly important, particularly given the differences in institutional size, missions, and development priorities across the system.

This issue is particularly relevant in light of Taiwan's changing higher education funding policy. Earlier initiatives concentrated additional resources in selected universities to strengthen international competitiveness, whereas the Higher Education SPROUT Project (HESP), introduced in 2018, broadened policy attention toward teaching quality, institutional development, educational accessibility, and social responsibility while retaining selective support for academic excellence (Hou, 2023; MOE, 2017). Taiwan therefore presents a policy setting in which broad institutional support and selective investment in excellence coexist. However, the expansion of institutional coverage does not necessarily imply a less concentrated distribution of funding. Existing studies have examined selective funding and disparities in

resource allocation under earlier excellence initiatives and HESP (Hou et al., 2012; Wang & Chang, 2025), but several aspects of institution-level funding concentration remain insufficiently examined. In particular, limited attention has been given to how HESP funding compares with the broader category of government-funded project funding, how concentration differs when funding is considered relative to institutional size, and how these distributional patterns changed between 2018 and 2024.

To address these gaps, this study examines the distribution of government-funded project funding and HESP funding across Taiwanese higher education institutions from 2018 to 2024. It first compares the concentration of the two funding types using institution-level funding totals. Recognizing that universities differ substantially in the numbers of faculty members they employ and students they serve, the study further examines funding per full-time faculty member and per enrolled student to assess how concentration patterns differ when institutional scale is considered. It then examines annual changes in these patterns from 2018 to 2024. Using the Gini coefficient and the Herfindahl–Hirschman Index (HHI) as complementary measures, the study integrates comparisons across funding types, institutional size, and time. By distinguishing the breadth of institutional support from the distribution of funding amounts, it provides a more comprehensive assessment of public project funding concentration and contributes to understanding the distributional dimensions of higher education funding policy.

The study addresses the following research questions:

RQ1. How does funding concentration differ between government-funded project funding and HESP funding across Taiwanese higher education institutions?

RQ2. How do patterns of funding concentration differ when funding is measured relative to the numbers of full-time faculty members and enrolled students?

RQ3. How have funding concentration patterns evolved between 2018 and 2024?

2. Literature Review

2.1 Public Funding as a Policy Instrument in Higher Education

Public funding serves multiple functions within higher education systems. It provides universities with resources for teaching, research, and institutional development, while also representing an important means through which governments invest in human capital, knowledge production, and innovation (Becker, 1964; OECD, 2008, 2025). At the same time, the significance of public funding extends beyond the amount of financial support provided.

OECD (2008) emphasizes that funding arrangements increasingly form part of a broader shift "from subsidy to steering," whereby governments use financial incentives and allocation mechanisms to guide institutions toward policy objectives. Public funding can therefore be understood not only as a source of institutional resources but also as an instrument of higher education governance.

This steering role is particularly evident in the expansion of performance-based and competitive funding mechanisms. OECD (2008, 2025) documents the growing use of targeted allocations, competitive funding, performance-related mechanisms, and other forms of conditional support in higher education financing. In the research sector, Hicks (2012) shows how performance-based research funding systems use assessments of research performance to inform the allocation of public resources across universities. Teixeira et al. (2022) further describe the relationship between funding and institutional competition as both "competition for funding" and "funding for competition," while Matveeva (2025) shows that performance-based funding systems, despite variation in their design, share a common logic of linking resource allocation more explicitly to institutional results. These developments illustrate how governments increasingly use funding mechanisms not only to support institutions but also to differentiate levels of support according to policy priorities and performance criteria.

Research also shows that such funding arrangements can influence institutional behavior and governance. From a resource dependence perspective, universities may adjust their strategies in response to the priorities and requirements of external funding providers (Teixeira et al., 2022). Fochler et al. (2026), for example, show that changes in research funding can affect university research governance, including institutional priority-setting and the organization of research activities. Stephan (2015) similarly illustrates, through the historical development of federal research funding in the United States, how sustained public investment helped reshape university research capacity and institutional engagement with government funding. In Taiwan, Liu (2013) demonstrates how the linkage between university evaluation and government funding can function as a policy instrument, while Hsieh (2025) highlights the interaction among funding, institutional autonomy, accountability, and broader political and institutional contexts. Together, these studies indicate that public funding can shape institutional incentives and priorities as well as provide financial resources.

The use of funding as a policy instrument also has important distributional consequences. When public resources are allocated according to particular policy objectives, performance criteria, or competitive processes, funding mechanisms determine not only what activities are supported but also how resources are distributed across institutions (OECD, 2008, 2025; Teixeira et al., 2022; Matveeva, 2025). Funding allocation is therefore both a governance mechanism and a distributive policy choice. As higher education funding becomes increasingly

strategic and selective, attention must be paid not only to the incentives created by these arrangements but also to the resulting distribution of resources across universities. This distributional dimension becomes particularly important in excellence-oriented policies, in which additional resources are deliberately directed toward selected institutions and areas of activity.

2.2 Selective Funding, Excellence, and Resource Concentration

As performance and competition have become increasingly embedded in higher education funding, public resource allocation has also become more selective (OECD, 2008, 2025; Hicks, 2012; Teixeira et al., 2022; Matveeva, 2025). Such selectivity raises an important distributional question: where are public resources directed, and to what extent are they concentrated among particular institutions?

The pursuit of academic excellence provides an important rationale for selective allocation. Salmi (2009) argues that the development of world-class universities depends on three interrelated conditions: a high concentration of talent, abundant resources, and favorable governance. From a policy perspective, governments seeking to strengthen internationally competitive universities may therefore direct additional resources toward institutions considered capable of achieving excellence. Salmi (2009) identifies the upgrading of selected existing institutions, or "picking winners," as one strategy through which governments have pursued this objective. This approach has been particularly visible in Asian higher education. Reviewing excellence initiatives in China, Japan, South Korea, and Taiwan, Hou et al. (2012) describe these policies as a "policy of funding concentration," whereby additional resources were allocated to a relatively small number of universities to strengthen research capacity and international competitiveness. In this context, resource concentration can represent a deliberate policy strategy rather than merely an unintended outcome of funding allocation.

National excellence initiatives in South Korea and Japan illustrate how this strategy has operated in practice. In South Korea, the Brain Korea 21 (BK21) project, launched in 1999, sought to develop world-class research universities and strengthen graduate education through competitively allocated funding (Shin, 2009). Shin (2009) describes BK21 as following a principle of "selection and concentration." Among the universities in science, engineering, and medicine included in his analysis, Seoul National University received 20.4% of BK21 funding, while Seoul National University, the Korea Advanced Institute of Science and Technology, and Pohang University of Science and Technology together accounted for 50.2%. Japan adopted a similarly selective approach through the 21st Century Center of Excellence Program and the subsequent Global COE Program (Arimoto, 2009). In the first year of the Global COE Program, 63 of 281 applications were selected, and the former seven imperial universities

accounted for 27% of applications but 51% of successful projects. These cases show how policies intended to promote academic excellence can translate into competitive selection and concentrated support for a limited number of universities and research programs.

Taiwan followed a similar trajectory in its pursuit of internationally competitive universities. In 2006, the government launched the Development Plan for World Class Universities and Research Centers of Excellence, commonly associated with the Five-Year Fifty-Billion Program, to strengthen the research capacity and international competitiveness of leading universities (Hou et al., 2012). Eleven universities were selected to receive additional funding during the first phase from 2006 to 2010, and the allocation was concentrated even among these recipients. National Taiwan University received 30% of total funding, followed by National Cheng Kung University with 17%, National Tsing Hua University with 11.2%, and National Chiao Tung University with 8.6%; together, these four universities received 66.8% of the program funding (Hou et al., 2012). During the same period, recipient universities recorded substantial growth in research publications and internationalization activities, although the magnitude of these changes varied across indicators. Taiwan's experience therefore illustrates how selective participation and differentiated funding levels were combined in the pursuit of academic excellence.

Research has also drawn attention to the broader distributional consequences associated with selective funding. In Japan, Arimoto (2009) argues that the expansion of competitive funding occurred within an already hierarchical higher education system and was accompanied by growing differences in access to research resources between research and non-research universities. Jeon and Kim (2018) similarly describe South Korea's research funding system as characterized by "concentration by selection," reporting that the top 20 universities received approximately 62% of public university research funding. Their analysis also identifies continuing inequality in research output, although the direction of change differed depending on whether inequality was measured in relative or absolute terms. More recently, Yonezawa (2023) observes that Japan's continued reliance on performance-based and selective funding has allowed leading universities to maintain or strengthen their financial position, while less competitive national universities have faced greater budgetary constraints. These studies suggest that selective funding can operate alongside persistent institutional hierarchies and uneven access to resources.

Taken together, these findings point to a broader tension between the pursuit of excellence and the distribution of public resources across higher education systems. Selective investment may serve the policy objective of strengthening research capacity and international competitiveness, yet it can also produce highly differentiated patterns of resource allocation across institutions. Salmi (2009) cautions that strategies centered on selected universities may create distortions in

resource allocation, while Hou et al. (2012) identify both improvements in research performance and internationalization among funded Taiwanese universities and concerns about widening differences in educational resources between recipient and non-recipient institutions. Yonezawa (2023) similarly argues that sustainable higher education development requires attention not only to leading universities but also to broader participation across the system. Understanding excellence-oriented funding therefore requires examining not only the performance of supported institutions but also how public resources are distributed across the wider higher education sector.

