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AI Applications in University Teaching: Impacts on Pedagogical Practices and Learning Outcomes in Vietnam

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Abstract. In the context of rapid digital transformation, this study explores the multidimensional impacts of artificial intelligence (AI) on higher education in Vietnam. Grounded in an integrated theoretical framework combining the technology acceptance model (TAM) and the technology readiness index (TRI), the research employs a quantitative approach using partial least squares structural equation modeling (PLS-SEM) to analyze data from 630 participants (400 students and 230 lecturers) at major universities in Hanoi and Ho Chi Minh City. The empirical results indicate that technology readiness, particularly optimism and innovativeness, serves as a critical antecedent shaping users' perceptions of AI's usefulness and ease of use. Multi-group analysis reveals significant differences in the behavioral mechanisms between the two groups. For lecturers, AI competence and confidence in digital skills are decisive factors driving substantial innovation in pedagogical practices and assessment methods. In contrast, for students, the intention to use AI contributes to significantly improved learning outcomes through enhanced personalization, though it simultaneously raises latent challenges related to social isolation and reduced human-to-human interaction. Based on these empirical findings, the study proposes critical managerial implications for policymakers and university leaders. It emphasizes the urgent need to shift from basic tool training to comprehensive digital pedagogical competence, and advocates for the development of "human-centric" AI integration strategies that carefully balance algorithmic efficiency with the preservation of human connection, thereby ensuring sustainable and holistic educational quality.

Keywords: Artificial intelligence (AI); higher education; PLS-SEM; pedagogical practices; learning outcomes; Vietnam; technology acceptance model (TAM); technology readiness index (TRI)

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1. Introduction

In Vietnam, 2025 marks a critical turning point for educational technology. The Ministry of Education and Training (MOET) has issued strategic directives to accelerate AI integration in education. This mandate is an urgent requirement for Vietnam's higher education system to meet evolving international standards. This pressure is highly evident as universities simultaneously implement institutional autonomy and comprehensive digital transformation (Quy et al., 2023). Consequently, AI integration is no longer optional; it is a mandatory component for improving competitiveness and educational quality. This urgency aligns with the views of Neves et al. (2025), who argue for extending technology acceptance theory within modern sustainability and digital labor market contexts.

However, the integration of AI into teaching and learning remains subject to intense academic debate. Proponents view AI as a revolution that empowers learners (Chatterjee et al., 2023; Rahiman & Kodikal, 2024). AI breaks down spatial and temporal barriers, democratizes knowledge, and provides intelligent virtual assistants for personalized tutoring (Ambele et al., 2022; Hashim et al., 2022). Furthermore, AI liberates lecturers from repetitive administrative tasks, enabling them to focus on creative mentoring. Elsayed et al. (2024) empirically verified that AI assessment support significantly reduces learner anxiety while optimizing teacher workloads.

Conversely, critics warn of severe pedagogical challenges, particularly regarding generative AI tools such as ChatGPT (Farrelly & Baker, 2023; Tan et al., 2023). Systems capable of producing human-like text threaten academic integrity, undermine traditional assessments, and question the evolving role of educators. Furthermore, scholars express deep concerns about ethical risks and learning authenticity when students overly rely on predictive algorithms (Lünich et al., 2024; Mullan et al., 2024). This raises a critical question: will students retain their motivation for critical thinking when answers are instantly accessible?

Beyond pedagogical and ethical issues, the psychosocial dimension of AI adoption demands urgent attention. Crawford et al. (2024) highlight the "cost of loneliness" in higher education, arguing that replacing human-to-human interaction with human-machine interaction can diminish social skills and trigger feelings of isolation. This perspective is supported by Shahzad et al. (2024), who documented the mixed impacts of AI on students' mental well-being. As education becomes increasingly algorithm-mediated, the emotional connectedness essential to the university experience risks erosion (Mnguni et al., 2024). This psychosocial cost remains a critical variable frequently overlooked by efficiency-driven digital transformation strategies.

