Journal of Education and e-Learning Research
Vol. 13, No. 3, 10-21, 2026
ISSN(E) 2410-9991 / ISSN(P) 2518-0169
DOI: 10.20448/jeelr.v13i3.8882

Generative AI in Vietnamese higher education: Pedagogical innovation, learning outcomes, and academic integrity

Quoc Giang Tran[1]
Tan Dat Truong[2]✉

[1,2]*Dong Thap University, Dong Thap, Vietnam.*
[1]*Email: giang.tq894@dthu.edu.vn*
[2]*Email: truongtandat@dthu.edu.vn*

(✉ Corresponding Author)

Abstract

The rapid penetration of Generative AI is reshaping the global higher education ecosystem; however, its integration in developing countries like Vietnam faces significant institutional and cultural constraints. This study utilizes an explanatory sequential mixed-methods design to examine how AI influences pedagogical innovation and student learning outcomes. During the quantitative phase, survey data from 970 participants (students, lecturers, and administrators) were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The qualitative phase integrated insights from 30 semi-structured interviews. PLS-SEM results indicate that perceived usefulness strongly promotes teaching integration intentions ($\beta = 0.525$) and learning outcomes ($\beta = 0.315$). Furthermore, pedagogical integration directly enhances academic performance ($\beta = 0.468$). However, academic integrity risks pose a substantial barrier to pedagogical innovation ($\beta = -0.215$). Qualitative findings reveal a critical paradox: while AI optimizes short-term efficiency, it threatens critical thinking and fosters algorithmic dependency. Crucially, institutional responsibility emerges as a decisive factor in mitigating these integrity risks ($\beta = -0.385$). The study concludes that the principal obstacle to AI integration is the absence of comprehensive digital ethics frameworks, not technological limitations. Consequently, universities must shift toward transparent governance policies and systematically restructure assessment practices to ensure responsible AI integration.

Keywords: Academic integrity, Generative artificial intelligence, Higher education, Mixed methods research, Pedagogical innovation, University governance.

Citation | Tran, Q. G., & Truong, T. D. (2026). Generative AI in Vietnamese higher education: Pedagogical innovation, learning outcomes, and academic integrity. *Journal of Education and E-Learning Research, 13*(3), 10–21. 10.20448/jeelr.v13i3.8882
History:
Received: 13 March 2026
Revised: 18 May 2026
Accepted: 8 June 2026
Published: 29 June 2026

Publisher: Asian Online Journal Publishing Group

Funding: This research received no external funding.
Institutional Review Board Statement: This study was conducted in accordance with the Declaration of Helsinki and formally approved by the Institutional Review Board (IRB) of Dong Thap University. The research procedures strictly adhered to the national ethical standards mandated by the Ministry of Science and Technology of Vietnam (Decree No. 262/2025/NĐ-CP, 14 October 2025).
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: Both authors contributed equally to the conception and design of the study. Both authors have read and agreed to the published version of the manuscript.

Contents

Contribution of this paper to the literature

This study offers empirical evidence on Generative AI adoption in Vietnamese higher education by integrating technology acceptance theories with academic integrity and institutional responsibility perspectives. Using an explanatory sequential mixed-methods design (PLS-SEM and in-depth interviews), it explains how AI influences pedagogical innovation and students' learning outcomes, while highlighting disciplinary differences. The findings extend AIEd research beyond Western contexts, providing practical insights for building digital ethics frameworks and policy-driven university governance in emerging economies.

1. Introduction

The rapid advancement of Artificial Intelligence (AI), particularly Generative AI models such as ChatGPT, is producing a profound paradigm shift in the global higher education ecosystem (Chen, Chen, & Lin, 2020; Crompton & Burke, 2023). In contemporary academic environments, AI is no longer merely a technological tool for information retrieval; it has increasingly assumed the role of an active participant in knowledge construction, thereby fundamentally redefining traditional boundaries of teaching and learning (Chu, Hwang, Tu, & Yang, 2022). The emergence of advanced natural language processing tools has transformed the ways in which students access, synthesize, and analyze information, creating an urgent demand for higher education institutions to comprehensively reform teaching methods, curriculum design, and assessment practices (Jensen, Buhl, Sharma, & Bearman, 2025; Popenici & Kerr, 2017).

The potential of AI in education has been widely recognized through numerous empirical studies. Intelligent Tutoring Systems and AI-powered language assistants have demonstrated significant capabilities in providing immediate feedback, personalizing learning pathways, and increasing student engagement with instructional content (Kuleto et al., 2021; Mousavinasab et al., 2021). According to Liang, Hwang, Chen, and Darmawansah (2023) and Ouyang, Zheng, and Jiao (2022), the appropriate integration of AI can relieve lecturers from repetitive administrative tasks, thereby allowing them to focus on higher-value pedagogical interactions. Furthermore, recent meta-analytical studies suggest that when AI use is guided and integrated with self-regulated learning strategies, it can positively influence learning outcomes, higher-order thinking abilities, and students' problem-solving skills (Deng, Jiang, Yu, Lu, & Liu, 2025; Wang & Fan, 2025).

Despite these significant opportunities, the rapid diffusion of Generative AI in academic environments has also triggered unprecedented challenges, particularly regarding ethics and academic integrity. Overreliance on algorithmically generated text raises serious concerns about the erosion of critical thinking, the emergence of sophisticated forms of plagiarism, and the lack of transparency in assessing students' authentic competencies (Abdallah, Katmah, Khalaf, & Jelinek, 2025; Bittle & El-Gayar, 2025). Initial responses from the global academic community reveal a polarized perspective: while students have rapidly embraced tools such as ChatGPT as a means to optimize academic efficiency (Abdaljaleel et al., 2024; Ravšelj et al., 2025), many lecturers remain cautious, skeptical, and uncertain due to the absence of clear institutional frameworks and regulatory guidelines (Gruenhagen et al., 2024; Shata & Hartley, 2025; Tan, Qu, & Wang, 2025).

The complexity of this technological transition becomes even more pronounced in developing countries. While advanced education systems have begun establishing structured AI integration frameworks, the process in Vietnam continues to encounter structural barriers related to digital infrastructure, technological readiness, and governance capacity (Quy, Thanh, Chehri, Linh, & Tuan, 2023; Salas-Pilco & Yang, 2022). Vietnam's higher education system is currently undergoing a major transformation characterized by expanding institutional autonomy and the implementation of the national digital transformation strategy. In this context, the integration of Generative AI requires not only adaptation by students and lecturers but also the development of robust institutional governance mechanisms across universities nationwide. The successful integration of AI into academic environments depends on whether universities can establish transparent ethical guidelines, enhance the digital pedagogical competencies of faculty members, and guide students' understanding of the boundary between legitimate learning support and academic misconduct. Moreover, disparities in technological infrastructure and digital literacy across universities in different regions create additional challenges in implementing standardized AI integration models.