2.3 The Evolution of Higher Education Funding Policy in Taiwan

Taiwan's higher education funding policy has gradually expanded from a predominantly selective emphasis on academic excellence toward a broader framework of institutional development. As discussed above, the Development Plan for World Class Universities and Research Centers of Excellence, launched in 2006, concentrated additional public resources on selected universities to strengthen research capacity and international competitiveness. This approach continued under the Moving into Top Universities Program from 2011 to 2016, maintaining a strong emphasis on developing internationally competitive research universities (Hou, 2023). By the end of this period, however, concerns had emerged over the consequences of relying heavily on competitive funding. The Ministry of Education identified increasing polarization among universities and institutional homogenization as problems associated with the previous competitive funding regime (Ministry of Education [MOE], 2017). Against this background, the Higher Education SPROUT Project (HESP) was launched in 2018, with its first five-year phase running from 2018 to 2022. The new framework placed greater emphasis on teaching quality, institutional diversity, educational accessibility, and social responsibility while continuing to support international competitiveness (Hou, 2023; MOE, 2017).

Rather than replacing selective funding for academic excellence, HESP incorporated it into a broader funding framework. The first phase consisted of two major components. The first sought to improve the overall quality and diversity of higher education through support for teaching innovation, institutional development, university social responsibility, and disadvantaged and Indigenous students (MOE, 2017). The second continued to support international excellence and the development of leading research centers, thereby retaining selective funding for institutions and research areas with strong international competitiveness (MOE, 2017; Hou, 2023). The difference in coverage across these forms of support was substantial. During the first phase, programs supporting disadvantaged students reached approximately 146–150 institutions annually, whereas the whole-university excellence program supported four universities each year and the research-center program involved

approximately 23–24 universities (MOE, 2022). HESP therefore combined broad institutional participation in some areas of support with substantially more selective investment in academic excellence.

HESP operates through successive five-year planning cycles, while funding allocations are approved annually and may be adjusted through the review process (MOE, 2022). Universities submit institutional development plans specifying their objectives, implementation strategies, performance indicators, and funding needs, while block funding provides institutions with flexibility in the use of approved resources. The second phase, covering 2023–2027, retained the general architecture of HESP while placing greater emphasis on evidence-based planning and performance monitoring through institutional research. It also expanded the planned scale of investment, with a five-year budget of NT$97 billion, compared with approximately NT$83.7 billion actually allocated during the first phase (MOE, 2022). At the same time, the second phase continued both broad-based institutional development and selective support for internationally competitive universities and research centers. The transition to the second phase therefore represented a continuation and expansion of the HESP framework rather than a shift away from its combination of broad institutional support and selective investment in excellence.

The broader institutional coverage of HESP does not, however, necessarily imply a more even distribution of funding across universities. Hou (2023) characterizes HESP as representing a broader approach to higher education development than earlier excellence initiatives, yet its combination of widespread institutional support and selective excellence funding allows substantial differences in allocation levels to remain. Empirical evidence also points to continuing disparities. Examining HESP funding from 2018 to 2023, Wang and Chang (2025) identify persistent differences in funding across institutions and regions, with universities in northern Taiwan receiving approximately 65% of total funding in 2022–2023. Their findings demonstrate that substantial distributional differences remained under HESP, but they do not directly quantify the degree of concentration across individual institutions or compare HESP with the broader category of government-funded project funding. The broader coverage of HESP and the continuing differentiation of funding allocations therefore need to be considered as distinct dimensions of the policy.

2.4 Funding Concentration: Empirical Evidence and Research Gap

While selective funding may produce uneven patterns of resource allocation, the degree of concentration cannot be inferred from policy design alone and requires empirical assessment. Previous studies have therefore employed quantitative measures to examine how research and higher education funding is distributed across institutions and researchers (Shibayama, 2011; Wu, 2015; Zhi & Meng, 2016; Kelly, 2023; Mohr et al., 2026). Among these measures, the

Gini coefficient has been widely used to assess inequality across the overall distribution and to facilitate comparisons across populations and over time (Giorgi & Gigliarano, 2017; Shibayama, 2011). The Herfindahl–Hirschman Index (HHI), by contrast, focuses on the shares held by individual recipients and gives greater weight to larger shares. Recent studies have applied these measures to examine the concentration of research funding across institutions and funding systems (Kelly, 2023; Mohr et al., 2026). Used together, the Gini coefficient and HHI provide complementary perspectives on the distribution and concentration of funding.

Evidence from different higher education systems shows that research funding can be highly concentrated among a relatively small number of institutions, although both the level and development of concentration vary across contexts. In Japan, Shibayama (2011) found that the seven largest recipients accounted for approximately half of national research grants in 2005, with a Gini coefficient of 0.919 across all universities. Despite this high level of concentration, the distribution changed relatively little over the preceding three decades. Research on China presents a different pattern. Wu (2015), examining National Natural Science Foundation of China funding from 2000 to 2013, found that funding remained concentrated among leading universities despite an overall decline in inequality, while Zhi and Meng (2016) identified increasing concentration in life-science funding and reported that the top 10% of institutions received more than half of the funding by 2010. Studies in other higher education systems have likewise documented uneven distributions of competitive and research funding (Koenig et al., 2017; Kelly, 2023). These findings indicate that substantial funding concentration can coexist with different temporal trajectories, making both the level of concentration and its change over time important dimensions of analysis.

The interpretation of funding concentration also depends on institutional scale and the scope of funding examined. Institutional size is particularly important because differences in aggregate funding may partly reflect differences in the scale of universities. Shibayama (2011), for example, found substantial inequality in faculty size across Japanese universities and cautioned that the concentration of research funding should be interpreted in relation to differences in institutional size. Similarly, Wu et al. (2018) showed that estimates of research funding inequality varied across levels of analysis, demonstrating how the distribution of researchers within and across institutions can affect observed patterns of inequality. Funding source also matters. Li et al. (2017) found substantial differences in funding inequality when comparing individual funding sources with overall research funding, indicating that the distribution of a specific funding stream may not reflect the broader distribution of resources. Assessments of funding concentration should therefore consider not only aggregate funding levels but also institutional scale and the particular funding stream under examination.

Despite growing attention to the distribution of higher education funding, evidence on funding concentration in Taiwan remains limited. Existing research has documented disparities in public resource allocation under Taiwan's higher education funding policies (Hou et al., 2012; Wang & Chang, 2025), but several aspects of institution-level funding concentration remain insufficiently examined. In particular, it remains unclear whether HESP funding exhibits a different distributional pattern from the broader category of government-funded project funding, how concentration differs when funding is expressed relative to faculty and student size, and how these patterns changed between 2018 and 2024. The present study addresses these gaps by comparing the distribution of HESP and government-funded project funding across Taiwanese higher education institutions using institutional totals, funding per full-time faculty member, and funding per enrolled student, and by examining changes in these concentration patterns over time.

3. Method

3.1 Data Sources and Sample

This study examined higher education institutions in Taiwan from 2018 to 2024 using institution-level data. The observation period begins in 2018 because the Higher Education SPROUT Project (HESP) was launched that year, with its first phase commencing in January 2018 (Ministry of Education [MOE], 2017). The analysis covers general universities and colleges as well as technological and vocational higher education institutions in Taiwan, with the institution serving as the unit of analysis.

Data on institutional funding and size were obtained from publicly available sources provided by the MOE. Government-funded project funding was drawn from the University Database (MOE, n.d.), while HESP funding was obtained from annual funding allocations published by the Department of Higher Education, MOE (MOE, 2025). The numbers of full-time faculty members and enrolled students were also obtained from the University Database (MOE, n.d.) and were used to calculate funding per full-time faculty member and funding per enrolled student, respectively.

The number of institutions included in the analysis varied slightly between 2018 and 2024 because of institutional closures and mergers in Taiwan's higher education system. The analysis reflects the institutions operating in each year: institutions were no longer included following closure, while merged institutions were treated according to their institutional status after restructuring. After data preparation, the analytical sample consisted of 141 institutions in each year from 2018 to 2020, 140 institutions in each year from 2021 to 2023, and 139

institutions in 2024. The same annual institutional sample was used for both funding measures, and all included observations contained complete funding, faculty, and student data.

3.2 Funding Measures

This study compares the distribution of government-funded project funding and Higher Education SPROUT Project (HESP) funding across institutions. Government-funded project funding refers to funding received by institutions for projects supported by central or local government agencies (MOE, n.d.). According to the University Database, these projects include industry–university collaboration projects, infrastructure and capacity-building projects, academic research projects, commissioned training projects, and other government-funded projects. HESP funding represents a specific component of this broader category and consists of funding allocated to institutions by the Ministry of Education through the HESP (MOE, 2025). The two measures are therefore not mutually exclusive. Government-funded project funding captures the broader distribution of project-based government resources across institutions, whereas HESP funding represents a specific national higher education funding initiative within that broader category. Comparing the two allows the study to assess whether HESP exhibits a different pattern of funding concentration from government-funded project funding overall.

Funding was measured in three ways to distinguish the distribution of absolute funding from patterns observed when funding is expressed relative to institutional size. First, total funding refers to the amount of funding received by each institution and captures the distribution of absolute funding across institutions. Second, funding per full-time faculty member was calculated by dividing each institution's funding by its number of full-time faculty members, allowing funding concentration to be examined relative to faculty size. Third, funding per enrolled student was calculated by dividing each institution's funding by its student enrollment, allowing funding concentration to be examined relative to student size. Together, these three measures provide complementary perspectives on the distribution of government-funded project and HESP funding in absolute terms and relative to the faculty and student populations of each institution.