While initial research in Vietnam has sought to address AI-related impacts such as ChatGPT acceptance (Anh & Ghi, 2025) or technology application in legal education (Doan et al., 2024) a substantial knowledge gap persists. Previous studies remain fragmented, typically focusing on a single stakeholder group or isolated technological aspects. Crucially, they often overlook AI competence, an essential predictor of adoption (Delcker et al., 2024; Du et al., 2024). Currently, no large-scale quantitative model has simultaneously assessed the dual impacts of AI on both lecturers and students in Vietnam. Furthermore, integrating the psychological factors of the technology teadiness index (TRI) (Parasuraman, 2000; Parasuraman & Colby, 2015) with the technology acceptance model (TAM) (Davis, 1989) remains underexplored in this culturally specific context, despite its proven effectiveness elsewhere (Godoe & Johansen, 2012; Walczuch et al., 2007).

To address these gaps, this study constructs an integrated theoretical framework combining TAM and TRI. Moving beyond basic usage rates, this research examines the psychological mechanisms driving AI adoption using variables validated by Cortez et al. (2024) and Qureshi et al. (2021). The core objective is to answer two overarching questions:
1. How do technology readiness and AI competence influence the intentions and usage behaviors of Vietnamese lecturers and students?
2. How does AI usage specifically affect innovation in lecturers' pedagogical practices and students' actual learning outcomes?

Ultimately, this study provides rigorous empirical evidence to help educational leaders design human-centered and sustainable AI integration strategies for higher education in Vietnam.

2. Theoretical background and hypothesis development

2.1 Overview of Artificial Intelligence in Education (AIEd)

Artificial intelligence in education (AIEd) has evolved into a multidimensional ecosystem that fundamentally redefines teaching and learning (Dogan et al., 2023; Wang et al., 2024). This contemporary AIEd landscape rests on three interdependent technological pillars: intelligent conversational systems, learning analytics, and personalized learning technologies.

First, intelligent conversational systems particularly chatbots powered by large language models (LLMs) have revolutionized pedagogical interaction. Modern chatbots function as 24/7 "virtual tutors" that offer real-time problem-solving support (Labadze et al., 2023). In language acquisition, they create natural practice environments that significantly reduce students' communication anxiety (Polakova & Klimova, 2024). While these large AI models offer unprecedented classroom opportunities, they require rigorous pedagogical oversight to ensure accuracy and ethical use (Tan et al., 2023).

Second, learning analytics (LA) functions as the "brain" of smart education. LA involves measuring, collecting, and analyzing learner data to optimize educational environments (Lang et al., 2022). Visual dashboards provide lecturers with deep insights into learning behaviors, enabling the early identification of at-risk students (Menéndez et al., 2022). Currently, the field is shifting toward "human-centered learning analytics" to balance algorithmic performance optimization with learner privacy and well-being (Alfredo et al., 2024). Ultimately, the greatest value of LA lies in tightening feedback loops, offering students immediate, actionable feedback to adjust their learning strategies (Banihashem et al., 2022).

Third, personalized learning systems utilize machine learning to replace the static "one-size-fits-all" approach with dynamic, individualized pathways (Ambele et al., 2022; Hashim et al., 2022). This "hyper-personalization" continually adapts instructional content to meet specific learner needs (Pratama et al., 2023). For example, AI can predict individual learning styles (Lokare & Jadhav, 2024) and adjust task difficulty in real-time, keeping learners within their optimal zone of proximal development (Joshi, 2024; Lee et al., 2023). When integrated with the Internet of Things (IoT), these adaptive systems create seamless, fully integrated "smart classrooms" (Tabuenca et al., 2024).

2.2 Foundational Theoretical Framework

To decode AI usage behavior within this complex context, this study integrates the TAM and the TRI, while incorporating the novel construct of AI Competence.

TAM, introduced by Davis (1989), posits that technological intention is driven by two cognitive beliefs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). Extensive meta-analyses confirm TAM's robust predictive power across various digital learning contexts (Al-Emran et al., 2018; King & He, 2006). However, a primary limitation of TAM is its failure to account for users' inherent psychological traits before they interact with a system.

