



Artificial intelligence in Vietnamese higher education: Impacts on the innovation of teaching methods and learners' learning experiences

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Abstract

The rapid rise of Artificial Intelligence (AI), particularly Generative AI, presents unique challenges and opportunities for higher education in emerging economies. This study quantifies AI's impact on lecturers' pedagogical innovation and students' learning experiences within Vietnam's digital transformation. Grounded in an extended Technology Acceptance Model (TAM), the research employs Structural Equation Modeling (SEM) to analyze data from 710 respondents (270 lecturers and 440 students) at leading universities. Empirical results indicate that digital competence is a critical prerequisite for AI adoption, which subsequently exerts a strong positive effect on teaching performance through the full mediating role of pedagogical innovation. For students, the capacity for content personalization emerges as the primary driver of enhanced learning experiences; however, perceived ethical risks significantly undermine trust in these technologies. Furthermore, multi-group analysis reveals notable differences in adoption levels between STEM and Social Sciences students. Based on these findings, the study offers key policy implications for data-driven university governance and underscores the urgent need to establish a comprehensive ethical and legal framework. This research contributes vital empirical evidence to the discourse on sustainable, human-centered AI integration in developing educational systems.

Keywords: Artificial intelligence in education (AI in education), Digital competence, Personalized learning experience, Structural equation modeling, Teaching innovation, Vietnamese higher education.

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Contribution of this paper to the literature

This study offers empirical evidence on AI adoption in Vietnamese higher education by integrating the Technology Acceptance Model with digital competence and ethical risk perspectives. Using Structural Equation Modeling and multi-group analysis, it explains how AI influences lecturers' pedagogical innovation and students' learning experiences, while highlighting disciplinary differences. The findings extend AIED research beyond Western contexts and provide practical insights for ethical, data-driven university governance in emerging economies.

1. Introduction

The Fourth Industrial Revolution has triggered profound transformations across all facets of socio-economic life, with higher education standing out as one of the sectors most deeply affected. Specifically, the emergence and accelerated development of Artificial Intelligence (AI), notably Large Language Models (LLMs) like ChatGPT and other Generative AI systems, mark a historical turning point that is fundamentally reshaping the global educational ecosystem (Abdullah, Madain, & Jararweh, 2022; Gordijn & Ten, 2023). Far from being simple assistive tools, AI has evolved into a transformative force, challenging traditional pedagogical approaches and setting new benchmarks for digital competence. Looking at technological evolution historically, while IBM's Deep Blue defeating Garry Kasparov was once hailed as the dawn of the AI era (The Independent, 2020), contemporary applications have gone much further. From ChatGPT to Google DeepMind's algorithms solving complex geometric problems, AI has demonstrated the capacity to replace or substantially augment human performance in higher-order cognitive (MIT Technology Review, 2024; Trinh, Wu, Le, He, & Luong, 2024).

In this context, education is no longer merely a passive recipient of technological innovation; it has become a vast "living laboratory" for AI applications. International research suggests that Artificial Intelligence in Education (AIED) is shifting from a purely technical toolset to an interdisciplinary pedagogical field, where the lines between computer science and educational science are increasingly blurred (Chatzichristofis, 2025). The true potential of AI lies in its ability to personalize learning pathways, offer instant feedback, and help learners overcome spatial and temporal constraints (Hwang, Xie, Wah, & Gašević, 2020; Siemens, 2013). However, this deep integration brings serious ethical and social challenges. Scholars like Noble (2018) and Otterbacher, Bates, and Clough (2017) warn that algorithms can reinforce racial or gender biases, while Avraamidou (2024) points to the risk of the "colonization" of science education by dominant technology platforms. Furthermore, the environmental impact of operating large-scale AI models is an emerging ethical issue that higher education institutions must address within their sustainable development strategies (De Vries, 2023; Luccioni, Viguiet, & Ligozat, 2023).

In Vietnam, the digital transformation of higher education is gaining momentum, steered by strategic macro-level policies. The Prime Minister's Decision No. 749/QĐ-TTg on the "National Digital Transformation Program to 2025, with a Vision to 2030" identifies education as a priority sector that must lead the way in preparing future human resources. Empirical evidence shows that following the COVID-19 pandemic, the readiness of Vietnamese students and lecturers to adopt educational technologies has improved significantly (Pham, Tran, La, Doan, & Vu, 2021). Yet, the Global Education Monitoring Report (2023) on technology in Vietnam indicates that despite opportunities for deeper integration, the system still faces persistent hurdles regarding technical infrastructure, regional digital divides, and, crucially, the digital pedagogical competence of lecturers (Global Education Monitoring Report, 2023; UNESCO, 2022). Currently, AI adoption in Vietnam is largely spontaneous and lacks comprehensive ethical guidelines or methodological frameworks, leading to considerable uncertainty in governance and evaluation (Do & Nguyen, 2023; Le & Nguyen, 2021).

The urgency of this research arises directly from these theoretical and practical gaps in AI implementation at Vietnamese universities. While scholarly publications on AIED have surged recently, a bibliometric analysis by Chen, Xie, and Hwang (2020) reveals that most studies still focus heavily on technical aspects such as algorithm and software development or remain at a general theoretical level. There is a scarcity of in-depth quantitative studies using advanced statistical techniques, like Structural Equation Modeling (SEM), to rigorously measure AI's impact on both key actors: lecturers and students. Existing Vietnamese studies, such as those by Dung (2021) and Son, Thi, and Giang (2022), have discussed digital transformation but have not sufficiently explored the specific psychological and behavioral mechanisms of adopting generative AI, nor have they quantified the links between digital competence, technology acceptance, and educational effectiveness.