3.3 Measures of Funding Concentration

To assess how government-funded project funding and Higher Education SPROUT Project (HESP) funding were distributed across higher education institutions, this study employed two complementary measures of concentration: the Gini coefficient and the Herfindahl–Hirschman Index (HHI). The Gini coefficient captures inequality across the entire distribution, whereas the HHI is based on institutional shares and gives greater weight to institutions with larger

shares because these shares are squared. The two measures therefore capture different aspects of funding concentration and have been used in previous studies of university and research funding (Kelly, 2023; Koenig et al., 2017; Mohr et al., 2026).

The Gini coefficient is a widely used measure of distributional inequality, ranging from 0 to 1, with higher values indicating greater inequality across units (Giorgi & Gigliarano, 2017). It was calculated as follows:

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{2n^2\bar{x}}$$

where x_i and x_j denote the funding measures for institutions i and j, respectively; n is the number of institutions included in a given year; and $\bar{x}$ is the mean value of the funding measure across institutions. A Gini coefficient of 0 indicates an equal distribution across institutions, while values approaching 1 indicate increasingly unequal distributions. The Gini coefficient has also been applied to examine the concentration and distribution of university funding across institutions and regions (Koenig et al., 2017).

The HHI measures concentration on the basis of each institution's share of the distribution and was calculated as:

$$HHI = \sum_{i=1}^{n} s_i^2$$

Where

$$s_i = \frac{x_i}{\sum_{j=1}^{n} x_j}$$

and s_i represents institution i's share of the sum of the relevant funding measure across all institutions. Because institutional shares are squared, institutions with larger shares contribute disproportionately more to the index. Lower HHI values therefore indicate a more dispersed distribution across institutions, whereas higher values indicate greater concentration among institutions with relatively large shares. HHI has been applied in higher education and research funding studies to examine the concentration of research activity and public research funding across universities and other research institutions (Kelly, 2023; Mohr et al., 2026). This study reports the HHI on a 0–1 scale rather than multiplying the index by 10,000.

Both concentration measures were applied to the three funding measures defined in Section 3.2. Let F_i denote the funding received by institution i, T_i its number of full-time faculty members, and S_i its student enrollment. The value of x_i used in calculating the Gini coefficient and HHI was defined as follows:

$x_i = F_i$ Total funding

$x_i = \frac{F_i}{T_i}$ Funding per faculty

$x_i = \frac{F_i}{S_i}$ Funding per student

For the per-faculty and per-student measures, funding was first divided by the corresponding institutional size measure for each institution, and the Gini coefficient and HHI were then recalculated using these institution-level values. Thus, these measures capture the cross-institutional distribution of funding relative to faculty or student size rather than an adjustment made to the concentration indices derived from total funding. All indices were calculated separately for each year from 2018 to 2024 and for both government-funded project funding and HESP funding.

Because neither the Gini coefficient nor the HHI has universally established thresholds specifically for the distribution of higher education funding, the indices were interpreted comparatively rather than classified according to fixed levels of concentration. The analysis therefore focuses on differences between the two funding types, differences observed when funding is expressed relative to faculty and student size, and changes in concentration between 2018 and 2024.

3.4 Analytical Strategy

The analysis proceeded in three stages: descriptive analysis, concentration analysis, and comparison of annual patterns. First, descriptive statistics were calculated separately for government-funded project funding and Higher Education SPROUT Project (HESP) funding for each year. These statistics included total funding, mean, median, standard deviation, and maximum, providing an overview of the scale and cross-institutional distribution of the two funding types.

Second, Gini coefficients and HHIs were calculated separately for government-funded project funding and HESP funding using the three measures defined above: total funding, funding per full-time faculty member, and funding per enrolled student. The analysis first examined

concentration in absolute funding amounts and then compared these patterns with those observed when funding was expressed relative to faculty and student size. This comparison assessed how the observed degree of concentration differed across the three measurement approaches. Concentration was also compared between government-funded project funding and HESP funding to determine whether HESP exhibited a different distributional pattern from the broader category of government-funded project funding.

Finally, annual changes in the Gini coefficient and HHI were examined from 2018 to 2024 for both funding types and across all three funding measures. The analysis focused on whether observed concentration increased, declined, or remained relatively stable during the observation period. Temporal patterns were examined descriptively through year-to-year comparisons and graphical presentation; no statistical significance tests of temporal change were conducted. Accordingly, the analysis describes observed changes in funding concentration between 2018 and 2024 rather than making statistical inferences about longer-term trends.

4. Results

4.1 Descriptive Statistics

Table 1 presents descriptive statistics for government-funded project funding and Higher Education SPROUT Project (HESP) funding from 2018 to 2024. The annual sample included between 139 and 141 higher education institutions. Over the observation period, the total amount of both types of funding increased overall. Government-funded project funding rose from NT$57.52 billion in 2018 to NT$72.04 billion in 2024, an increase of approximately 25.2%. HESP funding increased from NT$15.24 billion to NT$18.49 billion over the same period, representing an increase of approximately 21.3%.

The descriptive statistics also reveal substantial differences in the amounts received across institutions. For both funding measures, the mean was consistently higher than the median in every year, a pattern consistent with positively skewed distributions. Because the mean is sensitive to relatively large values whereas the median represents the midpoint of the distribution, the persistent gap between the two indicates that many institutions received amounts below the overall average, while a smaller number of institutions received substantially larger amounts. These patterns therefore point to considerable cross-institutional variation in both types of funding.

This pattern is particularly evident in 2024. The mean amount of government-funded project funding was NT$518.28 million, compared with a median of NT$155.03 million. This means that at least half of the institutions received no more than approximately NT$155 million, even

though the average exceeded NT$500 million. The maximum amount received by a single institution was NT$9.86 billion. A similar pattern was observed for HESP funding: the mean was NT$133.04 million, the median was NT$57.94 million, and the maximum reached NT$2.59 billion. The standard deviations were also large relative to the corresponding medians, at NT$1.19 billion for government-funded project funding and NT$296.60 million for HESP funding in 2024. These descriptive statistics show that the higher overall funding levels observed by 2024 coexisted with substantial cross-institutional differences in the amounts received.

Table 1. Descriptive Statistics of Government-Funded Project and HESP Funding, 2018–2024

Year	Funding type	N	Total	Mean	Median	SD	Max
2018	Government projects	141	57,521.49	407.95	130.41	933.90	8,206.50
	HESP	141	15,243.29	108.11	48.42	215.42	1,800.00
2019	Government projects	141	59,233.04	420.09	121.56	980.09	8,529.33
	HESP	141	16,415.20	116.42	49.38	256.93	2,253.16
2020	Government projects	141	59,557.43	422.39	128.76	987.22	8,500.38
	HESP	141	17,350.31	123.05	54.95	268.11	2,373.71
2021	Government projects	140	61,213.78	437.24	123.84	1,019.47	8,508.40
	HESP	140	17,215.31	122.97	54.50	274.72	2,326.73
2022	Government projects	140	64,714.58	462.25	123.55	1,073.61	8,693.68
	HESP	140	17,147.97	122.49	54.91	274.48	2,325.87
2023	Government projects	140	65,641.05	468.86	116.18	1,094.74	9,390.35
	HESP	140	18,169.74	129.78	57.46	283.40	2,466.49
2024	Government projects	139	72,041.26	518.28	155.03	1,186.35	9,861.83
	HESP	139	18,492.50	133.04	57.94	296.60	2,593.13

Note. Monetary values are expressed in NT$ million. HESP = Higher Education SPROUT Project.

4.2 Funding Concentration across Institutions

Table 2 reports the Gini coefficients and Herfindahl–Hirschman Indices (HHIs) for total government-funded project funding and HESP funding between 2018 and 2024. The Gini coefficient captures inequality across the institutional distribution, with values closer to zero indicating a more even distribution and higher values indicating greater cross-institutional differences. For total funding, the Gini coefficients for government-funded project funding ranged from .724 to .742, compared with .623 to .644 for HESP funding. These values indicate marked differences in the absolute amounts received across institutions under both funding types. The HESP Gini coefficient was lower than that of government-funded project funding in every year, indicating consistently smaller cross-institutional differences in HESP funding.

The HHI provides a complementary perspective by focusing on each institution's share of total funding and giving greater weight to institutions accounting for relatively large shares. Between 2018 and 2024, the HHI for government-funded project funding ranged from .0440 to .0458, while that for HESP funding ranged from .0351 to .0428. The HHI results therefore show the same relative pattern as the Gini coefficients: HESP funding was less concentrated than government-funded project funding in every year when assessed using institutional funding totals.

Table 3 presents concentration measures when funding is expressed relative to the number of full-time faculty members at each institution. The Gini coefficients were substantially lower than those calculated from total funding for both funding types. The Gini coefficient for government-funded project funding ranged from .518 to .537, while that for HESP funding ranged from .314 to .376. Cross-institutional differences were therefore smaller when funding was expressed relative to faculty size, suggesting that part of the variation observed in absolute funding amounts is associated with differences in institutional scale. HESP nevertheless had a lower Gini coefficient than government-funded project funding in every year. The HHI values calculated from the institution-level per-faculty funding ratios ranged from .0149 to .0157 for government-funded project funding and from .0104 to .0120 for HESP funding. Thus, HESP also exhibited lower concentration when institutions were compared on the basis of funding per full-time faculty member.

A similar pattern emerged when funding was expressed relative to student enrollment. As shown in Table 4, the Gini coefficients for government-funded project funding ranged from .577 to .618, compared with .410 to .488 for HESP funding. Both ranges were lower than their corresponding Gini coefficients for total funding, indicating smaller cross-institutional differences when funding was expressed on a per-student basis. HESP funding again had a lower Gini coefficient than government-funded project funding in every year. The HHI values

calculated from the institution-level per-student funding ratios ranged from .0181 to .0207 for government-funded project funding and from .0132 to .0172 for HESP funding. These results likewise indicate lower concentration for HESP when funding was examined relative to student size.