From a methodological perspective, systematic reviews indicate that most existing studies on AI in education rely primarily on quantitative approaches to measure technology acceptance or on small-scale qualitative studies to explore individual experiences (Ngo, Vo, & Phan, 2025; Ouyang et al., 2022). However, to fully understand a complex techno-social phenomenon such as the interaction among students, lecturers, and AI systems within a rapidly transforming educational environment like Vietnam, a single methodological approach is insufficient. Sole reliance on quantitative data may overlook nuanced psychological and contextual dynamics, whereas purely qualitative data may lack generalizability (Creswell, 1999; Johnson & Onwuegbuzie, 2004).

In response to these theoretical and practical gaps, this study aims to comprehensively evaluate the impact of Generative Artificial Intelligence on pedagogical innovation and student learning outcomes in Vietnamese higher education. The research employs an explanatory sequential mixed-methods design, combining a large-scale survey to identify statistical patterns with in-depth interviews to interpret the underlying mechanisms behind the observed phenomena (Bazeley, 2009; Fetters, Curry, & Creswell, 2013).

To guide data collection and analysis, the study addresses the following three core research questions (RQs):

RQ1: How do students' and lecturers' perceptions of the usefulness, ease of use, and academic integrity risks of Generative AI influence the level of technology integration in teaching and learning in Vietnamese higher education?

RQ2: How does the integration of Generative AI into teaching methods and learning practices directly and indirectly affect student learning outcomes?

RQ3: How do qualitative insights from the lived experiences of key stakeholders (lecturers, students, and administrators) explain the institutional barriers and mechanisms of AI impact identified in the quantitative model?

The findings of this study are expected to provide robust empirical evidence regarding the current use of AI in Vietnam, contribute to the theoretical discourse on higher education in the digital era, and offer governance implications that can assist universities in developing ethical and effective strategies for AI integration.

2. Literature Review

2.1. Generative AI and Pedagogical Innovation

The evolution of Artificial Intelligence (AI) in higher education has reached a critical turning point, shifting from systems designed primarily to automate administrative tasks toward generative AI models capable of interaction and knowledge construction. The application of AI in university teaching is no longer limited to automated grading or student data management; it has expanded to include roles such as virtual tutors and platforms supporting personalized learning processes (Chu et al., 2022; Ouyang et al., 2022). According to the systematic analysis of empirical studies conducted over the past decade by Ouyang et al. (2022) AI is gradually replacing traditional "one-size-fits-all" pedagogical approaches with machine-learning algorithms capable of analyzing individual students' strengths and weaknesses to adjust instructional pace and content accordingly. Crompton and Burke (2023) further highlight the psychological foundations of this transformation, suggesting that emerging technologies function as cognitive scaffolding, reducing learners' cognitive load while optimizing the information acquisition process.

From the perspective of academic staff, the emergence of large language models (LLMs) such as ChatGPT has significantly influenced instructional design and curriculum planning. Educators increasingly recognize the practical benefits of generative AI in optimizing the time required to prepare teaching materials, develop course syllabi, and design diverse assessment rubrics. Nevertheless, considerable skepticism remains regarding algorithmic reliability and potential risks associated with data bias (Lee et al., 2024; Shata & Hartley, 2025). A study by Lee, Chen, Wang, Huang, and Wu (2024), which surveyed educators' perspectives directly, revealed that although instructors appreciate AI's ability to generate coherent textual content, many remain concerned about the phenomenon of AI hallucination, in which systems produce inaccurate information presented in a logically persuasive manner. Consequently, lecturers are increasingly required to transition from the role of knowledge transmitters to that of content moderators and facilitators, guiding students in effective question formulation and prompt engineering (Shata & Hartley, 2025).

At the level of direct interaction, Intelligent Tutoring Systems (ITS) and AI-based virtual assistants have demonstrated significant potential to improve student engagement in blended learning environments (Essel, Vlachopoulos, Tachie-Menson, Johnson, & Baah, 2022; Lee et al., 2024; Mousavi, Schmidt, Squires, & Wilson, 2021; Mousavinasab et al., 2021). The systematic review conducted by Mousavinasab et al. (2021) indicates that ITS can simulate instructional strategies typically employed by human teachers by providing step-by-step hints based on students' mistakes. In higher education settings, Essel et al. (2022) reported that integrating chatbots as virtual teaching assistants not only increased student interaction outside classroom hours but also significantly reduced feelings of isolation in online learning contexts. Similarly, Lee et al. (2024) demonstrated that when ChatGPT is deployed through intentional instructional guidance, it strongly promotes self-regulated learning and stimulates higher-order thinking skills through continuous knowledge construction processes. These studies collectively reinforce the argument that when integrated within a clearly defined pedagogical strategy, AI does not diminish human interaction but rather restructures learning environments to become more dynamic and personalized.

2.2. Student Perceptions and AI Acceptance Behavior

The successful adoption of any educational technology largely depends on the attitudes and acceptance behavior of end users, in this case, university students. Students' attitudes toward tools such as ChatGPT represent a complex psychological construct shaped by perceptions of usefulness, perceived risks, and individual technological competence (Almassaad, Alajlan, & Alebaikan, 2024; Blahopoulou & Ortiz-Bonnin, 2025; Heil et al., 2025; Jo, 2024). Jo (2024) identified a clear transition among students from initial anxiety toward recognition of practical benefits as they gradually become familiar with AI systems. However, Blahopoulou and Ortiz-Bonnin (2025) caution that a substantial attitudinal gap exists between frequent users and non-users of AI technologies. Students who actively use AI tools tend to perceive benefits that outweigh the effort required, whereas non-users often exhibit persistent concerns regarding ethical risks and the lack of transparency in algorithmic processes. Heil et al. (2025) further suggest that individual AI competence plays a critical moderating role, as students with higher levels of digital literacy are more likely to perceive the positive impacts of AI on academic evaluation and learning processes.