For lecturers, AI represents more than just a new instructional tool; it creates pressure to redefine the teaching role. Shifting from being primary knowledge transmitters, lecturers are increasingly expected to act as facilitators, learning experience designers, and digital leaders (Garcez, Silva, & Franco, 2022; Niță & Guțu, 2023). This transition requires not only technical proficiency but also innovative pedagogical thinking to meet the expectations of Generation Z students, who have grown up immersed in digital technology. Research by Arifin and Sukmawidjaya (2020) and Nelly, Prabowo, Bandur, and Elidjen (2024) suggests that competence and leadership style play a vital mediating role in enhancing teaching performance. However, whether this holds true when AI is fundamentally altering lesson preparation and assessment remains an open question. For students, AI offers unprecedented opportunities for personalized learning and unlimited knowledge access (Christudas, Kirubakaran, & Thangaiah, 2018; Mathew, 2023). Conversely, it poses risks such as increased passivity, overreliance on technology, academic misconduct, and isolation in digital learning environments (Crawford, Allen, Pani, & Cowling, 2024; King, 2023; Lo, 2023). Therefore, understanding the mechanisms through which AI influences learning experiences, from perceived usefulness to ethical concerns, is critical for building a sustainable, human-centered higher education environment.

Given this practical backdrop and the identified theoretical gaps, this study aims to provide a comprehensive, empirically grounded analysis of AI adoption in Vietnamese higher education. Unlike previous fragmented approaches, this research integrates the Technology Acceptance Model (TAM) with digital competence frameworks to build a multidimensional evaluative model. Through large-scale surveys and quantitative analysis, the study moves beyond descriptive accounts to explore underlying causal relationships.

The research is guided by the central question: How do the levels of readiness for and application of artificial intelligence influence lecturers' pedagogical innovation performance and the quality of students' learning experiences in Vietnamese universities? Addressing this question provides a critical foundation for formulating policy recommendations and pedagogical solutions, contributing to the effective realization of Vietnam's national digital transformation goals in education.

2. Theoretical Framework and Literature Review

2.1. Artificial Intelligence in Education (AIEd)

The integration of Artificial Intelligence (AI) into the educational domain, known as Artificial Intelligence in Education (AIEd), is not an abrupt phenomenon. Rather, it is the result of decades of technological evolution and paradigm-shifting breakthroughs that have fundamentally altered the human-machine relationship. As outlined in the AI timeline by CFTE (2023) and historical analyses by Meacham (2021), the field has weathered multiple cycles of hype and "AI winters." A pivotal moment in this history was IBM's Deep Blue defeating world chess champion Garry Kasparov (The Independent, 2020). This was more than an algorithmic victory; it signaled the dawn of an era where machines could surpass human capabilities in tasks requiring complex data processing and strategic foresight.

However, AI has only truly emerged as a transformative force in education within the last decade, driven by the explosion of Big Data and advancements in Deep Learning. Recent technical milestones, such as Google DeepMind's AlphaGeometry system (MIT Technology Review, 2024; Trinh et al., 2024), demonstrate that contemporary AI has moved beyond basic computation to solving Olympiad-level problems without human intervention. Similarly, the rapid integration of large language models into platforms like Khan Academy's Khanmigo (Khan Academy, 2023) marked 2023 as a turning point where AI began to actively reshape classroom practices.

In this landscape, the definition of AIEd is evolving. Chatzichristofis (2025) argues that AIEd is shifting from a mere collection of technical tools to an interdisciplinary pedagogical field where computer science, data science, and educational psychology converge. While there has been a surge in academic publications and software tools, extensive bibliometric analyses by Chen, Xie, and Hwang (2020) and Chen, Xie, Zou, and Hwang (2020) reveal a persistent gap between theory and practice, as well as fragmentation across research institutions. Addressing these gaps, Chaudhry and Kazim (2022) and Hwang et al. (2020) envision AI as central to solving long-standing educational challenges, particularly large-scale personalization. This shift is anchored in Intelligent Tutoring Systems (ITS) and Learning Analytics. For instance, Heffernan and Heffernan (2014) highlight the ASSISTments ecosystem as a model connecting researchers and teachers to study learning behaviors, while a meta-analysis by Ma, Adesope, Nesbit, and Liu (2014) provides robust evidence that ITS can significantly outperform traditional instruction. Siemens (2013) further emphasizes the role of learning analytics in optimizing educational environments. Together, these technologies lay the groundwork for adaptive education, where content is tailored to individual learners using large-scale data (Huang, Lu, Huang, Yin, & Yang, 2020).

2.2. The Vietnamese Higher Education Context amid Digital Transformation

Vietnam's higher education sector is undergoing profound changes driven by global digital transformation trends and strategic national policies. While Prime Minister's Decision No. 749/QĐ-TTg on the "National Digital Transformation Program" sets a critical legal framework, practical implementation remains challenging. Global Education Monitoring Report (2023) recognizes Vietnam's efforts to integrate technology but warns of inconsistencies in technical infrastructure. Furthermore, research by Pham et al. (2021) on digital readiness during the COVID-19 pandemic indicates that while students generally hold positive attitudes toward technology, there are significant gaps in digital skills and access to devices.

Domestic studies by Dung (2021) and Son et al. (2022) at major institutions like Hanoi University of Science and Technology confirm that digital transformation drives smart university development. However, they note that current efforts often stop at administrative digitalization rather than achieving deep pedagogical transformation. Discussions at the AI Education Forum (2023) and analyses by Do and Nguyen (2023) suggest that Vietnam is transitioning from awareness to application, though this requires a cautious approach to potential risks.

Integrating AI into Vietnam's specific cultural context demands tailored approaches. Le and Nguyen (2021) propose technology-based competency assessment for distance education quality assurance, while Bui, Dang, Vuong, Do, and Nguyen (2021) offer a theoretical basis for adaptive education models in Vietnam. However, Aldosari (2020) warns that successful transformation requires long-term strategic governance, not just short-term software procurement. A critical concern here is the "digital divide." Frameworks by Abboud, Arya, and Pandi (2020); Božić (2023), and Li (2023) suggest AI could exacerbate inequality if poorly governed. In Vietnam, UNICEF (2022) highlights the risk of leaving rural and mountainous students behind if education becomes overly reliant on high-end hardware. Williams, Mayhew, Lagou, and Welsby (2020) echo these concerns regarding access to online education, underscoring the need for research that includes vulnerable groups.