Across the three measures, the observed degree of concentration differed depending on whether funding was examined in absolute terms or expressed relative to faculty and student size. Cross-institutional differences were greatest for total funding and became smaller for the per-faculty and per-student measures. This pattern indicates that institutional scale is associated with part of the variation observed in absolute funding amounts. The central comparison, however, remained consistent across all three measurement approaches: HESP funding had lower Gini coefficients and HHIs than government-funded project funding throughout the observation period. The relatively lower concentration of HESP was therefore evident both in institutional funding totals and in funding expressed relative to faculty and student size.

Table 2. Gini Coefficients and Herfindahl–Hirschman Indices of Total Funding, 2018–2024

Year	Government Gini	HESP Gini	Government HHI	HESP HHI
2018	.724	.623	.0440	.0351
2019	.732	.644	.0454	.0414
2020	.736	.630	.0456	.0405
2021	.740	.633	.0457	.0425
2022	.742	.634	.0454	.0428
2023	.740	.630	.0458	.0410
2024	.736	.635	.0446	.0427

Note. Government = government-funded project funding; HESP = Higher Education SPROUT Project.

Table 3. Gini Coefficients and Herfindahl–Hirschman Indices of Funding per Full-Time Faculty Member, 2018–2024

Year	Government Gini	HESP Gini	Government HHI	HESP HHI
2018	.526	.370	.0154	.0116
2019	.529	.376	.0156	.0120
2020	.537	.362	.0157	.0116
2021	.533	.340	.0155	.0111
2022	.534	.335	.0154	.0109
2023	.525	.321	.0150	.0104
2024	.518	.314	.0149	.0104

Note. Government = government-funded project funding; HESP = Higher Education SPROUT

Project.

Table 4. Gini Coefficients and Herfindahl–Hirschman Indices of Funding per Enrolled Student, 2018–2024

Year	Government Gini	HESP Gini	Government HHI	HESP HHI
2018	.617	.483	.0207	.0168
2019	.617	.488	.0204	.0172
2020	.618	.470	.0205	.0158
2021	.607	.442	.0195	.0147
2022	.601	.431	.0190	.0142
2023	.586	.413	.0182	.0132
2024	.577	.410	.0181	.0133

Note. Government = government-funded project funding; HESP = Higher Education SPROUT Project.

4.3 Changes in Funding Concentration, 2018–2024

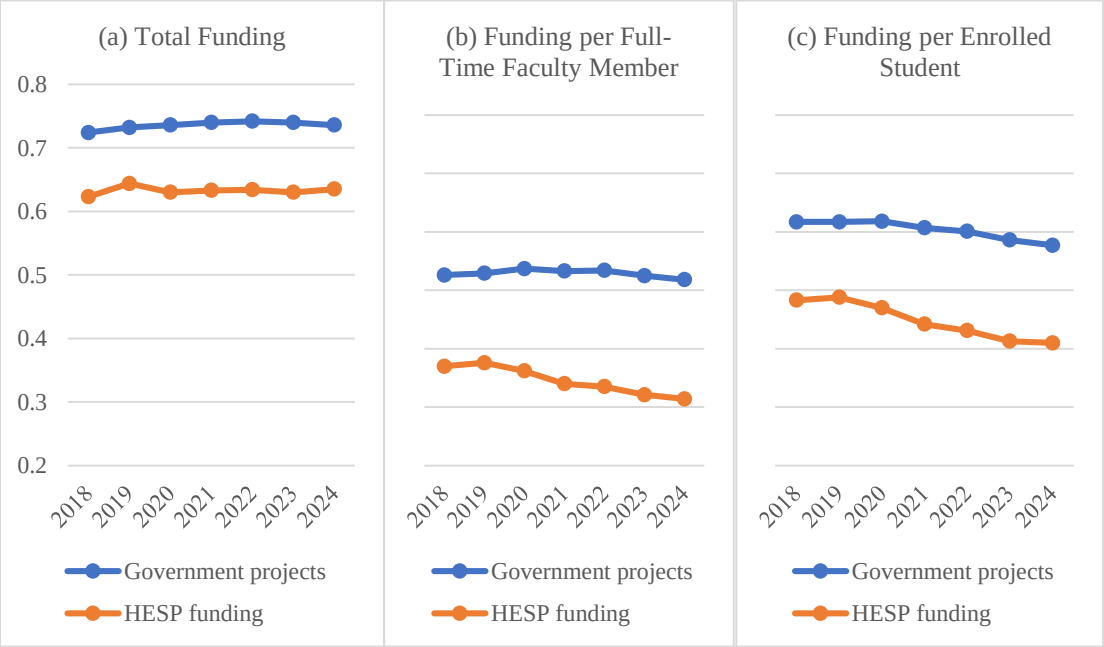
Figure 1 shows changes in the Gini coefficients for government-funded project funding and HESP funding between 2018 and 2024. For total funding, concentration remained relatively stable for both funding types. The Gini coefficient for government-funded project funding fluctuated within a narrow range, from .724 to .742, while the HESP coefficient ranged from .623 to .644. Although both measures varied from year to year, neither showed a clear overall increase or decrease between 2018 and 2024. The concentration of absolute funding across institutions therefore changed relatively little during the observation period.

A different pattern emerged when funding was expressed relative to institutional size. On a per-faculty basis, the concentration of government-funded project funding changed only modestly, whereas HESP funding showed a clearer overall decline. After reaching .376 in 2019, the HESP Gini coefficient declined to .314 in 2024. Declining concentration was also evident in the per-student measure and, in this case, appeared for both funding types. The Gini coefficient for government-funded project funding remained around .62 through 2020 before declining to .577 in 2024, while the HESP coefficient declined from .488 in 2019 to .410 in 2024. Thus, reductions in concentration were more evident when funding was expressed relative to faculty or student size than when institutions were compared using absolute funding amounts.

The observed changes therefore differed across the three measurement approaches. Concentration in total funding remained broadly stable according to the Gini coefficient,

whereas the per-faculty and per-student measures generally showed lower concentration by the later years of the observation period, particularly for HESP funding. The HHI estimates reported in Tables 2–4 provided broadly consistent evidence of lower concentration in the size-relative measures, although the magnitude and year-to-year movement of the HHI did not always correspond exactly to those of the Gini coefficient. Taken together, these results show that the distribution of absolute funding changed relatively little between 2018 and 2024, while funding expressed relative to faculty and student size became less concentrated over the same period, most clearly for HESP funding.

Figure 1. Changes in Gini Coefficients for Government-Funded Project and HESP Funding, 2018–2024



Note. Government projects refer to government-funded project funding. HESP = Higher Education SPROUT Project.

5 Discussion

5.1 Broad-Based Funding Does Not Eliminate Resource Concentration

A central result is the distinction between broad institutional support and the distribution of funding amounts. Although the Higher Education SPROUT Project (HESP) was designed to extend public support across a wider range of higher education institutions, substantial differences in funding remained across universities. At the same time, HESP consistently

exhibited a lower degree of concentration than the broader category of government-funded project funding. This finding is consistent with Wang and Chang (2025), who documented persistent institutional and regional disparities in HESP allocations. By systematically comparing HESP with the broader government-funded project funding category, the present study extends this evidence from the identification of funding disparities to a comparative assessment of institution-level funding concentration.

This pattern can be understood in light of Taiwan's evolving approach to higher education funding. Whereas earlier excellence initiatives emphasized selective investment in leading universities (Hou et al., 2012), HESP introduced a broader framework of institutional development without abandoning targeted support for academic excellence (Hou, 2023). Its funding architecture combines widespread support for teaching quality, institutional development, and social responsibility with selective investment in internationally competitive universities and research centers (MOE, 2017, 2022). Broad institutional participation and differentiated funding allocations are therefore not necessarily contradictory features of the policy. This combination also resonates with Salmi's (2009) observation that concentrating resources in selected institutions can form part of a strategy to pursue academic excellence. The present analysis, however, does not determine how individual HESP components contribute to the observed pattern of concentration.

More broadly, the findings suggest that institutional coverage and funding concentration should be treated as distinct dimensions when evaluating higher education funding policies. A program may extend financial support to a large number of universities while allocating substantially different amounts across participating institutions. Conversely, a relatively less concentrated distribution does not imply that institutions receive similar levels of funding. This distinction is particularly relevant to funding frameworks that pursue multiple objectives, including broad institutional development and selective support for academic excellence. Examining HESP within the broader category of government-funded project funding highlights the importance of assessing not only which institutions receive support but also how the amounts of funding are distributed across them.

5.2 Institutional Funding Totals Do Not Tell the Whole Story

Comparisons across the three measures show that the concentration of government-funded project funding and HESP funding depends in part on the basis of comparison. While funding measured in institutional totals exhibited substantial concentration, the degree of concentration was considerably lower when funding was expressed relative to the numbers of full-time faculty members or enrolled students. Nevertheless, cross-institutional differences remained in both the per-faculty and per-student measures. These findings suggest that the concentration

observed in institutional funding totals should not be interpreted independently of differences in university size. Larger institutions may receive greater amounts of funding partly because they employ more faculty members and enroll more students, although institutional scale alone does not fully account for the observed distributional differences.