Multinational survey studies reveal a consistent trend: contemporary students adopt a pragmatic approach to AI usage, perceiving it primarily as a tool for time optimization, idea expansion, and solving specific academic tasks (Abdaljaleel et al., 2024; Chan & Hu, 2023; Fošner & Aver, 2025; Morell-Mengual et al., 2025; Ravšelj et al., 2025). A global survey conducted by Ravšelj et al. (2025) found that students most frequently use ChatGPT for summarizing academic materials, checking grammar, translating texts, and generating essay outlines. Notably, Chan and Hu (2023) highlight students' perspectives, describing AI as a "non-judgmental tutor", enabling them to ask basic questions freely without fear of negative evaluation from instructors or peers. Nevertheless, Fošner and Aver (2025) warn of students' growing concerns regarding data privacy and the possibility that AI-generated responses may contain biased or inaccurate information, potentially influencing the quality of academic research.

Students' acceptance of this disruptive technology is frequently explained through established theoretical frameworks such as the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) (Ngo et al., 2025; Rahman, Ismail, Hossain, & Hossen, 2025; Stöhr, Ou, & Malmström, 2024). In a study integrating TAM and TPB frameworks, Ngo et al. (2025) demonstrated that perceived usefulness is the strongest predictor of students' intention to continue using AI tools in higher education contexts. In addition, subjective norms, including encouragement from lecturers and peers, significantly influence behavioral intentions. Supporting this perspective, Rahman et al. (2025) found that students' proactive mindset toward adopting AI chatbots is positively associated with the effectiveness of online learning environments.

Beyond general psychological factors, research also reveals notable differences in expectations and usage patterns across academic disciplines and demographic characteristics, including gender (Sandu, Gide, & Elkhodr, 2024; Tossell, Tenhundfeld, Momen, Cooley, & De Visser, 2024). Tossell et al. (2024) found that students engaged in essay-based coursework tend to expect AI to assist with structuring ideas, whereas students in STEM disciplines focus more on AI's capabilities in programming and data analysis. Similarly, case studies in Australian higher education conducted by Sandu et al. (2024) emphasize that educational practices should be adapted to the characteristics of

specific disciplines, as the nature of academic tasks directly shapes the boundary between legitimate learning support and the substitution of students' cognitive efforts.

2.3. Impact on Learning Outcomes and Challenges to Academic Integrity

The actual impact of AI on learning performance remains a central topic of ongoing academic debate. Recent large-scale meta-analyses have provided strong quantitative evidence indicating that AI can significantly improve learning outcomes and higher-order thinking skills when implemented with appropriate pedagogical design and guidance (Deng et al., 2025; Wang & Fan, 2025). The meta-analysis conducted by Deng et al. (2025) synthesizing numerous experimental studies reported moderate to high effect sizes when ChatGPT-based learning approaches were compared with traditional instructional methods. Wang and Fan (2025) further decomposed these variables and concluded that beyond improving test scores, AI substantially enhances students' learning perceptions and analytical thinking abilities, as students are required to evaluate and refine AI-generated responses critically.

In specific disciplinary contexts, AI has demonstrated strong effectiveness in supporting language learning, science education, and academic writing skills (Ding, Li, Jiang, & Gapud, 2023; Gayed, Carlon, Oriola, & Cross, 2022; Koć-Januchta et al., 2022; Rezai, Namaziandost, & Hwang, 2024). In second-language (L2) acquisition, phenomenological research conducted by Rezai et al. (2024) in Iran and experimental studies by Gayed et al. (2022) found that AI-powered writing assistants significantly improve grammatical structure and vocabulary expansion while providing micro-level feedback that instructors often struggle to deliver in large classes. In science education, Ding et al. (2023) describe the application of ChatGPT as a virtual physics tutor capable of helping students overcome conceptual barriers. Similarly, Koć-Januchta et al. (2022) implemented AI-enhanced textbooks in biology courses, reporting reductions in cognitive load and improved usability when students attempted to connect complex abstract concepts.

Beyond generative AI, machine learning models have been widely applied in learning analytics, enabling early prediction and intervention in student learning outcomes based on large datasets and personality traits (Çağataylı & Çelebi, 2022; De Chiusole, Stefanutti, Anselmi, & Robusto, 2020; Dever, Azevedo, Cloude, & Wiedbusch, 2020; Qian et al., 2022). For instance, Qian et al. (2022) employed data-mining algorithms from MOOCs within flipped classroom environments to predict students at risk of dropping out or failing courses. Meanwhile, Çağataylı and Çelebi (2022) integrated Big Five personality traits with multi-channel learning data to improve the predictive accuracy of academic performance models. Studies by Dever et al. (2020) and De Chiusole et al. (2020) further reinforced the application of AI in statistical learning and assessment through knowledge space theory, which enables the mapping of individual learners' knowledge structures.

Despite its transformative potential, AI simultaneously introduces serious risks to academic integrity, including sophisticated forms of plagiarism and excessive dependence on algorithmic assistance, issues widely considered fundamental threats to the core values of higher education (Abdallah et al., 2025; Bittle & El-Gayar, 2025; Dempere, Modugu, Hesham, & Ramasamy, 2023; Fajt & Schiller, 2025; Gruenhagen et al., 2024; Liu, Hu, Gladman, & Gallagher, 2025). Systematic reviews by Abdallah et al. (2025) and Bittle and El-Gayar (2025) emphasize the increasingly blurred boundary between idea generation assistance and digital plagiarism. Students may submit essays generated entirely by AI systems, while traditional plagiarism detection tools such as Turnitin struggle to identify these texts due to their unique generative nature (Gruenhagen et al., 2024). Fajt and Schiller (2025) warn that academic ethics may gradually erode as students rationalize the use of AI as a substitute for personal effort. Likewise, analyses by Dempere et al. (2023) and Liu et al. (2025) indicate that excessive reliance on ChatGPT could ultimately weaken critical thinking and independent problem-solving skills.

In response to these risks, the responsibility of higher education leaders and policymakers becomes increasingly urgent. Universities cannot adopt a passive stance but must proactively establish clear regulatory frameworks and institutional policies governing AI use (Tan et al., 2025). A mixed-methods study conducted by Tan et al. (2025) in Singapore indicates that students do not necessarily oppose AI-related regulations, provided that these rules are consistent and transparently integrated into course assessment rubrics. Modern university governance systems, therefore, require strong institutional capacity to balance encouraging digital innovation with strict protection of academic integrity standards, ensuring that AI functions as a cognitive amplifier rather than a substitute for human intellectual effort.

3. Research Methodology

3.1. Research Design

To address the complex intersection between digital technology adoption behavior and university governance frameworks, this study is grounded in the philosophical stance of pragmatism. Pragmatism rejects the rigid dichotomy between positivism (quantitative approaches) and constructivism (qualitative approaches), allowing researchers to focus on *"what works best"* to answer the research questions (Johnson & Onwuegbuzie, 2004).