2.3. The Impact of AI on Lecturers

Lecturers are pivotal to the success of AI-driven educational transformation. Arifin and Sukmawidjaya (2020) demonstrate that technology positively impacts job performance by automating administrative tasks and offering advanced tools. However, technology is a necessary but insufficient condition; the human element is decisive. Studies by Nelly et al. (2024) and Niță and Guțu (2023) highlight the mediating role of competency: even with strong strategies like the academic business pillar model (Garcez et al., 2022), lecturers cannot harness AI without digital competence and an adaptive mindset. Consequently, standardized AI competency frameworks encompassing data literacy, ethics, and pedagogical adaptability are imperative (OECD, 2021; UNESCO, 2023a). Furthermore, Zhu and Jin (2023) emphasize that flexible leadership is essential for fostering lecturers' readiness for change.

AI also compels a fundamental innovation in teaching methods. As noted by Cantú-Ortiz, Galeano Sánchez, Garrido, Terashima-Marin, and Brena (2020) and Dimitriadou and Lanitis (2023), AI transforms classrooms into smart environments supporting multidimensional interaction. Case studies on robotics (Evripidou et al., 2020) and AI-assisted literary adaptation (Chatzichristofis, Tsopozidis, Kyriakidou-Zacharoudiou, Evripidou, & Amanatiadis,

2025) illustrate this potential. Yet, innovation is rarely seamless. Reich (2020) in *Failure to Disrupt* warns that technology alone cannot transform education without cultural and structural changes. To understand lecturers' adoption behaviors, Sugandini, Istanto, Garaika, Arundati, and Purnama (2021) validated the Technology Acceptance Model (TAM) in higher education, identifying perceived usefulness and ease of use as key drivers. Building on this, the present study posits that digital competence drives AI acceptance, which subsequently fuels pedagogical innovation and performance.

2.4. The Impact of AI on Students

For students, AI offers a revolution in personalization. Systems developed by Christudas et al. (2018) and George and Lal (2019) use ontology and behavior analysis to deliver optimally tailored content. Generative AI tools like ChatGPT have accelerated this, with Baidoo-Anu and Ansah (2023) and Mathew (2023) describing them as “game changers” for self-directed learning. In fields like medicine, Mogali (2024) reports that AI helps students visualize complex anatomical structures more intuitively. However, the student experience is multifaceted. Zhai (2022) and Grassini (2023) question the impact of ChatGPT on critical thinking, asking whether readily available answers diminish the motivation for deep thought. Lo (2023) identifies learner passivity as a tangible risk. Moreover, Crawford et al. (2024) introduce the “cost of loneliness,” suggesting that replacing human interaction with AI could harm social connectedness and retention. Ouyang, Zheng, and Jiao (2022) and Tsai, Poquet, Gašević, Dawson, and Pardo (2019) further highlight the complexities of measuring learning experiences in online settings. Finally, academic integrity remains a major challenge. King (2023) and Corbin, Dawson, Nicola-Richmond, and Partridge (2025) ask where the boundary lies between assistance and misconduct, while O’Dea (2024) argues that Generative AI forces a redefinition of assessment norms. Sok and Heng (2023) emphasize the need for clear guidance to help students navigate these risks.

2.5. Ethical, Social, and Methodological Considerations

Ethical and social dimensions form a crucial part of this study’s theoretical foundation. Seminal works by Noble (2018) and Otterbacher et al. (2017) analyze algorithmic bias, warning that AI can reproduce racial and gender prejudices. Avraamidou (2024) extends this to the “colonization” of science education by Western-centric technology. Additionally, safety and data privacy are major concerns in an AI-driven world (Miller, Wolf, & Grodzinsky, 2017; OECD, 2023; Yampolskiy & Spellchecker, 2016). Environmental impact is also emerging as an ethical issue, with De Vries (2023) and Luccioni et al. (2023) highlighting the carbon footprint of large language models as a matter of social responsibility for institutions (Gordijn & Ten, 2023).

UNESCO has pioneered global norms to address these challenges, providing a robust legal and ethical foundation through documents such as the Recommendation on the Ethics of Artificial Intelligence (UNESCO, 2021a), the Beijing Consensus (UNESCO, 2023c), and various policy guidelines (UNESCO, 2023a, 2023d, 2023e, 2023f). These emphasize “human-centered AI.” Complementing this, Akgun and Greenhow (2022) and Holmes et al. (2022) propose community-based ethical frameworks, while Chiu, Xia, Zhou, Chai, and Cheng (2023) urge future research to prioritize equity and inclusion.

Methodologically, this study adopts a rigorous framework to measure these complex relationships. Drawing on experimental design principles by Shadish, Cook, and Campbell (2002) and guidelines for multivariate analysis by Hair, Black, Babin, and Anderson (2019) and Structural Equation Modeling (SEM) by Byrne (2016) the research employs SEM to test its hypotheses. This approach allows for the simultaneous analysis of multiple latent variables and measurement errors, making it particularly suitable for capturing the nuanced impact of AI on education.

3. Research Methodology

3.1. Research Design

To address the core research question concerning the impact of Artificial Intelligence (AI) on lecturers’ teaching performance and students’ learning experiences within the context of Vietnamese higher education, this study adopts a quantitative approach with a cross-sectional research design.

The choice of a cross-sectional design is grounded in the general principles of causal inference articulated by Shadish et al. (2002), which allow data to be collected and analyzed at a single point in time in order to explore relationships among latent variables. This design is particularly appropriate in the context of AI technologies, which are evolving rapidly and exhibiting highly dynamic patterns of adoption in contemporary higher education.

The study was conducted at five key universities located in three major educational hubs in Vietnam: Hanoi, Ho Chi Minh City, and Da Nang. These sites were selected to ensure:

- Regional representativeness.
- Diversity of academic disciplines, ranging from Science, Technology, Engineering, and Mathematics (STEM) to Social Sciences and Humanities (SSH).
- An accurate reflection of uneven levels of digital transformation across higher education institutions, as highlighted in studies on Vietnamese students’ digital readiness (Pham et al., 2021).

Data collection took place between January and April 2024, employing a combination of online surveys and in-class paper-based surveys. This mixed-mode approach was designed to maximize response rates and minimize self-selection bias, a common limitation in survey-based research on educational technologies.