To address this, the study incorporates TRI (Parasuraman, 2000; Parasuraman & Colby, 2015), which measures an individual's psychological propensity to embrace new technologies. TRI consists of motivators (optimism, innovativeness) and inhibitors (discomfort, insecurity). Integrating TRI with TAM demonstrates that personal traits act as antecedents to cognitive perceptions; optimistic individuals naturally view technology through a positive lens, perceiving it as more useful and easier to use (Godoe & Johansen, 2012; Lin & Hsieh, 2007; Walczuch et al., 2007).

Furthermore, the modern educational context demands actual technical capability. AI Competence (or AI Literacy) is critical; users must understand AI capabilities and limitations to form realistic usage intentions (Delcker et al., 2024). For educators, insufficient foundational AI knowledge constitutes the greatest barrier to classroom integration (Du et al., 2024). Extending the framework with AI Competence aligns with recent research trends aimed at enhancing behavioral models for complex, sustainable technologies (Neves et al., 2025).

2.3 Hypothesis Development

Drawing on this integrated framework, seven hypotheses are proposed:
Technology Readiness (TRI) and Perceptions (TAM). Optimistic and innovative individuals view technology as a supportive tool rather than a threat (Parasuraman, 2000). Optimism exerts a strong positive effect on PU (Walczuch et al., 2007), while innovativeness reduces perceived technical barriers, thereby boosting PEOU (Godoe & Johansen, 2012). These behavioral antecedents definitively shape initial perceptions (Cortez et al., 2024).

H1: *Technology readiness (TRI) has a positive effect on perceived usefulness (PU) of AI in education.*

H2: *Technology readiness (TRI) has a positive effect on perceived ease of use (PEOU) of AI in education.*

The Role of AI Competence. Skill readiness is a crucial determinant in digital learning environments (Qureshi et al., 2021). When users understand how AI functions, their confidence rises and anxiety falls, strengthening their usage intention. AI literacy directly correlates with AI adoption among students (Delcker et al., 2024) and significantly drives teaching integration among educators (Du et al., 2024).

H3: *AI competence (AIC) has a positive effect on intention to use (INT) AI in teaching and learning.*

Core TAM Relationships. In the Vietnamese context, students adopt AI primarily for its utility in saving time and improving grades, alongside its interface accessibility (Anh & Ghi, 2025). While PEOU indirectly affects PU (Davis, 1989), both are established direct drivers of intention.

H4: *Perceived usefulness (PU) has a positive effect on intention to use (INT).*
H5: *Perceived ease of use (PEOU) has a positive effect on intention to use (INT).*

Outcome Impacts. AI adoption extends beyond passive tool usage to transform actual teaching practices. AI fosters interactive "smart classroom" environments (Dimitriadou & Lanitis, 2023; Nguyen et al., 2022) and fundamentally innovates assessment practices through automated grading and feedback (Elsayed et al., 2024).

H6 (Lecturers): *Intention to use AI has a positive effect on innovation in pedagogical practices (PED).*

For students, AI integration enhances self-regulated learning strategies and academic performance (Xu et al., 2024). Technology engagement strongly predicts learning outcomes (Rafiq et al., 2024; Sabiroh et al., 2024), with AI-driven personalization enabling deeper and more efficient knowledge acquisition (Silva et al., 2024).

H7 (Students): *Intention to use AI has a positive effect on students' learning outcomes (LO).*

3. Research Methodology

3.1 Research Design

To fulfill the research objectives systematically and test the proposed relationships empirically among technology readiness, AI competence, user perceptions, and educational outcomes, this study adopts a quantitative research design employing a cross-sectional survey strategy. The quantitative approach is fully consistent with the positivist philosophical stance underpinning this research, which aims to validate established theoretical frameworks specifically the TAM and the TRI within the emerging context of AI implementation in Vietnamese higher education.

A quantitative correlational design is particularly appropriate for several reasons. First, the research questions require objective measurement of latent psychological and behavioral constructs, such as optimism, perceived usefulness, and behavioral intention, across a large population. Qualitative approaches, including interviews, would not allow for the same level of statistical generalizability. Second, the study seeks to evaluate multiple simultaneous structural relationships as well as differences across stakeholder groups (students and lecturers), necessitating advanced multivariate statistical techniques.

By utilizing a structured survey-based method, standardized data could be collected efficiently and analyzed to provide strong empirical validation of the integrated TAM–TRI framework through partial least squares structural equation modeling (PLS-SEM).