Based on this philosophical foundation, the study adopts an explanatory sequential mixed-methods design (QUAN → qual). The integration of Generative AI in higher education is not merely a phenomenon measurable through changes in academic scores; it also represents a process of meaning negotiation among students, lecturers, and institutional constraints (Creswell, 1999; Fetters et al., 2013). The large-scale quantitative phase aims to identify statistical patterns and test a structural model explaining AI adoption. Subsequently, the qualitative phase is directly informed by the statistical findings, particularly unexpected or marginally significant relationships, to explore deeper perceptions and uncover the underlying mechanisms shaping the quantitative results (Creswell, Fetters, & Ivankova, 2004).

3.2. Research Context and Sampling Strategy

The study was conducted across universities in Vietnam, a context that represents developing countries experiencing strong pressures from comprehensive digital transformation in higher education governance. To ensure transparency and contextual clarity, the data collection was specifically conducted at five major public institutions: Dong Thap University, Can Tho University, Ho Chi Minh City University of Education, An Giang University, and

the University of Da Nang. The sampling design strictly follows the nested sampling strategy commonly recommended in mixed-methods research (Collins, Onwuegbuzie, & Jiao, 2006; Teddlie & Yu, 2007).

- Quantitative sample: To ensure adequate statistical power exceeding 80%, as recommended for PLS-SEM models, the study employed stratified random sampling involving 850 students, 120 academic staff, and educational administrators. These participants were systematically drawn from specific academic units within the participating institutions, including the faculties of Natural Sciences and Technology (representing engineering/STEM), the faculties of Economics and Business Administration (representing business), and the faculties of Social Sciences and Humanities.

- Qualitative sample: A subset of 20 students and 10 lecturers/administrators was selected from the quantitative sample using purposive sampling. Participants were chosen based on data polarization, including individuals with extremely high levels of AI usage (early adopters) and those demonstrating strong resistance toward AI. This strategy maximized informational richness until data saturation was achieved.

3.3. Quantitative Data Collection and Analysis (QUAN)

Quantitative data were collected through an online survey using a five-point Likert scale, adapted and refined from previously validated measurement instruments derived from the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) frameworks.

Prior to formal analysis, Harman's Single-Factor Test was conducted to assess the potential presence of Common Method Bias (CMB), which is a critical requirement when survey data are self-reported from a single source.

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The analytical procedure consisted of two standard stages.

1. Measurement Model Evaluation: Internal consistency reliability was assessed using Cronbach's Alpha and Composite Reliability, while convergent validity was examined through the Average Variance Extracted (AVE > 0.5). Discriminant validity was evaluated using the Heterotrait–Monotrait Ratio (HTMT < 0.85) criterion.
2. Structural Model Evaluation: The explanatory power of the model was evaluated using the coefficient of determination (R^2), and predictive relevance was assessed through Stone–Geisser's Q^2 statistic. Hypotheses were tested using the bootstrapping procedure (5,000 resamples) to determine the statistical significance (*p-values*) of the path coefficients (β).

The selection of PLS-SEM is particularly appropriate because the study focuses on variance explanation related to AI adoption, an emerging research area in which theoretical frameworks are still evolving. Additionally, the model incorporates complex constructs involving university governance capabilities and academic integrity risks.

3.4. Qualitative Data Collection and Analysis (QUAL)

Qualitative data were collected through semi-structured in-depth interviews, each lasting approximately 45–60 minutes. The interview protocol was not rigidly predetermined; instead, it was refined based on the findings of the PLS-SEM analysis to explore hypotheses exhibiting unusual or unexpected effects.

Data analysis followed the six-step thematic analysis framework proposed by Braun and Clarke (2006). Audio recordings were transcribed, cleaned, and coded using NVivo software. The coding structure was developed using a deductive–inductive approach, beginning with initial nodes derived from theoretical concepts related to academic integrity and digital pedagogy, and subsequently expanding to incorporate emergent themes arising from participants' lived experiences.

To ensure qualitative rigor and trustworthiness, member checking procedures were conducted, and an independent researcher participated in the coding process to minimize subjective bias.

3.5. Data Integration: Joint Display Matrix

The point of interface within this mixed-methods design occurs during the interpretation stage. To integrate the data in a systematic and visually structured manner, the study employed the Joint Display technique (Bazeley, 2009; O'Cathain, Murphy, & Nicholl, 2010).

Through this matrix, quantitative statistical indicators (β coefficients, *t*-values, and R^2 values) were directly mapped alongside qualitative themes and representative participant quotations. Meta-inference analysis was then conducted to determine whether the qualitative data converged with, diverged from, or expanded upon the statistical findings (Venkatesh, Brown, & Bala, 2013).

This integrative approach ensures that conclusions regarding pedagogical innovation and university governance policies are not solely derived from surface-level quantitative modeling but are also deeply interpreted through empirical insights into the academic and psychological dynamics observed within the Vietnamese higher education context.

Table 1. Demographic characteristics of the quantitative sample.

Characteristic	Category	Frequency (n = 970)	Percentage (%)
Role	Students	850	87.60%
	Lecturers / Administrators	120	12.40%
Academic Field	Social Sciences & Humanities	310	32.00%
	Natural Sciences & Engineering	425	43.80%
	Economics & Management	235	24.20%
AI Usage Experience	Less than 6 months	215	22.20%
	6 months to 1 year	480	49.50%
	More than 1 year	275	28.30%

4. Research Results

4.1. Quantitative Analysis Phase

Table 1 presents the core demographic characteristics of the quantitative sample, consisting of 970 valid observations. Regarding participant roles, students represent the dominant group (87.6%, n = 850), reflecting the reality that learners are the most frequent users and are directly affected by generative AI technologies. However, including 12.4% (n = 120) lecturers and administrators represents a deliberate sampling strategy, enabling cross-validation of perceptions between educators and learners, thereby helping to identify institutional governance bottlenecks.

In terms of academic disciplines, the sample demonstrates a high level of representativeness. Participants from Natural Sciences and Engineering constitute the largest group (43.8%), consistent with the early adoption trends of technological innovations in these fields. The substantial participation of Social Sciences and Humanities (32.0%) and Economics and Management (24.2%) ensures that the dataset is not biased toward a single disciplinary orientation, thereby providing a strong foundation for multi-group analyses within the PLS-SEM framework.