This finding is consistent with previous research emphasizing the importance of institutional scale in interpreting funding concentration. Shibayama (2011), examining the distribution of research funding among Japanese universities, highlighted substantial differences in faculty size across institutions and the need to consider these differences when assessing the concentration of research resources. Similarly, Wu et al. (2018) demonstrated that estimates of research funding inequality can vary across levels of analysis, reflecting the importance of how funding recipients and institutional structures are represented in distributional assessments. Although these studies employed different analytical approaches and examined different funding systems, they underscore a common methodological concern: the apparent degree of concentration depends on the unit and basis of comparison. Applying these different bases of comparison to Taiwan shows that the apparent degree of funding concentration varies with how institutional scale is represented.

Importantly, lower concentration in the per-faculty and per-student measures should not be interpreted as evidence of more equitable funding allocation. These measures represent institution-level ratios rather than resources directly received by individual academics or students. Moreover, universities differ in their missions, research intensity, disciplinary composition, and resource requirements, which cannot be fully captured by faculty or student numbers alone. Institutional totals and size-relative measures therefore provide complementary rather than interchangeable perspectives on resource distribution. The former indicates where public project funding is concentrated across universities, while the latter shows how funding levels are distributed when expressed relative to faculty and student populations. Considering both perspectives is therefore important for interpreting institutional funding concentration more comprehensively.

5.3 Different Patterns of Change across Funding Measures

Annual comparisons show that changes in funding concentration between 2018 and 2024 differed depending on how funding was measured. When assessed using institutional funding totals, concentration remained relatively stable for both government-funded project funding and HESP funding. In contrast, concentration based on funding per full-time faculty member and per enrolled student generally declined over the observation period, although the magnitude and consistency of these changes varied across funding types and measures. These contrasting patterns indicate that relative stability in the distribution of institutional funding totals can coexist with changes in the distribution of funding when it is expressed relative to faculty and student size.

Previous research similarly shows that funding concentration does not necessarily change in a uniform direction. Shibayama (2011) found that research funding concentration among Japanese universities remained relatively stable over an extended period, whereas Wu (2015) documented declining inequality in research funding among Chinese universities despite the continued concentration of resources among leading institutions. In Taiwan, Wang and Chang (2025) likewise identified persistent institutional and regional disparities in HESP allocations. The Taiwan case further shows that, within the same higher education system, different patterns of change can emerge depending on whether funding is examined in institutional totals or relative to faculty and student populations.

The contrasting patterns also provide a more nuanced view of changes in Taiwan's higher education funding system. As Hou (2023) describes, the introduction of HESP represented a shift from earlier excellence-oriented initiatives toward a broader framework of institutional development. However, the observed changes identified in this study should not be interpreted as evidence that this policy transition directly reduced funding concentration. Rather, the results show that the distribution of public project funding can change differently depending on whether resources are examined in institutional totals or relative to faculty and student populations. This distinction is important when assessing funding policies over time, as relatively stable concentration in institutional funding totals may coexist with changes in per-faculty and per-student distributions.

5.4 Universal Access and Funding Distribution Are Distinct Dimensions of Higher Education Development

The results also raise a system-level question about the relationship between the expansion of higher education and the distribution of public resources across institutions. Trow's (2007) framework of elite, mass, and universal higher education provides an important perspective on the expansion of participation in higher education. Taiwan's experience, however, shows that wider access and the distribution of institutional resources represent distinct dimensions of higher education development. Despite the development of a highly accessible higher education system, substantial concentration remains in the distribution of government-funded project funding across universities. The expansion of participation therefore does not necessarily correspond to a more even distribution of institutional resources.

The governance implications become clearer when public funding is understood as an instrument of higher education governance. Governments increasingly use funding arrangements not only to provide financial support but also to pursue policy objectives and influence institutional development (OECD, 2008, 2025). Differences in funding allocation may therefore reflect multiple and sometimes competing objectives, including broad institutional development, research competitiveness, and academic excellence. As Yonezawa (2023) argues in the Japanese context, maintaining a strong higher education and research system requires attention not only to leading universities but also to the wider institutional base. From this perspective, differentiated funding should be understood in relation to the purposes that particular funding arrangements are intended to serve.

Taken together, the findings suggest that the relationship between excellence and equity in higher education funding cannot be understood solely through the presence or absence of resource concentration. The per-faculty, per-student, and temporal comparisons further show that the interpretation of concentration depends on the basis and period of assessment. These patterns do not, by themselves, establish whether existing allocations are equitable or efficient. Rather, they highlight the importance of examining how public funding is distributed across institutions alongside the policy objectives it is intended to serve. In a universal higher education system, the central question is therefore not simply whether resources are concentrated or dispersed, but how differentiated funding arrangements relate to the multiple purposes of higher education.

6. Conclusion and Policy Implications

This study examined the concentration of government-funded project funding across Taiwanese higher education institutions from 2018 to 2024, with particular attention to the Higher Education SPROUT Project (HESP). The findings show that HESP funding continued to exhibit substantial cross-institutional differences, although its distribution was consistently less concentrated than that of the broader category of government-funded project funding. Concentration was considerably lower when funding was expressed relative to faculty and student populations, while differences across institutions remained. Moreover, relatively stable concentration in institutional funding totals coexisted with generally declining, though not uniform, concentration in the per-faculty and per-student measures. Overall, the results indicate that the distribution of public project funding cannot be adequately understood through institutional funding totals or a single basis of comparison.

The findings have important implications for the design and evaluation of higher education funding policies. Governments should distinguish clearly between funding intended to provide broad institutional support and funding designed to promote selective academic excellence. These objectives need not be mutually exclusive, but they may involve different allocation principles and distributional outcomes. In Taiwan, HESP provides an example of a funding framework that combines broad institutional development with targeted investment in academic excellence. Rather than assuming that wider institutional participation necessarily produces a more even distribution of resources, policymakers should evaluate funding allocations in relation to the specific objectives and criteria of each funding mechanism. Greater transparency regarding allocation principles and their distributional implications could strengthen the accountability of public funding policies without presuming that concentration is inherently undesirable.

A second policy implication concerns the need for systematic monitoring of institutional funding distributions across multiple years. Assessments based solely on total funding received by universities may overlook important differences associated with institutional scale. Policymakers should therefore consider complementary measures, including institutional funding totals, funding per full-time faculty member, and funding per enrolled student, alongside concentration indicators such as the Gini coefficient and Herfindahl–Hirschman Index. Monitoring these measures over time can help distinguish relatively persistent patterns of concentration from changes in funding distributions relative to institutional size. Such assessments should also consider institutional missions and characteristics when interpreting distributional differences, rather than treating any single indicator as a definitive measure of funding equity. A more comprehensive monitoring framework could provide a stronger

empirical basis for reviewing funding arrangements and assessing their alignment with policy objectives.

This study contributes to the literature by providing multi-year evidence on the concentration of government-funded project funding in Taiwanese higher education and by systematically comparing HESP funding with the broader funding category of which it forms a part. Its integration of institutional funding totals, per-faculty and per-student measures, and annual comparisons provides a more differentiated understanding of how public project funding is distributed across universities. More fundamentally, the findings suggest that the relationship between excellence and equity should not be reduced to a choice between concentrating and dispersing resources. The central policy challenge is to establish funding arrangements whose distributional characteristics can be transparently assessed and meaningfully justified in relation to the diverse purposes of higher education.

7. Limitations and Future Research

This study has several limitations that should be considered when interpreting its findings. First, the analysis focused on government-funded project funding and the Higher Education SPROUT Project (HESP) between 2018 and 2024 rather than the full range of financial resources available to Taiwanese universities. Government-funded project funding represents project-based support from government agencies and therefore does not capture all forms of public funding, institutional revenue, or other financial resources available to universities. In addition, funding per full-time faculty member and per enrolled student represents institution-level ratios rather than resources directly received by individual academics or students. The findings should therefore be interpreted as patterns of resource distribution across institutions rather than as measures of individual-level resource availability.

Second, the Gini coefficient and Herfindahl–Hirschman Index provide descriptive measures of funding concentration but cannot, on their own, establish whether observed allocations are equitable or efficient. The analysis also does not identify the institutional or policy mechanisms underlying differences in funding concentration or the changes observed between 2018 and 2024. In particular, because HESP consists of multiple components with different objectives and allocation mechanisms, the present study cannot determine how individual components contribute to the overall distribution of HESP funding.

Future research could extend the analysis by incorporating additional funding sources and examining how institutional characteristics, such as mission, research intensity, disciplinary composition, and institutional type, are associated with funding distribution. Disaggregating HESP into its major funding components could further clarify how broad institutional support

and selective excellence-oriented funding contribute to the overall pattern of concentration. Finally, examining the relationship between funding distributions and institutional outcomes would help determine how different allocation arrangements relate to the broader objectives of higher education policy.

References

Arimoto, A. (2009). The competitive environment of academic productivity and the academic research enterprise in the case of Japan. *Asia Pacific Education Review, 10*(1), 29–46. https://doi.org/10.1007/s12564-009-9008-1

Becker, G. S. (1964). *Human capital: A theoretical and empirical analysis, with special reference to education*. Columbia University Press.