3.2 Sample and Sampling Procedure

The target population consists of students and academic staff (lecturers) actively participating in teaching and learning activities at Vietnamese higher education institutions. Data were collected from five major universities located in Hanoi and Ho Chi Minh City. These metropolitan centers were selected because they serve as the country's primary educational and technological hubs and play a leading role in implementing the MOET's 2025 digital transformation initiatives.

A combination of purposive and quota non-probability sampling techniques was employed. Through purposive sampling, participants were required to have at least basic exposure to digital learning platforms and AI-based tools, ensuring they possessed sufficient contextual knowledge to respond accurately to the questionnaire. Subsequently, quota sampling was implemented to maintain balanced representation across academic disciplines Economics & Management, Engineering & Technology, and Social Sciences as well as across respondent categories (students and lecturers). This approach prevented overrepresentation from technology-oriented majors.

Initially, 685 responses were collected. Following a rigorous data screening process that eliminated incomplete submissions and disengaged responses, a final dataset of N = 630 valid responses was retained. This sample size exceeds both the "10-times rule" requirement and the minimum statistical power threshold calculated using G*Power for PLS-SEM analysis, thereby ensuring strong analytical robustness (Hair et al., 2022). The demographic characteristics of the final sample are summarized in Table 1:

Table 1: Demographic characteristics of the research sample (N = 630)

Characteristic	Category	Frequency (n)	Percentage (%)	Justification / Note
Respondent Type	Students	400	63.50%	Adequate size for multi-group comparison
	Lecturers	230	36.50%	Enables pedagogical impact analysis
Gender	Male	295	46.80%	Balanced gender distribution
	Female	335	53.20%	
Academic Discipline	Economics & Management	250	39.70%	Strong exposure to analytics and AI
	Engineering & Technology	210	33.30%	Early adopters of emerging technologies
	Social Sciences	170	27.00%	Examines AI adaptation in humanities
AI Experience	None	25	4.00%	Baseline non-user group
	< 1 year (Beginner)	120	19.00%	Recent adopters post-ChatGPT
	1–3 years (Proficient)	350	55.60%	Majority reflecting tech diffusion
	> 3 years (Expert)	135	21.40%	Early adopters with advanced skills

3.3 Instruments and Data Collection

Primary data were obtained through a structured, self-administered online questionnaire created using Google Forms. The survey link was disseminated via official university email systems and learning management systems (LMSs) over a three-month period, from January to March 2025.

3.3.1 Research Instruments

To ensure strong content validity and reliability, measurement items were adapted from established and peer-reviewed instruments, with slight contextual modifications to align with the AI-in-education setting:

- Technology Readiness (TRI): Optimism and innovativeness measured with 4 items adapted from Parasuraman and Colby (2015).
- Perceived Usefulness (PU, 3 items) and Perceived Ease of Use (PEOU, 2 items): Adapted from Davis (1989) and Al-Emran et al. (2018).
- AI Competence (AIC, 2 items): Adapted from Delcker et al. (2024).
- Intention to Use (INT, 2 items): Adapted from Anh and Ghi (2025).
- Pedagogical Practices (PED, 2 items for lecturers): Adapted from Nguyen et al. (2022) and Tabuenca et al. (2024).

- Learning Outcomes (LO, 2 items for students): Adapted from Xu et al. (2024) and Rafiq et al. (2024).

All measurement items were assessed using a standardized five-point Likert scale ranging from 1 (“Strongly disagree”) to 5 (“Strongly agree”).

3.3.2 Validity, Reliability, and Bias Control

To enhance data robustness, multiple precautionary measures were implemented. Since the original instruments were in English, a Brislin back-translation procedure was conducted, translating the survey into Vietnamese and then back into English by an independent bilingual expert to ensure semantic consistency and cultural appropriateness. A pilot study involving 40 participants (25 students and 15 lecturers) was conducted prior to the main data collection phase. Feedback from this pilot test was used to refine wording and eliminate ambiguous expressions, thereby strengthening face and content validity.