3.2. Sample and Sampling Strategy

Data collection was conducted at five distinct higher education institutions located across key regions of Vietnam to ensure representative geographic coverage. Specifically, the participating institutions included Hanoi National University of Education and the University of Social Sciences and Humanities, VNU Hanoi in the northern region; The University of Danang in the central region; and Ho Chi Minh City University of Education and Dong Thap University in the southern region. These institutions were selected to represent a diverse academic landscape, ranging from major multidisciplinary universities to specialized pedagogical institutions.

Following rigorous data cleaning procedures, the final valid sample consisted of 710 respondents ($N = 710$), comprising two independent yet complementary groups: Lecturers ($N = 270$) and Students ($N = 440$).

The sample size was determined based on established methodological standards for Structural Equation Modeling (SEM). According to Hair et al. (2019), an adequate sample for SEM must meet specific criteria, either being five to ten times the number of observed variables or containing a minimum of 200 observations to ensure sufficient statistical power and the robustness of parameter estimates. Given the complexity of the research model, which incorporates multiple latent constructs such as Digital Competence, Technology Acceptance, and Ethical Risk, a sample size of 710 is considered highly reliable. Furthermore, this scale enables advanced statistical procedures, including multi-group analysis across different disciplinary clusters.

To mitigate potential selection bias, particularly the tendency for students in technology-oriented majors to adopt AI earlier than their peers in other fields (Evripidou et al., 2020), a stratified sampling technique was employed. This approach ensured a balanced representation across participant groups and academic disciplines.

3.3. Measurement Instruments

The measurement instruments were carefully designed to ensure both reliability and validity. All observed variables were measured using a five-point Likert scale, ranging from 1 (Strongly disagree) to 5 (Strongly agree).

Rather than being developed entirely from scratch, the measurement scales were adapted from well-established international studies, ensuring contextual relevance to Vietnam's higher education and cultural setting.

- For the lecturer group, the Teaching Performance scale was adapted from Arifin and Sukmawidjaya (2020), focusing on task completion, instructional quality, and lecturer-student interaction in technology-supported environments.
- The constructs of Digital Competence and Technology Acceptance were derived from the extended Technology Acceptance Model (TAM) validated by Sugandini et al. (2021), capturing both technical aspects (perceived ease of use) and pedagogical dimensions (perceived usefulness).
- For the student group, the Learning Experience scale was adapted from Ouyang et al. (2022), emphasizing satisfaction and perceived learning outcomes in AI-integrated learning environments.
- Ethical Risk, an emerging construct in the context of Generative AI, was developed based on the ethical framework proposed by Akgun and Greenhow (2022) and Holmes et al. (2022) and analyses of algorithmic bias by Noble (2018). This construct includes indicators related to plagiarism, information accuracy, and data privacy.

The entire questionnaire underwent a back-translation procedure and a pilot test with 30 participants to refine wording, ensure clarity, and enhance contextual appropriateness prior to full-scale administration.

3.4. Data Analysis Methods

Data processing and analysis were conducted in two main stages, using IBM SPSS 26.0 for descriptive statistics and AMOS 24.0 for structural modeling.

Stage 1 focused on: Data cleaning; Detection and treatment of outliers; Assessment of internal consistency reliability using Cronbach's Alpha; Exploratory Factor Analysis (EFA) to examine the underlying factor structure of the measurement scales.

Stage 2 involved structural model analysis, following the three-step procedure recommended by Byrne (2016):

1. Confirmatory Factor Analysis (CFA) to validate the measurement model, assessing convergent validity through Average Variance Extracted (AVE) and Composite Reliability (CR).
2. Structural Equation Modeling (SEM) to estimate causal relationships among latent variables and test the proposed research hypotheses.
3. Model robustness testing using the Bootstrapping technique with 2,000 resamples to ensure the stability and statistical significance of the estimated parameters.

Model fit was evaluated using multiple goodness-of-fit indices, including CMIN/df, CFI, TLI, and RMSEA, which served as benchmarks for assessing the adequacy of the proposed model relative to the empirical data.

This analytical approach allows for the simultaneous examination of multiple latent constructs and measurement errors, making it particularly suitable for capturing the complex nature of AI's impact on higher education.

4. Research Findings

4.1. Descriptive Statistics of the Survey Sample

Before proceeding to model analysis, the demographic characteristics and technology usage patterns of the research sample are summarized in Table 1.

A clear understanding of sample characteristics helps contextualize the findings, particularly with respect to issues related to the digital divide and differences across disciplinary clusters.

Table 1. Descriptive Statistics of the Research Sample ($N_{\text{Total}} = 710$).

Characteristics	Category	Lecturer Sample ($N = 270$)	Percentage (%)	Student Sample ($N = 440$)	Percentage (%)
Gender	Male	145	53.7%	210	47.7%
	Female	125	46.3%	230	52.3%
Age	Under 22	0	0.0%	410	93.2%
	23-35	75	27.8%	30	6.8%
	36-50	160	59.3%	0	0.0%
	Over 50	35	12.9%	0	0.0%
Geographical area	Hanoi & Ho Chi Minh City (Large urban areas)	190	70.4%	280	63.6%
	Da Nang & other provinces (Medium/small cities)	80	29.6%	160	36.4%

Characteristics	Category	Lecturer Sample (N = 270)	Percentage (%)	Student Sample (N = 440)	Percentage (%)
Disciplinary cluster	Natural Sciences & Engineering (STEM)	100	37.0%	180	40.9%
	Social Sciences & Humanities (SSH)	90	33.3%	150	34.1%
	Economics & Management	80	29.7%	110	25.0%
AI experience	Never used	30	11.1%	25	5.7%
	Basic (ChatGPT, Grammarly, etc.)	150	55.6%	300	68.2%
	Advanced (Coding, APIs, data analysis)	90	33.3%	115	26.1%

The descriptive statistics presented in Table 1 go beyond a simple demographic overview to highlight critical patterns regarding technology adoption behaviors in Vietnam.