Fochler, M., Janger, J., Stampfer, M., Strassnig, M., Benner, M., Charos, A., Ferent, L., & Unterlass, F. (2026). Just following the money? How research funding shapes the governance of university research. *Science and Public Policy, 53*(4), 576–591. https://doi.org/10.1093/scipol/scaf056

Giorgi, G. M., & Gigliarano, C. (2017). The Gini concentration index: A review of the inference literature. *Journal of Economic Surveys, 31*(4), 1130–1148. https://doi.org/10.1111/joes.12185

Hicks, D. (2012). Performance-based university research funding systems. *Research Policy, 41*(2), 251–261. https://doi.org/10.1016/j.respol.2011.09.007

Hou, A. Y.-C. (2023). Did Taiwan academic excellence initiatives build world-class universities? Governance, funding schemes, and policy shifts. In M. Yudkevich, P. G. Altbach, & J. Salmi (Eds.), *Academic Star Wars: Excellence initiatives in global perspective* (pp. 107–128). The MIT Press. https://doi.org/10.7551/mitpress/14601.003.0009

Hou, A. Y.-C., Ince, M., & Chiang, C.-L. (2012). A reassessment of Asian Pacific excellence programs in higher education: The Taiwan experience. *Scientometrics, 92*(1), 23–42. https://doi.org/10.1007/s11192-012-0727-4

Hsieh, C. C. (2025). Global prescriptions and local adaptations: The role of political culture in shaping governance strategies for university funding. *Studies in Higher Education, 50*(11), 2229–2242. https://doi.org/10.1080/03075079.2024.2420190

Jeon, J., & Kim, S. Y. (2018). Is the gap widening among universities? On research output inequality and its measurement in the Korean higher education system. *Quality & Quantity, 52*(2), 589–606. https://doi.org/10.1007/s11135-017-0652-y

Kelly, A. (2023). The end of the line? A quantitative analysis of two decades of competitive assessment and research funding in UK higher education. *Assessment & Evaluation in Higher Education, 48*(5), 701–722. https://doi.org/10.1080/02602938.2022.2120961

Koenig, J., Brenner, T., & Buenstorf, G. (2017). Regional effects of university funding: Excellence at the cost of regional disparity? *Review of Regional Research, 37*, 111–133. https://doi.org/10.1007/s10037-017-0117-8

Li, J., Xie, Y., Wu, D., & Chen, Y. (2017). Underestimating or overestimating the distribution inequality of research funding? The influence of funding sources and subdivision. *Scientometrics, 112*, 55–74. https://doi.org/10.1007/s11192-017-2402-2

Liu, H.-H. (2013). 高等教育政策工具之探析：大學評鑑結果與政府經費分配之連結 [An analysis of policy instruments for higher education: The connection between the results of university evaluation and the allocation of funding]. *教育研究與發展期刊 [Journal of Educational Research and Development]*, *9*(3), 31–58. https://doi.org/10.3966/181665042013090903002

Matveeva, A. (2025). Performance-based funding in higher education: A meta-narrative review and renewed research agenda proposal. *Tertiary Education and Management, 31*(1), 21–44. https://doi.org/10.1007/s11233-025-09151-y

Ministry of Education. (n.d.). *大專校院校務資訊公開平臺* [University database]. Retrieved September 30, 2026, from https://udb.moe.edu.tw/udata/Index

Ministry of Education. (2017). *高等教育深耕計畫（行政院核定版）* [Higher Education SPROUT Project]. https://sprout.moe.edu.tw/zh-tw/docdata.aspx?fid=70&id=55

Ministry of Education. (2022). *高等教育深耕計畫第二期（112–116 年）* [Higher Education SPROUT Project, Phase II (2023–2027)]. https://sprout.moe.edu.tw/zh-tw/docdata.aspx?fid=70&id=55

Ministry of Education. (2025, June 11). *高等教育深耕計畫核定經費* [Approved funding for the Higher Education SPROUT Project]. https://depart.moe.edu.tw/ed2200/News_Content.aspx?n=5E9ABCBC24AC1122&s=20994098C3459E18

Mohr, N. M., Cyndari, K. I., Vakkalanka, P., Faine, B., Shea, T., & Shah, M. N. (2026). Emergency medicine funding within NIH is the least concentrated of any specialty. *Academic Emergency Medicine, 33*(5), e70316. https://doi.org/10.1111/acem.70316

OECD. (2008). *Tertiary education for the knowledge society* (Vols. 1–2). OECD Publishing. https://doi.org/10.1787/9789264046535-en

OECD. (2025). *The financial sustainability of higher education: Insights from policy in OECD countries*. OECD Publishing. https://doi.org/10.1787/f544ccfe-en

Salmi, J. (2009). *The challenge of establishing world-class universities*. World Bank. https://doi.org/10.1596/978-0-8213-7865-6

Shibayama, S. (2011). Distribution of academic research funds: A case of Japanese national research grant. *Scientometrics, 88*, 43–60. https://doi.org/10.1007/s11192-011-0392-z

Shin, J. C. (2009). Building world-class research university: The Brain Korea 21 project. *Higher Education, 58*(5), 669–688. https://doi.org/10.1007/s10734-009-9219-8

Stephan, P. (2015). The endless frontier: Reaping what Bush sowed? In A. B. Jaffe & B. F. Jones (Eds.), *The changing frontier: Rethinking science and innovation policy* (pp. 321–366). University of Chicago Press. https://doi.org/10.7208/chicago/9780226286860.003.0011

Teixeira, P., Biscaia, R., & Rocha, V. (2022). Competition for funding or funding for competition? Analysing the dissemination of performance-based funding in European higher education and its institutional effects. *International Journal of Public Administration, 45*(2), 94–106. https://doi.org/10.1080/01900692.2021.2003812

Trow, M. (2007). Reflections on the transition from elite to mass to universal access: Forms and phases of higher education in modern societies since WWII. In J. J. F. Forest & P. G. Altbach (Eds.), *International handbook of higher education* (pp. 243–280). Springer. https://doi.org/10.1007/978-1-4020-4012-2_13

Wang, X., & Chang, A. (2025). Sustainable higher education policy: The strategic implication of Taiwan's SPROUT Project and fiscal sustainability. *Sustainability, 17*(19), 8769. https://doi.org/10.3390/su17198769

Wu, D., Yuan, L., Li, R., & Li, J. (2018). Decomposing inequality in research funding by university-institute sub-group: A three-stage nested Theil index. *Journal of Informetrics, 12*(4), 1312–1326. https://doi.org/10.1016/j.joi.2018.10.007

Wu, J. (2015). Distributions of scientific funding across universities and research disciplines. *Journal of Informetrics, 9*(1), 183–196. https://doi.org/10.1016/j.joi.2014.12.007

Yonezawa, A. (2023). Japan's higher education policies under global challenges. *Asian Economic Policy Review, 18*(2), 220–237. https://doi.org/10.1111/aepr.12421

Zhi, Q., & Meng, T. (2016). Funding allocation, inequality, and scientific research output: An empirical study based on the life science sector of Natural Science Foundation of China. *Scientometrics, 106*, 603–628. https://doi.org/10.1007/s11192-015-1773-5

RCG-JF Taiwan -3

From Indicators to Data-Informed Governance: A Strategic Framework for University Social Responsibility in Teacher Education Institutions

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ABSTRACT

University social responsibility (USR) has become an important mechanism for aligning higher education with public needs, sustainable development, and institutional accountability. However, most USR frameworks are designed for comprehensive universities and do not sufficiently reflect the distinctive multiplier responsibility of universities with teacher education programs, whose decisions influence future teachers, schools, students, families, and local education systems. This study developed and prioritized a strategic indicator framework for implementing USR in teacher education institutions in Taiwan. An initial framework was constructed through document and literature analysis and refined through expert review. The Fuzzy Delphi Method was then used with 16 experts to assess indicator relevance and establish consensus, followed by the Analytic Hierarchy Process with 15 experts to determine relative weights and strategic priorities. The final framework contains four dimensions, 12 categories, and 48 indicators. Teacher Education received the highest weight (43.6%), followed by Institutional Governance (22.8%), Network Collaboration (21.9%), and Innovation Diffusion (11.7%). The highest-ranked indicator was the development of short-, medium-, and long-term goals for USR curricula and dedicated teaching teams (8.30%), followed by competency-oriented curriculum planning connected to social issues (6.90%). The findings show that USR in teacher education should begin with curriculum and professional preparation, be institutionalized through governance and quality assurance, and be extended through sustained school-community partnerships and innovation. The framework provides a data-informed basis for institutional planning, resource allocation, internal quality assurance, and continuous improvement in teacher education.

Keywords: Analytic Hierarchy Process, Data-Informed Governance, Teacher Education, University Social Responsibility, Quality Assurance

1. Introduction

Universities are increasingly expected to contribute to social well-being, regional development, and environmental sustainability in addition to their traditional missions of teaching and research. This expanded mission is commonly expressed through university social responsibility (USR), civic engagement, and the scholarship of engagement. Boyer (1990, 1996) argued that academic work should connect discovery, integration, application, and teaching with public purposes. Similarly, campus-community engagement requires reciprocal

relationships rather than one-directional service delivery (Bringle & Hatcher, 2002). USR therefore concerns not only isolated outreach projects, but also how an institution integrates social responsibility into its curriculum, research, governance, partnerships, and assessment systems (Vallaeys et al., 2009; Vasilescu et al., 2010).

The need for such integration is particularly strong in universities with teacher education programs. These institutions prepare future teachers, support practicing educators, conduct educational research, and frequently work with schools and local governments. Their institutional choices can produce a multiplier effect: a curriculum decision made within a teacher education program may later shape the learning experiences of many pupils, while a sustained partnership with a local school can influence teacher development, school improvement, and community trust. Consequently, the social responsibility of teacher education institutions extends beyond the immediate university community to the wider education system.

Despite this distinctive role, existing USR research has largely examined institutional reputation, student engagement, sustainability, or general community engagement. Studies have also reported persistent implementation problems, including fragmented leadership, limited resource coordination, weak links between curricula and social needs, and insufficient mechanisms for evaluating impact (Coelho & Menezes, 2022; Sánchez-Hernández & Mainardes, 2016; Sasaki & Horng, 2023). In teacher education, the gap between university-based preparation and field-based practice further complicates the implementation of social responsibility. A framework that identifies both the content and relative priority of strategies is therefore needed.