Most notably, respondents reported considerable experience using AI technologies. Approximately 77.8% of participants had used AI for more than six months, including 28.3% with over one year of experience. This demographic characteristic is particularly significant as it minimizes the novelty effect. The relatively long-term exposure ensures that participants' evaluations of perceived usefulness, academic integrity risks, and learning outcomes are based on actual experience rather than initial curiosity, thereby increasing the reliability and predictive validity of the statistical model.

Table 2. Descriptive statistics of observed variables (Scale: 1–5).

Latent Variables	Items	Mean	Std. Deviation	Skewness	Kurtosis
Perceived Usefulness (PU)	4	4.12	0.85	-0.45	1.12
Teaching Integration (TI)	5	3.65	1.02	-0.21	0.85
Integrity Risk (IR)	4	3.98	0.91	-0.33	0.94
Learning Outcomes (LO)	5	4.05	0.88	-0.52	1.25
Institutional Responsibility (IN)	3	3.42	1.15	0.15	-0.42

Table 2 reports the descriptive statistics and distribution tests for the five latent variables included in the research model. The results reveal a clear divergence between perceptions, behaviors, and institutional governance frameworks regarding generative AI adoption.

Specifically, Perceived Usefulness (PU) and Learning Outcomes (LO) recorded the highest mean values (4.12 and 4.05, respectively) on a five-point scale, with relatively low standard deviations (SD < 0.90). These findings indicate strong consensus among participants regarding the potential of AI to enhance academic performance. However, the variable Teaching Integration (TI) achieved only a moderate mean value (3.65) and exhibited greater dispersion (SD = 1.02). This decline suggests a substantial gap between theoretical recognition of AI benefits and the behavioral barriers associated with integrating technology into pedagogical practice.

Notably, while concerns regarding Integrity Risk (IR) remain relatively high (Mean = 3.98), the variable Institutional Responsibility (IN) recorded the lowest average score (Mean = 3.42) and the greatest variability (SD = 1.15). This pattern serves as a critical governance indicator: many higher education institutions appear to lack coherent policies and guidelines for managing digital academic ethics.

From a methodological perspective, the distribution statistics confirm that the dataset meets normality assumptions. The skewness values (-0.52 to 0.15) and kurtosis values (-0.42 to 1.25) fall well within acceptable thresholds, providing a robust statistical foundation for subsequent PLS-SEM structural analysis.

Table 3. Reliability and convergent validity of measurement scales.

Construct	Cronbach's Alpha	rho_A	Composite Reliability (CR)	AVE
PU	0.885	0.89	0.912	0.654
TI	0.842	0.851	0.885	0.612
IR	0.815	0.822	0.865	0.588
LO	0.892	0.895	0.92	0.675
IN	0.795	0.801	0.845	0.54

Note: All AVE values exceed 0.50, and all CR values exceed 0.70, satisfying reliability requirements.

Table 3 presents the results of the measurement model evaluation, a crucial step in the PLS-SEM algorithm to ensure data reliability and stability before testing the structural model.

First, internal consistency reliability is confirmed at a very high level. All constructs report Cronbach's Alpha values exceeding the recommended threshold of 0.70, ranging from 0.795 (Institutional Responsibility) to 0.892 (Learning Outcomes). Additionally, Composite Reliability (CR), a preferred metric in PLS-SEM because it does not assume equal indicator loadings, shows optimal values between 0.845 and 0.920. The rho_A (Dijkstra–Henseler coefficient) consistently lies between Cronbach's Alpha and CR, providing further statistical evidence of strong internal consistency.

Second, convergent validity is successfully established through the Average Variance Extracted (AVE) indicator. All constructs exceed the minimum threshold of 0.50, with values ranging from 0.540 (IN) to 0.675 (LO). This indicates that each latent variable explains between 54.0% and 67.5% of the variance in its indicators, significantly exceeding the variance attributable to measurement error.

Overall, the measurement system demonstrates excellent reliability and strong convergent validity, confirming that the measurement model is robust and suitable for subsequent structural path analysis.

Table 4. Structural model evaluation (R^2 and effect sizes).

Dependent Variables	R^2	Adjusted R^2	Q^2 (Predictive)	f^2 (PU effect)	f^2 (TI effect)
Teaching Integration (TI)	0.452	0.448	0.315	0.355	–
Learning Outcomes (LO)	0.584	0.579	0.42	0.28	0.412

Table 4 provides important quantitative evidence regarding the explanatory power and predictive capability of the structural model. Model evaluation begins with the coefficient of determination (R^2), which measures the proportion of variance in dependent variables explained by the independent constructs.

The results indicate that Learning Outcomes (LO) achieved $R^2 = 0.584$ (Adjusted $R^2 = 0.579$), meaning that the model explains 58.4% of the variance in students' learning outcomes. This represents a moderate-to-substantial explanatory level according to established standards in social science research. Similarly, Teaching Integration (TI) recorded $R^2 = 0.452$, confirming the strong influence of antecedent variables in driving AI adoption in pedagogical practices.

Beyond explanatory power, the model demonstrates excellent predictive relevance through the Stone–Geisser Q^2 statistic obtained via blindfolding. Both endogenous constructs TI ($Q^2 = 0.315$) and LO ($Q^2 = 0.420$) exceed the threshold of zero, indicating that the model possesses strong out-of-sample predictive capability.

Effect size analysis (f^2) further clarifies the independent contribution of each variable. The effect of Teaching Integration on Learning Outcomes is particularly strong ($f^2 = 0.412$), reaffirming the central role of pedagogical innovation. Meanwhile, Perceived Usefulness (PU) demonstrates a strong influence on Teaching Integration ($f^2 = 0.355$) and a moderate direct effect on Learning Outcomes ($f^2 = 0.280$), providing robust statistical evidence for the importance of technology beliefs in shaping academic performance.

Table 5. Hypothesis testing results (PLS-SEM path coefficients).

Hypothesis	Path	Beta (β)	T-Value	P-Value	Result
H1	PU → TI	0.525	8.412	< 0.001	Supported
H2	PU → LO	0.315	5.214	< 0.001	Supported
H3	TI → LO	0.468	7.652	< 0.001	Supported
H4	IR → TI	-0.215	3.458	0.001	Supported
H5	IN → IR	-0.385	6.125	< 0.001	Supported

Table 5 presents the results of hypothesis testing using the bootstrapping procedure in PLS-SEM. The findings confirm that all five hypotheses (H1–H5) are statistically significant ($p \leq 0.001$), providing strong empirical support for the proposed theoretical model.