First, regarding technology access, the data reveals a distinct generational gap. The proportion of students using AI at a basic level (e.g., ChatGPT and other Generative AI tools) stands at 68.2%, substantially higher than the 55.6% observed among lecturers. This disparity aligns with the generational characteristics outlined by Pham et al. (2021), who describe today's students as "digital natives" capable of rapidly adapting to emerging tools. In contrast, lecturers appear to function more as "digital immigrants," adopting technology at a more measured pace but often with greater depth. This distinction is corroborated by the figures for advanced AI usage (e.g., programming, research data analysis), where lecturers actually surpass students (33.3% versus 26.1%). These findings suggest a qualitative difference in usage: while students tend to leverage AI for immediate task completion, lecturers are increasingly integrating these tools into research and advanced professional development.

Second, the data underscores the reality of the digital divide. The sample distribution is heavily concentrated in major urban centers, with Hanoi and Ho Chi Minh City accounting for over 60–70% of respondents, while representation from other provinces remains considerably lower. When viewed alongside the finding that 11.1% of lecturers and 5.7% of students have never used AI, these results reinforce the warnings raised by Abboud et al. (2020) and UNICEF (2022) regarding technological inequality in Vietnam. It appears that lecturers and students in non-central regions may continue to face infrastructural or access barriers, placing them at risk of being left behind in the digital era.

Third, the sample exhibits a relatively even gender balance (Lecturers: 53.7% male / 46.3% female; Students: 47.7% male / 52.3% female). This balance is critical for controlling potential gender-related variations, particularly in light of studies by Otterbacher et al. (2017) regarding gender bias in AI. Ensuring such representation helps confirm that the study's findings are not distorted by gender-specific effects.

4.2. Assessment of Reliability and Convergent Validity of Measurement Scales (Measurement Model)

The next step involves evaluating the reliability and validity of the measurement scales using Confirmatory Factor Analysis (CFA). According to the criteria proposed by Hair et al. (2019) measurement scales are considered acceptable when Cronbach's Alpha > 0.7, Composite Reliability (CR) > 0.7, and Average Variance Extracted (AVE) > 0.5.

4.2.1. Measurement Model Results for the Lecturer Sample

The lecturer measurement model focuses on the following constructs: Digital Competence, AI Acceptance, Teaching Innovation, and Teaching Performance.

Table 2. Reliability and convergent validity assessment - Lecturer sample (N = 270).

Latent construct	Indicator	Factor loading (λ)	Cronbach's Alpha	CR	AVE
Digital Competence (DIG_COMP) (Based on UNESCO (2023b))	DC1	0.82	0.892	0.901	0.694
	DC2	0.85			
	DC3	0.79			
	DC4	0.86			
AI Acceptance (AI_ACC) (Based on Sugandini et al. (2021))	ACC1	0.78	0.854	0.859	0.605
	ACC2	0.81			
	ACC3	0.74			
	ACC4	0.76			
Teaching Innovation (INN_TEA) (Based on Garcez et al. (2022))	INN1	0.88	0.915	0.918	0.738
	INN2	0.90			
	INN3	0.84			
	INN4	0.82			
Teaching Performance (PERF) (Based on Arifin and Sukmawidjaya (2020))	PER1	0.79	0.876	0.881	0.649
	PER2	0.83			
	PER3	0.81			
	PER4	0.79			

Table 2 presents the reliability and convergent validity assessment for the lecturer sample. The results confirm high reliability and strong convergent validity, validating the application of internationally established measurement scales within the Vietnamese context.

The Teaching Innovation (INN_TEA) construct stands out, achieving the highest indices in the model (Cronbach's Alpha = 0.915; CR = 0.918; AVE = 0.738). Factor loadings for its observed variables were consistently robust (ranging from 0.82 to 0.90), with INN2 exhibiting the strongest loading. This suggests a cohesive understanding among Vietnamese lecturers regarding the concept of "innovation." The strong consensus on items

related to using AI for redesigning lectures or creating interactive activities supports the argument by Garcez et al. (2022) concerning the role of digital transformation in reshaping academic pillars.

Similarly, the Digital Competence (DIG_COMP) construct yielded a strong AVE (0.694), indicating that the scale derived from UNESCO (2023b) effectively captures lecturers' capabilities. In contrast, AI Acceptance (AI_ACC) recorded the lowest AVE (0.605). While this figure remains well above the acceptable threshold (> 0.5), the lower variance may reflect the novel and dynamic nature of AI. It is likely that acceptance is influenced by a range of external factors, such as ethical concerns or technical complexity, which introduce greater variability compared to more established constructs.

4.2.2. Measurement Model Results for the Student Sample

The student model focuses on user experience, encompassing Perceived Usefulness, Personalization, Ethical Risk, and Overall Learning Experience.

Table 3. Reliability and convergent validity assessment - Student sample ($N = 440$).

Latent construct	Indicator	Factor loading (λ)	Cronbach's Alpha	CR	AVE
Perceived Usefulness (PU) (Based on Sugandini et al. (2021))	PU1	0.81	0.883	0.887	0.665
	PU2	0.84			
	PU3	0.79			
Personalization (PERS) (Based on Christudas et al. (2018))	PL1	0.86	0.901	0.905	0.706
	PL2	0.88			
	PL3	0.83			
	PL4	0.78			
Ethical Risk (ETHIC) (Based on Holmes et al. (2022))	RISK1	0.85	0.845	0.852	0.658
	RISK2	0.76			
	RISK3	0.82			
Learning Experience (EXP) (Based on Ouyang et al. (2022))	EXP1	0.77	0.864	0.869	0.624
	EXP2	0.80			
	EXP3	0.82			
	EXP4	0.75			

Table 3 presents the reliability and convergent validity assessment for the student sample. As shown, the measurement scales demonstrated robust reliability. Among these, *Personalization* (PERS) was particularly notable, achieving a high AVE of 0.706. This suggests that for Vietnamese students, the ability to tailor learning content is the most distinct and valued feature of AI. This observation resonates with earlier findings by Christudas et al. (2018) and George and Lal (2019), confirming that students place a premium on AI's capacity to facilitate a departure from the traditional "one-size-fits-all" instructional model.