This study addresses that need by developing a weighted strategic indicator system for USR in universities with teacher education programs. Rather than treating every strategy as equally urgent, it uses expert consensus and pairwise comparison to identify priorities. The framework is positioned as an institutional research tool: it converts expert knowledge into organized indicators and weights that can inform strategic planning, internal quality assurance, resource allocation, and improvement monitoring. The study asks: (1) What dimensions, categories, and indicators constitute USR in teacher education institutions? (2) What are their relative priorities? and (3) How can the resulting framework support data-informed institutional governance and improvement?

2. Literature Review and Conceptual Background

2.1 University Social Responsibility as an Institutional Mission

USR developed from debates on corporate social responsibility, university civic engagement, sustainable development, and the third mission of higher education. However, a university is not simply a corporation providing public relations activities. Its responsibilities are embedded in knowledge production, education, organizational conduct, and relationships with stakeholders. Vallaeys et al. (2009) conceptualized USR as an institution-wide responsibility that includes organizational, educational, cognitive, and social impacts. Wigmore-Alvarez and Ruiz-Lozano (2012) similarly emphasized that USR requires the ethical management of institutional effects and stakeholder relationships.

This whole-institution perspective is consistent with sustainable higher education. International frameworks call on universities to integrate sustainability into curricula, professional development, operations, research, and community partnerships rather than confining it to stand-alone projects (Lozano et al., 2013; UNESCO, 2020). USR should therefore be understood as an institutional architecture linking mission, curriculum, research, governance, and engagement. It becomes meaningful when public commitments are translated into operational mechanisms, responsibilities, indicators, and feedback processes.

2.2 The Distinctive Responsibility of Teacher Education Institutions

Teacher education institutions occupy an intermediary position between higher education and the school system. They prepare preservice teachers, provide professional development for practicing teachers, and generate knowledge for educational improvement. Teacher preparation is also practice-dependent: professional learning is strengthened when coursework, clinical experiences, school partnerships, and inquiry are coherently connected (Darling-Hammond, 2016). Professional development school models and community-based placements further demonstrate that teacher learning is shaped by the quality of institutional partnerships and field contexts (Boyle-Baise & McIntyre, 2008).

This distinctive position creates a multiplier form of social responsibility. A socially responsive teacher education curriculum may cultivate future teachers' ethical judgement, concern for educational equity, and capacity to address local problems. Long-term partnerships can support schools that face resource constraints, while practice-oriented research can transform field problems into shared inquiry. UNESCO's guidance on integrating education for sustainable development into teacher education also emphasizes that teacher educators and institutions must prepare teachers to connect sustainability with pedagogy and community contexts (UNESCO, 2018). Thus, USR in teacher education should encompass preservice preparation, professional communities, place-based engagement, practice-oriented research, and institutional governance.

2.3 From Indicators to Data-Informed Governance

Institutional aspirations are difficult to implement without observable indicators. Indicators make abstract commitments discussable, assessable, and actionable. A strategic indicator system can clarify expected practices, compare priorities, guide resource allocation, and provide a foundation for monitoring. This is particularly useful in USR because institutions often support many desirable activities but lack a transparent basis for deciding what should be developed first.

The Fuzzy Delphi Method (FDM) and Analytic Hierarchy Process (AHP) offer complementary functions. FDM integrates expert judgements expressed as ranges and supports consensus building under uncertainty. AHP structures a complex decision problem into levels and uses pairwise comparisons to calculate relative priorities (Saaty, 1980, 1990). When combined, the two methods can first establish the relevance of an indicator set and then identify the strategic importance of its components. In an institutional research context, the resulting weights should not be treated as permanent performance scores. Rather, they provide a transparent starting point for converting mission statements into institutional priorities, measurable evidence, and iterative improvement.

3. Methodology

3.1 Research Design and Framework Development

The study employed a multi-stage indicator-development design. First, domestic and international literature on USR, sustainable higher education, teacher education, school-university partnerships, institutional governance, and educational indicators was reviewed. Relevant policies and institutional frameworks were also examined. The analysis generated an initial hierarchical framework and indicator pool. Expert review was then used to improve wording, remove redundancy, and strengthen the alignment between the proposed indicators and teacher education practice.

Experts were selected purposively to include complementary knowledge of educational administration, higher education, teacher education policy and practice, and USR implementation. Participants included scholars, teacher educators, and individuals with policy

or administrative experience. The study protected participant identities and reported results in aggregate form.

3.2 Fuzzy Delphi Method

FDM was used to determine the relevance and consensus of the proposed indicators. Sixteen experts evaluated the importance of each item. Their judgements were converted into triangular fuzzy numbers representing conservative and optimistic estimates. A consensus threshold of

0.70 was adopted. Indicators falling below the threshold were deleted or revised, while

qualitative comments were used to improve clarity and reduce overlap. The initial pool contained 50 indicators; 48 indicators met the consensus criterion and were retained. Reliability analysis showed strong internal consistency across the subdimensions, with Cronbach's alpha values ranging from .785 to .982.

3.3 Analytic Hierarchy Process

After the framework was confirmed, 15 experts completed AHP pairwise comparisons across the dimensions, categories, and indicators. Expert Choice 11.5 was used to calculate local and global weights. The consistency ratio (CR) was examined for every comparison matrix; values below .10 were considered acceptable. All matrices met this criterion, indicating logically consistent expert judgements. Global indicator weights were calculated by multiplying weights across the relevant levels of the hierarchy. The final results were interpreted as strategic priorities rather than direct measures of current institutional performance.

4. Results

4.1 Final Strategic Indicator Framework

The FDM process produced a three-level framework consisting of four dimensions, 12 categories, and 48 indicators. The dimensions were Teacher Education, Network Collaboration, Innovation Diffusion, and Institutional Governance. Each dimension contained three categories. Teacher Education included Preservice Curriculum Planning, Social Service Practice, and Professional Community Empowerment. Network Collaboration included Collaborative Mechanism Development, Local Engagement, and Long-Term Support. Innovation Diffusion included Expansion of Practice Settings, Integration of Research and Practice, and Professional Innovation Development. Institutional Governance included Governance Mechanism Operation, Sustainable Partnership Development, and Continuous Evaluation and Feedback.
The structure demonstrates that USR in teacher education is not equivalent to volunteering or short-term service learning. It includes curriculum planning, school-university partnership structures, practice-oriented inquiry, innovation, institutional vision, quality assurance, data use, and stakeholder feedback.

4.2 Relative Priorities of Dimensions and Categories

Teacher Education received the highest dimension weight at 43.6%, indicating that experts viewed the preparation and continuing development of teachers as the central pathway for institutional social responsibility. Institutional Governance ranked second at 22.8%, followed closely by Network Collaboration at 21.9%. Innovation Diffusion received 11.7%. The overall dimension comparison satisfied the AHP consistency requirement.
Within Teacher Education, Preservice Curriculum Planning carried the highest local weight (51.8%). Within Network Collaboration, Collaborative Mechanism Development ranked first (51.4%). Expansion of Practice Settings led Innovation Diffusion (52.9%), while Governance Mechanism Operation led Institutional Governance (49.7%). These results suggest a consistent preference for foundational structures: curriculum architecture, collaboration mechanisms,

practice settings, and institutional governance were prioritized over later-stage dissemination activities.

Table 1: Relative Weights of the Four USR Dimensions and Leading Categories

Dimension	Dimension Weight	Highest-Weighted Category	Local Category Weight
Teacher Education	43.6%	Preservice Curriculum Planning	51.8%
Institutional Governance	22.8%	Governance Mechanism Operation	49.7%
Network Collaboration	21.9%	Collaborative Mechanism Development	51.4%
Innovation Diffusion	11.7%	Expansion of Practice Settings	52.9%

Note. Category weights are local weights within each dimension.

4.3 Highest-Priority Indicators

The global ranking further clarified the sequence of implementation. The highest-ranked indicator was A1-1, planning short-, medium-, and long-term goals for USR curricula and establishing dedicated teaching teams (8.30%). A1-2, implementing competency-oriented teacher education curricula connected to social issues, ranked second (6.90%). A1-4, engaging exemplary field educators in practice-based mentoring, ranked third (5.10%). These three indicators show that experts placed curricular direction, socially responsive pedagogy, and field expertise at the center of USR implementation.

Governance and partnership indicators were also prominent. D1-1, integrating internal and external resources to establish an institutional USR vision and framework, ranked fourth (4.70%). B1-3, establishing professional development school partnerships with local schools, ranked fifth (4.20%). Other high priorities included future-oriented teacher education courses, local professional communities, sustained support for teacher professional growth, and collaboration among universities, government, industry, and local partners.

Table 2: Ten Highest-Ranked Strategic Indicators

Rank	Code	Strategic Indicator	Global Weight
1	A1-1	Plan short-, medium-, and long-term goals for USR curricula and establish dedicated teaching teams.	8.30%
2	A1-2	Implement competency-oriented teacher education curricula connected to social issues.	6.90%
3	A1-4	Engage exemplary field educators in practice-based mentoring and curriculum implementation.	5.10%
4	D1-1	Integrate internal and external resources to establish an institutional USR vision and framework.	4.70%

Rank	Code	Strategic Indicator	Global Weight
5	B1-3	Establish professional development school partnerships with local schools.	4.20%
6	A1-3	Develop future-oriented courses, including rural teacher preparation and digital experimentation.	4.00%
7	A3-1	Develop local teacher professional communities for instructional innovation and knowledge sharing.	3.90%
8	A3-3	Establish long-term support mechanisms for sustained teacher professional growth.	3.50%
9	B1-2	Connect practice-oriented teacher education courses with local government, industry, and academic partners.	2.90%
10	A2-2	Use diverse strategies to strengthen social responsibility awareness and practice.	2.70%

Note. Global weights reflect priorities across the complete three-level hierarchy.