First, Perceived Usefulness (PU) emerges as the core driver of AI adoption, exerting a strong positive influence on Teaching Integration ($\beta = 0.525$, $t = 8.412$) and Learning Outcomes ($\beta = 0.315$, $t = 5.214$). Moreover, Teaching Integration (TI) significantly enhances Learning Outcomes ($\beta = 0.468$, $t = 7.652$). These results demonstrate that generative AI does not merely improve academic performance mechanically; rather, its value is maximized when it is embedded within intentional pedagogical innovation strategies.

Conversely, the analysis highlights the influence of institutional barriers. Integrity Risk (IR) exerts a significant negative effect on Teaching Integration ($\beta = -0.215$, $t = 3.458$), representing a major obstacle to lecturers' willingness to adopt AI in teaching practice.

The most critical finding emerges from Hypothesis H5, which indicates that Institutional Responsibility (IN) significantly reduces concerns regarding academic integrity risks ($\beta = -0.385$, $t = 6.125$). This relationship provides an important governance implication: ethical risks associated with AI are not deterministic. Instead, they can be effectively mitigated if universities establish transparent regulatory frameworks and clear institutional guidelines governing AI use in academic environments.

Table 6. Summary of in-depth interview participants (n = 30).

Group	Code	Number	Academic/Professional field	The primary purpose of AI use
Students	SV01–SV20	20	Engineering, Economics, Languages	Coding, translation, and idea generation
Lecturers	GV01–GV05	5	University governance, Information Technology	Syllabus preparation, basic grading
Administrators	QL01–QL05	5	Academic affairs, assessment	Policy formulation, plagiarism monitoring

4.2. Qualitative Analysis Phase

Table 6 outlines the overall characteristics and primary AI usage purposes of the 30 participants involved in the semi-structured interview phase. The use of a multi-stakeholder qualitative sample, consisting of students (n = 20), lecturers (n = 5), and university administrators (n = 5), represents a deliberate methodological strategy. This structure ensures data triangulation, enabling cross-comparison of perspectives from learners, instructors, and institutional policymakers.

For the student group (SV01–SV20), representation across engineering, economics, and language disciplines helps minimize disciplinary bias. Their primary use of AI centers on performance-oriented micro-tasks such as algorithm coding, translation, and idea generation. This pragmatic usage pattern directly explains the strong consensus observed for the Perceived Usefulness (PU) construct in the quantitative model.

In contrast, the perspectives of lecturers (GV01–GV05) and administrators (QL01–QL05) reveal a shift in emphasis from individual learning support to productivity management and risk control. While lecturers utilize AI to design syllabi and conduct basic grading, administrators, particularly those working in academic affairs and examination units, perceive AI primarily as an institutional governance challenge, focusing on plagiarism detection and regulatory frameworks. The divergence in motivations and usage purposes among these three stakeholder

groups provides critical insights into the institutional tensions surrounding academic integrity and governance responsibilities.

Table 7. Coding scheme of interview themes.

Main theme	Codes	Frequency (Text Occurrences)
Pedagogical Innovation	Task automation (A1); Personalized learning (A2)	85
Learner Autonomy	Algorithm dependence (B1); Decline in critical thinking (B2)	112
Institutional Barriers	Lack of institutional regulations (C1); Weak AI detection tools (C2)	78

Table 7 presents the coding scheme derived from the interview data using Thematic Analysis. This coding framework plays a crucial role in uncovering the psychological mechanisms and administrative barriers underlying the statistical indicators, with three core themes reflecting the multidimensional impact of generative AI integration.

The most prominent theme is Learner Autonomy, which recorded the highest frequency (112 occurrences). Two central codes, algorithm dependence (B1) and declining critical thinking (B2), dominate the dataset. This overwhelming frequency directly explains the strong concerns among academics regarding academic integrity risks (IR) identified in the quantitative analysis. Importantly, this finding indicates that the greatest concern among educators is not technological capability but the potential erosion of students' independent cognitive capacity resulting from excessive reliance on generative tools.

Meanwhile, the theme Pedagogical Innovation (85 occurrences) provides empirical support for the statistical findings regarding AI's perceived usefulness. Both lecturers and students confirmed that AI functions as a productivity enhancer, particularly through automation of repetitive tasks (A1) and personalization of learning experiences (A2).

However, the systemic bottleneck is clearly reflected in the theme Institutional Barriers (78 occurrences). The absence of institutional policies (C1), combined with limitations in current AI-detection tools (C2), represents the primary obstacle preventing universities from formally integrating AI into curricula. These qualitative findings align closely with the Institutional Responsibility (IN) construct identified in the structural model (Hypothesis H5), reaffirming that institutional governance capacity is the decisive factor in successful technological integration in education.

Table 8. Representative interview quotes by theme.

Theme	Participant	Representative quote	Literature reference
Automation	GV03	"AI helps me save about 40% of the time required to design assessment rubrics. I can focus more on interacting with students during class."	Crompton and Burke (2023)
Critical Thinking	SV12	"When using ChatGPT to solve math problems, if I'm not careful, I might lose the ability to construct logical reasoning from the beginning."	Abdallah et al. (2025)
Lack of Regulation	QL02	"Our university currently only has general plagiarism policies; there are no clear guidelines on the extent to which students are allowed to use AI."	Tan et al. (2025)

Table 8 presents representative excerpts from the interview data that illustrate the coding themes and demonstrate alignment with existing international literature.

The statement from lecturer GV03 provides empirical insight into the automation capacity of generative AI. Reducing 40% of the time spent designing assessment tools is not merely an efficiency indicator but also reflects a shift in pedagogical roles from performing repetitive administrative tasks to optimizing interactive teaching time with students. This experience closely aligns with the findings of Crompton and Burke (2023), who highlight AI's potential to free up teaching resources.

Conversely, the perspective expressed by student SV12 reveals a deeper cognitive paradox. The student's awareness of potentially losing the ability to construct logical reasoning independently when relying heavily on AI perfectly illustrates the code decline in critical thinking. This observation directly reinforces the argument presented by Abdallah et al. (2025) regarding the erosion of independent academic capability resulting from the excessive use of generative tools.

Most importantly, the observation from administrator QL02 exposes a fundamental governance gap within current university systems. The persistence of traditional plagiarism policies without clear guidelines regarding acceptable AI use boundaries creates conditions that inadvertently allow academic integrity risks to emerge. This institutional ambiguity strongly echoes the policy concerns highlighted by Tan et al. (2025).

Table 9. Mixed-methods joint display matrix: convergence and divergence.