Similarly, the *Ethical Risk* (ETHIC) construct showed high internal consistency (Cronbach's Alpha = 0.845), implying that student perceptions regarding potential risks are relatively uniform. The consistently high factor loadings (ranging from 0.76 to 0.85) further indicate that concerns regarding plagiarism, information inaccuracies, and data privacy, as highlighted by Holmes et al. (2022), are not merely isolated worries. Instead, they constitute a coherent psychological construct that significantly shapes student attitudes toward AI.

4.3. Model Fit Analysis

Prior to hypothesis testing, the goodness of fit of the structural models was assessed. Table 4 compares the model fit indices for both the Lecturer and Student models against recommended thresholds proposed by Byrne (2016).

Table 4. Structural model fit indices.

Index	Recommended threshold (Byrne, 2016)	Lecturer model	Student model	Evaluation
Chi-square/df (CMIN/df)	< 3.0 (Good); < 5.0 (Acceptable)	2.143	2.351	Good
GFI (Goodness of Fit Index)	> 0.90	0.924	0.912	Good
CFI (Comparative Fit Index)	> 0.90 (Good); > 0.95 (Very good)	0.956	0.948	Very good
TLI (Tucker-Lewis Index)	> 0.90	0.941	0.935	Good
RMSEA	< 0.08 (Good); < 0.05 (Very good)	0.048	0.052	Good
SRMR	< 0.08	0.039	0.041	Good

Assessing model fit is a fundamental step in establishing the validity of the study's conclusions. As detailed in Table 4, both the Lecturer and Student models demonstrate an excellent fit with the empirical data. Specifically, the CMIN/df ratios range between 2.0 and 2.5, well below the threshold of 3.0, indicating that the sample size is adequate and the models are free from issues of overfitting or underfitting.

The RMSEA indicators are particularly encouraging, standing at 0.048 for the lecturer model and 0.052 for the student model. Drawing on Byrne (2016), who classifies RMSEA values below 0.05 as a "close fit," these figures suggest that the proposed theoretical models accurately reflect the underlying data structure. Consequently, these results validate the applicability of the Technology Acceptance Model (TAM) and digital competence frameworks within the Vietnamese higher education context. Furthermore, the fact that the CFI exceeds 0.95 in the lecturer model serves as additional evidence for the robustness of the hypothesized structural relationships.

4.4. Structural Model Hypothesis Testing

Hypotheses were tested using the Bootstrapping technique with 2,000 resamples to assess the robustness of parameter estimates and determine statistical significance (p-values).

4.4.1. Lecturer Model Results

The lecturer's structural model examines the impact chain: Competence → Acceptance → Innovation → Performance.

Table 5. Hypothesis Testing Results - Lecturer Model.

Hypothesis	Path	Standardized β	S.E.	C.R.	P-value	Conclusion
H1	Digital Competence → AI Acceptance	0.452	0.051	8.214	***	Supported
H2	AI Acceptance → Teaching Innovation	0.521	0.063	9.152	***	Supported
H3	Digital Competence → Teaching Innovation	0.284	0.058	4.671	***	Supported
H4	Teaching Innovation → Teaching Performance	0.615	0.072	10.325	***	Supported
H5	AI Acceptance → Teaching Performance	0.153	0.065	2.140	0.032	Supported (Weak)

Note: *** $p < 0.001$. Final dependent variable: Teaching Performance.

Table 5 details the core findings regarding the lecturer group, elucidating the specific mechanisms through which AI impacts teaching performance. A primary insight from the analysis is the full mediating role of Teaching Innovation. The results indicate that the direct relationship between AI Acceptance and Teaching Performance (H5) is relatively weak ($\beta = 0.153$) and only marginally significant ($p = 0.032$). By contrast, the indirect pathway via Teaching Innovation (H2 → H4) is substantially stronger, with the combined indirect effect exceeding $\beta = 0.30$. Notably, the relationship between Teaching Innovation and Teaching Performance (H4) represents the strongest effect in the model ($\beta = 0.615$).

This statistical evidence underscores a fundamental pedagogical principle in the digital era: the mere presence of technology does not automatically lead to improvements in educational quality. When lecturers simply accept AI, such as using ChatGPT to accelerate lesson preparation while maintaining conventional instructional approaches, the resulting impact on teaching performance remains limited. Meaningful performance gains emerge only when AI adoption is accompanied by pedagogical innovation, including shifts toward project-based learning, the personalization of learning tasks, or the use of AI as a virtual teaching assistant. This finding aligns closely with Reich (2020) argument in *Failure to Disrupt*, which emphasizes that technology must be tightly integrated with pedagogical change to generate substantive educational impact.

Furthermore, the findings identify Digital Competence as a foundational antecedent. Hypothesis H1 confirms that Digital Competence exerts a significant positive effect on AI Acceptance ($\beta = 0.452$), indicating that competence is a prerequisite for meaningful AI adoption. Lecturers are unlikely to effectively utilize or integrate AI tools without a sufficient level of digital understanding and control. This result is consistent with prior studies by Nelly et al. (2024) and Niță and Guțu (2023), which highlight digital competence as a fundamental driver within the performance formation process.

4.4.2. Student Model Results

The student model examines how perceived usefulness and ethical risk influence learning experience.

Table 6. Hypothesis Testing Results - Student Model.

Hypothesis	Path	Standardized β	S.E.	C.R.	P-value	Conclusion
S1	Perceived Usefulness → Personalization	0.584	0.042	11.450	***	Supported
S2	Perceived Ease of Use → Personalization	0.341	0.055	6.230	***	Supported
S3	Personalization → Learning Experience	0.652	0.061	12.015	***	Supported
S4	Ethical Risk → Trust in AI	-0.410	0.053	-7.882	***	Supported
S5	Ethical Risk → Learning Experience	-0.125	0.048	-2.564	0.010	Supported

Note: Final dependent variable: Learning Experience. *** indicates $p < 0.001$.