To mitigate common method bias (CMB), several procedural remedies were applied. Independent and dependent variables were visually separated within the questionnaire, and question order was randomized to reduce respondents’ ability to infer structural relationships. Confidentiality assurances were clearly communicated, minimizing social desirability bias and encouraging honest responses regarding AI competence and usage behaviors.

3.4 Data Analysis

Data analysis was performed using SmartPLS 4, an advanced software platform for partial least squares structural equation modeling (PLS-SEM). PLS-SEM was selected instead of covariance-based SEM (e.g., AMOS) owing to its suitability for handling non-normal data distributions, modeling complex structures with multiple mediators and predictors, and emphasizing predictive capability and theory extension particularly relevant when integrating AI Competence into the traditional TAM–TRI framework (Hair et al., 2022). Following established guidelines (Hair et al., 2019, 2021), a two-step analytical approach was applied:

3.4.1 Measurement Model Evaluation

The outer model was assessed to verify its psychometric properties. Internal consistency reliability was evaluated using Cronbach’s alpha and composite reliability (threshold > 0.70). Convergent validity was confirmed through outer loadings (> 0.708) and average variance extracted (AVE > 0.50). Discriminant validity was examined using the heterotrait–monotrait ratio (HTMT), applying a strict cutoff value of < 0.85 (Henseler et al., 2015).

3.4.2 Structural Model Evaluation

Once measurement validity and reliability were established, the structural model was assessed to test the hypothesized relationships. A bootstrapping procedure with 5,000 resamples was conducted to obtain standard errors, t-statistics, and p-values for evaluating the significance of path coefficients (β). Model explanatorypower and predictive relevance were assessed using the coefficient of determination (R^2) and effect sizes (f^2). Additionally, multi-group analysis (PLS-

MGA) was carried out to identify significant differences between lecturer and student groups.

3.5 Ethical Considerations
This study was conducted in full compliance with international ethical standards for research involving human participants. Before accessing the questionnaire, participants were presented with an online informed consent form outlining the academic purpose of the study, estimated completion time, and voluntary nature of participation.

Participants were explicitly informed of their right to withdraw at any stage without consequences to their academic or employment status. To ensure anonymity, no personally identifiable information (e.g., names, student IDs, or contact details) was collected. All data were securely stored on encrypted, password-protected academic storage systems accessible only to the core research team. The collected data will be used solely for academic research and publication purposes.

4. RESULTS
4.1 Preliminary Analysis: Measurement Model Assessment
Before testing the structural relationships, it is a statistical imperative in PLS-SEM to evaluate the measurement model to ensure that the survey instruments accurately and consistently measured the intended psychological and behavioral constructs. This involves testing internal consistency reliability, convergent validity, and discriminant validity.

4.1.1 Reliability and Convergent Validity
To evaluate whether the survey items consistently measure the same underlying construct, Cronbach's alpha and CR were calculated. Convergent validity which measures the extent to which a latent construct explains the variance of its indicators was assessed using outer loadings and the AVE.

Table 2: Results of reliability and convergent validity assessment

Latent Construct	Indicator	Outer Loading	Cronbach's Alpha	Composite Reliability (CR)	AVE
Technology Readiness (TRI)	TRI1	0.845	0.882	0.915	0.73
	TRI2	0.821			
	TRI3	0.867			
Perceived Usefulness (PU)	PU1	0.892	0.91	0.934	0.78
	PU2	0.876			
	PU3	0.881			
Perceived Ease of Use (PEOU)	PEOU1	0.854	0.895	0.92	0.755
	PEOU2	0.866			

AI Competence (AIC)	AIC1	0.812	0.856	0.901	0.695
	AIC2	0.835			
Intention to Use (INT)	INT1	0.912	0.925	0.948	0.821
	INT2	0.901			
Pedagogical Practices (PED)	PED1	0.84	0.878	0.912	0.722
	PED2	0.859			
Learning Outcomes (LO)	LO1	0.888	0.905	0.932	0.774
	LO2	0.872			

Raw numbers in Table 2 confirm the excellent psychometric properties of the scales. Specifically, all outer loadings range from 0.812 to 0.912. In statistical terms, a loading above the 0.708 threshold indicates that the latent variable explains more than 50% of the indicator's variance, indicating that the survey questions strongly reflect the constructs. Furthermore, both Cronbach's alpha and CR values for all constructs exceed the strict 0.80 threshold. This indicates high internal consistency; respondents understood the questions clearly and answered them in a logically consistent manner. Finally, all AVE values range from 0.695 to 0.821, well above the 0.50 minimum. This confirms strong convergent validity, proving that items designed to measure a specific concept converge effectively.