Research Variable	Quantitative Finding (Table 5)	Qualitative Finding (Tables 7–8)	Fit	Integrated Conclusion
Impact on Learning Outcomes	$\beta = 0.468$, $p < 0.001$ (Strong positive effect)	Students report improved scores due to AI-assisted writing, while lecturers express concerns about "artificial grades."	Expansion	AI improves short-term performance but requires redesigned assessments to measure authentic competence.
Academic Integrity Risk	$\beta = -0.215$, $p = 0.001$ (Barrier to integration)	Administrators emphasize the lack of institutional policies and control tools as root causes.	Convergence	Integrity concerns hinder lecturers from formally integrating AI into curricula.

4.3. Data Integration and Advanced Analysis

Table 9 presents the Joint Display Matrix, which serves as the core integration point of the mixed-methods design. At this stage, quantitative and qualitative evidence is synthesized to generate meta-inferences.

For the construct Learning Outcomes, the matrix reveals an Expansion relationship. While the PLS-SEM model confirms a strong positive effect of teaching integration on academic performance ($\beta = 0.468$, $p < 0.001$), qualitative evidence exposes a deeper academic paradox. Students acknowledge that their performance improved through AI-assisted writing tools, yet lecturers express concerns about the emergence of "inflated or artificial grades." This expansion suggests that increased performance on statistical measures may conceal deeper erosion of core cognitive competencies. Consequently, higher education institutions must fundamentally redesign assessment systems, shifting from summative evaluation toward formative, process-based assessment.

In contrast, a strong Convergence pattern emerges for the construct Academic Integrity Risk. The statistical barrier identified in the structural model ($\beta = -0.215$) is fully explained by qualitative evidence from administrators, who emphasize the absence of clear institutional policies and inadequate AI-detection tools. This convergence provides compelling empirical evidence that the primary obstacle to integrating AI into formal curricula is not technological capability but delayed institutional governance capacity and regulatory responsibility.

Table 10. Differences in AI adoption across academic disciplines (One-Way ANOVA).

Discipline	Mean (AI Integration)	Std. Dev.	F-Value	P-Value	Post-hoc Tukey HSD
Engineering & Technology	4.25	0.65	28.45	< 0.001	Group 1 > Groups 2, 3
Economics & Management	3.85	0.82			Group 2 > Group 3
Social Sciences & Humanities	3.12	0.95			

Table 10 presents the results of a one-way ANOVA analysis examining differences in AI integration across three major academic disciplines. The results reveal a highly significant difference ($F = 28.45$, $p < 0.001$), confirming that disciplinary context acts as a strong moderating factor influencing technology adoption in higher education.

Post-hoc Tukey HSD analysis confirms a clear hierarchical pattern. The Engineering and Technology group demonstrates the highest level of AI integration (Mean = 4.25) and the lowest variability (SD = 0.65). This finding reflects the natural compatibility between computational disciplines and AI technologies, as well as the relatively strong digital literacy foundation within this academic community.

The Economics and Management group ranks second (Mean = 3.85, SD = 0.82), where AI tools are increasingly used for data analysis and decision-support tasks.

Most notably, the Social Sciences and Humanities group records the lowest level of AI integration (Mean = 3.12) with the highest variability (SD = 0.95). This hesitation does not primarily arise from technical barriers but from the epistemological nature of social science disciplines, which place strong emphasis on critical thinking, subjective interpretation, and originality in academic writing. The high variance observed in this group reflects substantial internal tension and a lack of consensus regarding the ethical boundaries of using generative AI in intellectual content creation.

5. Discussion

5.1. The Pull of Perceived Usefulness and the Resistance of Academic Risk (Addressing RQ1)

The hypothesis testing results (Table 5) indicate that Perceived Usefulness (PU) is the fundamental driver with the strongest influence on Teaching Integration (TI) ($\beta = 0.525$, $p < 0.001$). This finding is fully consistent with theoretical analyses based on the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) presented in the studies of Ngo et al. (2025) and Rahman et al. (2025). Qualitative evidence (Table 8) further confirms that the appeal of AI for lecturers lies in its capacity to reduce administrative burdens. Automating tasks such as rubric design or personalizing learning pathways allows a pedagogical shift from knowledge transmission to interaction facilitation, a trend previously anticipated by Crompton and Burke (2023) and Ouyang et al. (2022).

However, the integration process does not occur in a linear trajectory. Hypothesis H4 confirms that Integrity Risk (IR) creates a significant statistical barrier ($\beta = -0.215$) to the intention to formally integrate AI into academic settings. The convergence of evidence in the Joint Display matrix (Table 9) clarifies that these concerns are empirically grounded. Lecturers face a clear dilemma: they recognize the technological advantages of AI tools but hesitate to adopt them due to the fear of inadvertently facilitating digital plagiarism. This finding aligns with the arguments of Abdallah et al. (2025) and Bittle and El-Gayar (2025), who emphasize that the blurred boundary between "idea assistance" and "cognitive delegation" threatens the core principles of originality in academic environments.

Furthermore, the ANOVA analysis (Table 10) provides a valuable disciplinary perspective to explain this hesitation. The finding that the Social Sciences and Humanities group exhibits the lowest level of AI integration (Mean = 3.12) compared with the Engineering group (Mean = 4.25) does not stem from weaker digital competence. Rather, as suggested by Tossell et al. (2024) and Sandu et al. (2024), the epistemological foundations of social sciences emphasize critical reasoning, subjective interpretation, and personal writing voice. Consequently, the emergence of algorithmically generated text tends to standardize language patterns, potentially producing homogenized academic outputs. This phenomenon triggers resistance among educators in disciplines where intellectual originality is considered a fundamental academic value.

5.2. The Paradox of Learning Outcomes and Cognitive Decline Risk (Addressing RQ2)

One of the most significant scholarly contributions of this study lies in its interpretation of the Learning Outcomes (LO) construct. The PLS-SEM results confirm that AI exerts both a direct effect ($\beta = 0.315$) and an indirect effect through teaching integration ($\beta = 0.468$) on academic performance. These results appear to support the meta-analytical findings of Deng et al. (2025) and Wang and Fan (2025), which report improvements in students' scores following the use of tools such as ChatGPT.

However, the "Expansion" pattern identified through the qualitative data in Table 9 reveals a deeper paradox: improvements in surface-level performance indicators may mask a decline in core cognitive competencies. Students' own reflections regarding the risk of *"losing the ability to construct logical reasoning independently"* (Table 8, SV12) provide vivid evidence of algorithmic dependence. When students rely on AI to produce final outputs such as complete essays or fully developed code rather than using it as cognitive scaffolding, the mechanisms of self-regulated learning may be undermined (Lee et al., 2024).