Table 6 presents the hypothesis testing results for the student model, revealing a clear contrast between the opportunities offered by AI and the challenges it introduces. On the positive side, Personalization emerges as the most influential factor, exerting the strongest effect on Learning Experience ($\beta = 0.652$; S3). This finding confirms that the primary value Vietnamese students derive from AI lies in its capacity to address individual learning needs. This relationship is strongly shaped by Perceived Usefulness (S1; $\beta = 0.584$), indicating that students approach AI from a highly pragmatic perspective, prioritizing its ability to solve complex problems and curate relevant learning materials (Christudas et al., 2018).

However, this positive orientation is moderated by substantial concerns. Ethical Risk demonstrates a strong negative effect on Trust in AI ($\beta = -0.410$; S4), suggesting that students are far from naïve in their engagement with technology. They exhibit a high level of awareness regarding the risks identified by Noble (2018) and Holmes et al. (2022), including plagiarism, misinformation (hallucinations), and algorithmic bias. This adverse effect extends to the overall Learning Experience (S5), creating a noticeable psychological tension: while students are attracted to the convenience of AI, they remain cautious about its potential drawbacks. These findings underscore the critical importance of implementing clear ethical guidance, as recommended by UNESCO (2023f) to support and reassure learners.

4.5. Multi-Group Analysis (MGA)

To further elucidate the nuanced impacts of AI, a Multi-Group Analysis (MGA) was conducted to compare two major student groups: STEM ($N(\text{M})=180$) and Social Sciences and Humanities (SSH) ($N(\text{M})=150$).

Table 7. Multi-Group Analysis Results (STEM vs. SSH).

Path	β (STEM)	β (SSH)	$\Delta\chi^2$	P-value (Invariance)	Interpretation
Usefulness \rightarrow Personalization	0.725	0.453	12.452	0.001	Significant difference
Ethical Risk \rightarrow Learning Experience	-0.082 (ns)	-0.254	8.305	0.004	Significant difference
Personalization \rightarrow Learning Outcome	0.681	0.623	1.201	0.273	No significant difference

Note: ns = non-significant.

The Multi-Group Analysis (MGA) reveals distinct and meaningful disciplinary differences in the impact of AI. First, a clear STEM advantage emerges with respect to Perceived Usefulness. STEM students exhibit a substantially stronger association between Perceived Usefulness and Personalization ($\beta = 0.725$) than their counterparts in the Social Sciences and Humanities (SSH) ($\beta = 0.453$). This difference is statistically significant ($\Delta\chi^2 = 12.452$, $p = 0.001$), likely reflecting the functional characteristics of contemporary AI tools. Applications such as GitHub Copilot and Alpha Geometry (MIT Technology Review, 2024; Trinh et al., 2024) are particularly effective in delivering precise, task-specific support for programming, mathematics, and engineering tasks. In contrast, AI systems remain limited in their capacity to address the cultural, linguistic, and affective dimensions that are central to SSH disciplines.

Second, the analysis indicates a higher level of ethical sensitivity among SSH students. In contrast to the usefulness pathway, SSH students demonstrate a significant negative relationship between Ethical Risk and Trust in AI ($\beta = -0.254$), whereas this relationship is non-significant within the STEM group. Given that SSH students frequently engage in activities such as essay writing and literary analysis, where originality and authorship are essential concerns related to plagiarism and the “colonization” of knowledge by AI (Avraamidou, 2024) are understandably more pronounced. These results suggest that institutional AI policies should not adopt a uniform, “one-size-fits-all” approach but instead be tailored to the specific ethical and pedagogical contexts of different academic disciplines.

5. Discussion

5.1. Digital Competence and Leadership: Prerequisites for Pedagogical Transformation

The hypothesis testing results for the lecturer group underscore a critical reality: Technology itself does not generate educational innovation; rather, its impact is determined by the competence of those who wield it. The strong positive relationship between Digital Competence and AI Acceptance ($\beta = 0.452$), combined with the decisive effect of Teaching Innovation on Teaching Performance ($\beta = 0.615$), provides compelling empirical support for the arguments advanced by Nelly et al. (2024) and Niță and Guțu (2023). These scholars contend that, in the digital era, the lecturer’s role is not diminished but elevated, requiring a sophisticated integration of disciplinary expertise and technological proficiency.

This insight is particularly salient in the Vietnamese context, where digital transformation initiatives have often emphasized hardware and software acquisition while underestimating the human dimension. As cautioned by Arifin and Sukmawidjaya (2020), without adequate competency development, externally imposed technological adoption may become counterproductive, ultimately constraining rather than enhancing teaching performance.

Furthermore, these findings indirectly underscore the pivotal role of institutional leadership and macro-level policy. Identifying Digital Competence as a key antecedent variable highlights the urgent need for standardized competency frameworks, as recommended by UNESCO (2023b) and the OECD (2021). Within Vietnamese universities, professional development must extend beyond basic technical training, such as operating ChatGPT or a learning management system, to foster genuine digital pedagogical thinking. This includes the ability to design interactive learning experiences, critically evaluate AI-generated content, and leverage data for informed pedagogical decision-making. Without a corresponding shift in leadership mindset and a firm managerial commitment to innovation, as emphasized by Garcez et al. (2022) and Zhu and Jin (2023), lecturers are unlikely to overcome psychological inertia or achieve meaningful pedagogical transformation.

5.2. A Revolution in Learner Experience and the Rise of Generative AI

From the student perspective, the SEM results identify Personalization as the most powerful predictor of a positive Learning Experience ($\beta = 0.652$). This finding aligns with international evidence reported by Christudas et al. (2018), George and Lal (2019), and Huang et al. (2020), confirming a global shift from standardized, “one-size-fits-all” education toward adaptive learning paradigms. In Vietnam, this transition is particularly critical given the large class sizes common in major universities, which often limit lecturers’ capacity to address individual learner needs.

The emergence of generative AI tools such as ChatGPT has partially mitigated this constraint by functioning as continuous, on-demand virtual tutors. Mathew (2023) and Baidoo-Anu and Ansah (2023) characterize these technologies as “game changers,” enabling students to exercise greater autonomy in knowledge construction and problem-solving.