5. Discussion

5.1 Teacher Education as the Core of USR

The dominant weight of Teacher Education confirms that the social responsibility of these institutions should be expressed first through their core academic mission. Community engagement that is detached from curriculum may generate short-term visibility but limited institutional learning. By contrast, curriculum goals, teaching teams, competency-oriented design, and field-based mentoring embed social responsibility in the preparation of every cohort of future teachers. This aligns with the scholarship of engagement, in which academic expertise is connected with public problems rather than separated from them (Boyer, 1996).

The first two indicators also show that implementation requires both organizational continuity and pedagogical relevance. Short-, medium-, and long-term curriculum goals provide continuity beyond individual projects or funding cycles. Connecting coursework with social issues helps preservice teachers learn to interpret educational inequity, sustainability, demographic change, digital transformation, and community needs as professional concerns. The result is not an additional 'USR course' alone, but a coherent curriculum in which social responsibility is integrated into professional knowledge, ethics, inquiry, and practice.

5.2 Governance and Institutional Research as Enabling Infrastructure

Institutional Governance ranked second, slightly above Network Collaboration. This indicates that external engagement requires internal capacity. An institution needs a shared vision, clear coordination, resource integration, quality assurance, and feedback systems before partnerships can be sustained. D1-2 explicitly calls for linking institutional research with a quality assurance system for teacher education effectiveness, while D3-3 calls for a data-driven evaluation system for social practice. These indicators provide the strongest connection between the framework and the SEAAIR focus on institutional research and data-informed decision making.

The proposed framework can support a governance cycle. Institutions can first use the indicators to conduct a baseline self-review, then select evidence for each priority, establish targets, assign responsibility, and monitor progress. Evidence may include curriculum maps, participation records, partnership continuity, teacher and school feedback, student learning outcomes, resource allocation, research utilization, and documented improvements. The AHP weights can guide attention, but they should not mechanically determine budgets. Institutional leaders should combine the weights with local need, feasibility, equity, and performance data. In this way, the framework functions as a decision-support architecture rather than a ranking instrument.

5.3 Network Collaboration and Reciprocal Partnership

Network Collaboration received almost the same weight as Institutional Governance, demonstrating that USR is relational. The high ranking of professional development school partnerships and cross-sector collaboration reflects the need to move from occasional service to durable infrastructure. Reciprocal partnerships require jointly defined problems, shared decision making, appropriate recognition of school-based expertise, and mechanisms for continuity. This is consistent with Bringle and Hatcher's (2002) emphasis on the terms of engagement and with the broader literature on stakeholder-oriented USR.

The framework also distinguishes collaboration mechanisms from long-term support. Needs assessment, partnership agreements, and public-private collaboration create the structure; workshops, consultation, field presence, and shared platforms maintain the relationship. This distinction is useful for institutional assessment because counting the number of activities does not reveal whether a partnership is reciprocal, sustained, or educationally consequential.

5.4 Innovation Diffusion as a Developmental Priority

Innovation Diffusion received the lowest dimension weight. This should not be interpreted as unimportant. Rather, the ranking suggests that innovation is more likely to be effective after curriculum, governance, and partnerships are established. Indicators related to action research, technology-supported learning, professional development schools, interdisciplinary research, and international collaboration remain important for future growth. Their relatively lower global weights may reflect the experts' preference for first consolidating core capacity and local responsiveness.

A phased implementation model therefore emerges from the results. Phase 1 establishes curriculum goals, teaching teams, institutional vision, and quality assurance. Phase 2 builds durable school-community partnerships and professional learning communities. Phase 3 strengthens practice-oriented research, digital platforms, social innovation, cross-sector learning, and international exchange. This sequence provides a practical response to institutions with limited resources: innovation should be developed on a stable base rather than treated as a collection of disconnected pilot projects.

5.5 Contributions and Limitations

The study contributes a context-sensitive USR framework for teacher education institutions and demonstrates how expert knowledge can be translated into strategic priorities. Conceptually, it highlights the multiplier responsibility of teacher education. Methodologically, it combines consensus validation with hierarchical weighting. Practically, it provides a tool for institutional planning, self-assessment, quality assurance, and communication with stakeholders.

Several limitations should be noted. First, the framework was developed in Taiwan and reflects its teacher education and USR policy context. Second, the weights represent expert judgement rather than observed institutional performance or causal effects. Third, the framework has not

yet been tested through longitudinal implementation across different institution types. Future research should pilot the indicators in teacher education universities, comprehensive universities, and institutions with teacher education centers; examine inter-rater reliability; develop operational definitions and evidence rubrics; and test whether indicator use improves decision quality and social impact.

6. Conclusion and Recommendations

This study developed a strategic USR framework for universities with teacher education programs using FDM and AHP. The final system comprises four dimensions, 12 categories, and 48 indicators. Teacher Education was the highest-priority dimension, followed by Institutional Governance, Network Collaboration, and Innovation Diffusion. The pattern of results indicates that institutions should begin by embedding USR in curriculum planning and teacher preparation, build internal governance and quality assurance, develop reciprocal partnerships with schools and communities, and then expand research and innovation.

For institutional leaders, the framework can be used to create an annual USR self-assessment and improvement cycle. A cross-unit committee should define evidence for priority indicators, establish baselines and targets, assign responsibilities, and report progress to internal and external stakeholders. Institutional research units can support this process by integrating curriculum, partnership, resource, feedback, and outcome data into a concise dashboard. For policymakers and accreditation bodies, the framework offers a basis for dialogue and developmental review, but it should be applied flexibly to respect institutional mission and local need. For researchers, the next step is empirical validation through multi-institutional implementation and longitudinal analysis. USR in teacher education will be sustainable only when it is treated not as a temporary project, but as a core institutional commitment linking teacher preparation, governance, partnership, evidence, and continuous improvement.

Declaration of Generative AI Use

During preparation of this manuscript, OpenAI ChatGPT (GPT-5.6 Thinking) was used to support English-language editing, structural organization, and conformity with the conference template. The authors reviewed, verified, and revised all content, interpretations, data, citations, and references and remains fully responsible for the manuscript.

References

Boyer, E. L. (1990). Scholarship reconsidered: Priorities of the professoriate. Princeton University Press.

Boyer, E. L. (1996). The scholarship of engagement. Journal of Public Service & Outreach, 1(1), 11-20.

Boyle-Baise, M., & McIntyre, D. J. (2008). What kind of experience? Preparing teachers in PDS or community settings. In M. Cochran-Smith, S. Feiman-Nemser, D. J. McIntyre, & K. E. Demers (Eds.), Handbook of research on teacher education: Enduring questions in changing contexts (3rd ed., pp. 307-330). Routledge.

Bringle, R. G., & Hatcher, J. A. (2002). Campus-community partnerships: The terms of engagement. Journal of Social Issues, 58(3), 503-516.

Coelho, M., & Menezes, I. (2022). Universitas: How do students perceive university social responsibility in three European higher education institutions? International Journal of Sustainability in Higher Education, 23(4), 767-782. https://doi.org/10.1108/IJSHE-04-2021-0130

Darling-Hammond, L. (2016). Research on teaching and teacher education and its influences on policy and practice. Educational Researcher, 45(2), 83-91. https://doi.org/10.3102/0013189X16639597

Lozano, R., Lukman, R., Lozano, F. J., Huisingh, D., & Lambrechts, W. (2013). Declarations for

sustainability in higher education: Becoming better leaders through addressing the university system. Journal of Cleaner Production, 48, 10-19. https://doi.org/10.1016/j.jclepro.2011.10.006

Saaty, T. L. (1980). The analytic hierarchy process. McGraw-Hill.

Saaty, T. L. (1990). How to make a decision: The analytic hierarchy process. European Journal of Operational Research, 48(1), 9-26.

Sánchez-Hernández, M. I., & Mainardes, E. W. (2016). University social responsibility: A student base analysis in Brazil. International Review on Public and Nonprofit Marketing, 13, 151-169.

Sasaki, T., & Horng, C.-Y. (2023). Exploratory study about achievements and issues of university social responsibility: USR as a dynamic process. International Journal of Educational Development, 102, 102869. https://doi.org/10.1016/j.ijedudev.2023.102869

United Nations Educational, Scientific and Cultural Organization. (2018). Integrating education for sustainable development in teacher education in South-East Asia: A guide for teacher educators. UNESCO.

United Nations Educational, Scientific and Cultural Organization. (2020). Education for sustainable development: A roadmap. https://doi.org/10.54675/YFRE1448

Vallaeys, F., De la Cruz, C., & Sasia, P. M. (2009). Responsabilidad social universitaria: Manual de primeros pasos. Inter-American Development Bank.

Vasilescu, R., Barna, C., Epure, M., & Baicu, C. (2010). Developing university social responsibility: A model for the challenges of the new civil society. Procedia - Social and Behavioral Sciences, 2(2), 4177-4182.

Wigmore-Alvarez, A., & Ruiz-Lozano, M. (2012). University social responsibility in the global context: An overview of literature. Business and Professional Ethics Journal, 31(3/4), 475-498. https://doi.org/10.5840/bpej2012313/424


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