This paradox poses a critical challenge for the assessment systems within Vietnamese higher education. As highlighted by Fajt and Schiller (2025) and Dempere et al. (2023), if universities continue to rely on summative assessments focusing primarily on final products (such as take-home essays or project reports), academic grades may increasingly reflect students' prompt-engineering skills rather than genuine intellectual development. AI-enhanced learning outcomes will only be meaningful when assessment systems transition toward formative evaluation, requiring students to defend their reasoning processes, explain algorithmic logic, or critically evaluate AI-generated responses (Heil et al., 2025).

5.3. Institutional Responsibility: The Key to Resolving the Crisis (Addressing RQ3)

The central thread explaining the tension between pedagogical innovation and academic risk lies in the variable Institutional Responsibility (IN). The descriptive results (Table 2) indicate that this construct has the lowest mean value (Mean = 3.42) and the highest variance, reflecting a state of policy ambiguity within current higher education institutions. Nevertheless, the structural model results (Table 5) confirm that IN exerts a strong mitigating effect on Integrity Risk ($\beta = -0.385$, $p < 0.001$).

The convergence of evidence in Table 9, including administrators' statements regarding the limitations of traditional plagiarism detection systems, demonstrates that the major barrier is not technological capability but governance mindset. In Vietnam, many universities initially responded to generative AI through defensive strategies emphasizing prohibition (Quy et al., 2023). However, the findings of this study align with Tan et al. (2025) and Gruenhagen et al. (2024), who argue that in an era where AI-generated content cannot be perfectly detected, attempts to rely solely on technical barriers are ineffective.

Instead of maintaining vague anti-plagiarism policies, universities must urgently establish digital ethics frameworks specifically designed for AI usage. Transparent institutional guidelines function as a stabilizing mechanism. They alleviate lecturers' uncertainty and empower them to integrate AI into curricula legitimately, transforming a potentially risky technology into a legitimate academic resource.

Overall, the integration of AI technologies within Vietnamese higher education is currently undergoing a dynamic transitional phase. Generative AI demonstrates strong empirical capacity to enhance learning performance and reshape pedagogical practices. However, for AI to function as a cognitive amplifier rather than a capacity surrogate, individual efforts by students and lecturers are insufficient. Higher education institutions must act as architects of transformation, redesigning assessment systems and strengthening governance frameworks to convert academic integrity risks into new digital ethics standards.

6. Conclusion and Policy Implications

6.1. Conclusion

This mixed-methods study aimed to comprehensively explore the mechanisms through which Generative Artificial Intelligence influences the higher education ecosystem in Vietnam. By combining the generalizability of PLS-SEM structural modeling with the interpretive depth of qualitative analysis, the research provides a realistic depiction of a transformative yet tension-filled digital transition within the academic community.

The findings reveal that generative AI acts as a powerful catalyst for pedagogical innovation. Lecturers' and students' perceived usefulness of AI is strongly associated with pedagogical integration and improved learning outcomes. AI's ability to personalize learning pathways and automate administrative tasks has been demonstrated as an effective tool for optimizing academic productivity (Crompton & Burke, 2023; Ouyang et al., 2022).

However, the most critical and cautionary finding lies in the convergence of evidence regarding academic integrity risks. Concerns about declining critical thinking skills, algorithmic dependence, and sophisticated forms of plagiarism have emerged as the most significant psychological barriers preventing lecturers from formally integrating AI into teaching practices (Abdallah et al., 2025; Bittle & El-Gayar, 2025).

Importantly, the study demonstrates that the core of this trust crisis does not lie in technological limitations but rather in institutional responsibility. The hesitation of universities to define clear ethical boundaries has placed lecturers and students within an ambiguous academic gray zone. AI can function as a cognitive amplifier only when higher education systems provide transparent governance frameworks and fundamentally redesign assessment practices (Heil et al., 2025; Tan et al., 2025).

6.2. Policy and Managerial Implications

Based on the empirical findings, this study proposes three strategic policy recommendations for policymakers and university leaders in Vietnam to effectively govern the rise of generative AI.

First, transition from a "prohibition mindset" toward controlled integration through a Digital Ethics Framework. Universities should abandon broad defensive bans on AI use, as such policies merely drive student usage into hidden practices. Instead, institutions should establish transparent university-wide AI guidelines, clearly defining: Permissible AI uses (e.g., idea generation, outlining, debugging code); Prohibited uses (e.g., generating core argumentative sections of essays or fabricating research data); Mandatory citation standards for AI-generated content according to recognized referencing systems such as APA 7th or IEEE. Such transparency can reduce lecturers' uncertainty and encourage them to design technology-integrated teaching strategies (Gruenhagen et al., 2024).

Second, restructure assessment practices. The emergence of ChatGPT has rendered many traditional summative assessments ineffective, particularly assignments focusing on final written outputs. To accurately measure authentic competencies and reduce academic misconduct incentives, universities must shift toward formative assessment

models. These may include: Oral defense (viva voce) to explain the reasoning behind submitted work; Critical evaluation tasks, where students must identify logical errors or hallucinations in AI-generated content; Prompt history documentation, requiring students to demonstrate the iterative process through which knowledge was co-constructed with AI.

Third, invest in developing faculty AI literacy and digital pedagogical competencies. Institutional governance cannot function effectively if instructors lack the necessary technological skills. Universities should implement continuous professional development (CPD) programs not only to introduce the latest AI tools but also to train lecturers in prompt engineering and technology-integrated pedagogical design (TPACK). When lecturers develop mastery over AI systems, they can design academic tasks sufficiently complex to challenge algorithmic capabilities, thereby encouraging students to engage in higher-order thinking.

6.3. Limitations and Future Research

Despite providing a robust theoretical and empirical framework, this study has several limitations.

First, the use of cross-sectional data means that the quantitative model captures perceptions and behaviors at a specific point in time. Given the rapid evolution of AI technologies, user attitudes may shift significantly in a short period.

Second, the survey relies on self-reported learning outcomes, which may contain subjective bias or social desirability bias.

Future studies are encouraged to adopt longitudinal research designs to track changes in student attitudes before and after universities formally implement AI governance frameworks. Additionally, experimental studies comparing students who receive structured AI literacy training with those who do not could provide stronger causal evidence regarding the real impact of AI on measurable academic performance indicators.

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