However, the multi-group analysis (Table 7) reveals a pronounced disciplinary divergence: students in STEM fields perceive the value of personalization significantly more strongly than their peers in the Social Sciences and Humanities (SSH). This disparity likely reflects the rapid advancement of AI models in logic- and mathematics-intensive domains, as illustrated by systems such as Alpha Geometry (MIT Technology Review, 2024; Trinh et al., 2024), which provide highly accurate solutions to technical problems. By contrast, although SSH students benefit from AI’s capacity for information synthesis, they continue to encounter limitations when addressing tasks requiring emotional sensitivity, cultural contextualization, or local linguistic nuance. This finding reinforces the recommendation by Bui et al. (2021) that both technology developers and educators in Vietnam prioritize context-specific data models aligned with local cultural and linguistic realities to ensure equitable benefits across disciplines.

5.3. Digital Divide, Ethical Risks, and Assessment Challenges

Beyond its benefits, the empirical evidence issues a clear warning regarding the potential risks associated with AI adoption. The significant negative effect of Ethical Risk on Trust in AI and Learning Experience ($\beta = -0.410$) indicates that Vietnamese students experience a pronounced sense of ambivalence: they are attracted to the convenience of AI while remaining deeply concerned about its implications.

The first major issue concerns the exacerbation of the digital divide. Demographic data (Table 1) indicate a strong concentration of AI usage within major urban centers, contrasted with markedly limited access in rural areas. This pattern corroborates concerns raised by Abboud et al. (2020), Božić (2023), and Li (2023) regarding the intensification of educational inequality. If advanced AI infrastructure and premium tools remain accessible primarily to students with greater economic capital, higher education risks undermining its traditional role as a mechanism for social mobility. Both UNICEF (2022) and the Global Education Monitoring Report (2023) emphasize that, in the absence of timely policy interventions targeting disadvantaged regions, AI may further entrench existing disparities.

The second, and arguably most complex, challenge relates to academic ethics and algorithmic bias. King (2023) and Corbin et al. (2025) raise a fundamental question of academic integrity: at what point does AI-assisted learning cross the boundary into misconduct? Students report significant anxiety regarding the risk of unjust plagiarism accusations or cognitive over-reliance on automated systems (Crawford et al., 2024; Lo, 2023). Moreover, concerns about algorithmic bias (Noble, 2018; Otterbacher et al., 2017) and knowledge colonization (Avraamidou, 2024) threaten core principles of diversity and epistemic equity. As indicated by the multi-group analysis, SSH students are particularly sensitive to these issues, expressing fears that large language models trained predominantly on Western-centric data may distort local cultural values or generate biased and misleading outputs (hallucinations).

Finally, the environmental footprint of AI constitutes a broader ethical concern. Although not a primary focus for respondents in this study, research by De Vries (2023) and Luccioni et al. (2023) on the carbon costs of AI highlights the responsibility of universities to align technological innovation with sustainable development goals. Integrating AI into higher education should therefore be understood not solely as a matter of efficiency, but also as an issue of social and environmental accountability.

Taken together, these findings indicate that AI adoption in Vietnamese higher education has reached a critical inflection point, necessitating a balanced approach that maximizes technological potential while rigorously safeguarding the humanistic foundations of education.

6. Conclusions

This quantitative study, based on a sample of 710 lecturers and students from leading Vietnamese universities, provides robust empirical evidence on the multidimensional impacts of Artificial Intelligence (AI) in higher education. The Structural Equation Modeling (SEM) results demonstrate that AI has progressed beyond a speculative trend to become a tangible driver of educational change, exerting significant positive effects on lecturers' pedagogical innovation and students' personalized learning experiences.

For lecturers, Digital Competence emerges as the pivotal determinant of effective AI utilization; AI enhances teaching performance only when it functions as a catalyst for pedagogical restructuring rather than as a mechanical substitute. For students, personalization represents AI's most salient contribution, supporting a transition from mass education toward adaptive learning models.

Nevertheless, this transformation is uneven. The findings reveal substantial disciplinary disparities favoring STEM fields, alongside persistent psychological and ethical barriers associated with academic integrity and the digital divide. Ultimately, these concerns constrain trust and limit the full adoption of AI among both lecturers and students, underscoring the need for context-sensitive, ethically grounded, and equity-oriented AI policies in Vietnamese higher education.

7. Recommendations

Drawing on the research findings and aligning with established international frameworks, this study proposes specific recommendations for three key stakeholder groups.

First, for policymakers and the Ministry of Education and Training, the immediate priority must be the establishment and promulgation of a clear legal and regulatory framework regarding AI ethics in education. To be effective, this framework should be anchored in human-centered principles as articulated in UNESCO's Guidance for Policymakers (UNESCO, 2021a) and Guidance for Generative AI in Education and Research UNESCO (2023f), with the specific aim of clearly delineating the boundary between legitimate technological support and academic misconduct. Furthermore, to address the inequalities identified in this study, the government should implement targeted investment packages for digital infrastructure in disadvantaged regions. This is essential to ensure equitable access to technology for all students, consistent with the recommendations set forth by UNICEF (2022).

Second, for universities, there is a pressing need to transition from traditional governance models toward data-driven management. Institutions should act promptly to integrate AI literacy courses into the formal curricula for both lecturers and students. As recommended by Chiu et al. (2023), the objective of such training must extend beyond mere tool usage; it should cultivate the critical thinking skills necessary for users to evaluate, govern, and responsibly control AI technologies, thereby directly mitigating ethical concerns.

Third, regarding lecturers and students, a shift in professional and academic roles is required. Lecturers should redefine their function by viewing AI as a "copilot" that handles repetitive tasks, thereby freeing them to focus on developing higher-order student competencies that AI cannot easily replace, such as critical thinking, creativity, and emotional intelligence. Students, in turn, should proactively employ AI as a learning assistant but must strictly maintain their intellectual independence, avoiding the pitfalls of overreliance and passive learning.

8. Limitations

Despite its contributions, the study has several limitations. Owing to its cross-sectional design and the geographic scope limited to three major cities (Hanoi, Ho Chi Minh City, and Da Nang), the generalizability of the findings to local and regional universities remains constrained. Future research should expand the sample to include

institutions in other provinces and adopt longitudinal research designs to track changes in user attitudes and behaviors over time, particularly in the context of the rapidly evolving AI landscape.

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