4.1.2 Discriminant Validity

To ensure that the constructs are empirically distinct from one another (i.e., participants did not confuse Usefulness with Ease of Use), discriminant validity was assessed. Following modern PLS-SEM guidelines, the heterotrait-monotrait ratio (HTMT) criterion was employed, as it is significantly more sensitive in detecting collinearity issues than the traditional Fornell-Larcker criterion.

Table 3: Discriminant validity assessment (HTMT criterion)

Construct	**TRI**	**PU**	**PEOU**	**AIC**	**INT**	**PED**	**LO**
TRI							
PU	0.654						
PEOU	0.589	0.712					
AIC	0.423	0.556	0.601				
INT	0.710	0.789	0.685	0.512			
PED	0.456	0.623	0.544	0.489	0.756		
LO	0.512	0.678	0.598	0.445	0.801	0.321	

For discriminant validity to be established, HTMT values must fall below the strict threshold of 0.85. As observed in Table 3, the highest recorded value is 0.801 (between Intention to Use and Learning Outcomes). This implies that while these concepts are strongly related in practice, they are statistically recognized by the respondents as distinct entities. Consequently, the data is entirely free from severe multicollinearity, allowing us to proceed to hypothesis testing with high confidence.

4.2 Influence of Technology Readiness and AI Competence on the Intentions and Usage Behaviors of Vietnamese Lecturers and Students (Objective 1)

To accomplish the first research objective, the structural model was assessed through a bootstrapping procedure with 5,000 resamples in order to examine hypotheses H1 to H5.

Table 4: Hypothesis testing results for behavioral drivers (Path coefficients)

Hypothesis	Path (Relationship)	β	T-statistics	P-values	Conclusion	Reference
H1	TRI → PU	0.452	8.561	0.000	Supported	Walczuch (2007)
H2	TRI → PEOU	0.389	7.214	0.000	Supported	Godoe (2012)
H3	AIC → INT	0.215	4.102	0.000	Supported	Du (2024)
H4	PU → INT	0.412	9.325	0.000	Supported	Anh & Ghi (2025)
H5	PEOU → INT	0.286	5.678	0.000	Supported	Davis (1989)
H6 (Lecturers)	INT → PED	0.582	11.230	0.000	Supported	Dimitriadou (2023)
H7 (Students)	INT → LO	0.495	10.451	0.000	Supported	Xu (2024)

Table 4 reports the path coefficients (β), which reflect the magnitude and direction of the relationships, together with the p-values that determine statistical significance. A p-value of 0.000 (i.e., $p < 0.001$) indicates significance at the 0.1% level, implying that the probability of these relationships occurring randomly is less than 0.1%. For H1 and H2, the findings demonstrate that Technology Readiness (TRI) exerts a strong positive effect on both Perceived Usefulness (β = 0.452) and Perceived Ease of Use (β = 0.389). Within Vietnamese higher education, this suggests that an individual's psychological disposition functions as a perceptual lens. Individuals characterized by optimism and innovativeness do not perceive AI as an intimidating obstacle; rather, their readiness predisposes them to quickly recognize the value and usability of generative AI technologies.

Concerning the central TAM relationships (H4 and H5), both Perceived Usefulness ($\beta = 0.412$) and Perceived Ease of Use ($\beta = 0.286$) significantly predict Intention to Use. Notably, the effect of usefulness is nearly twice as large as that of ease of use. This indicates a highly pragmatic orientation among Vietnamese lecturers and students: AI adoption is primarily motivated by tangible academic performance gains (e.g., accelerated research processes, improved academic outcomes), rather than solely by user-friendly interfaces.

4.1.3 Anomalies and Deep Insights: Multi-Group Analysis (PLS-MGA)

Although H3 (AIC →INT) is statistically supported overall ($\beta = 0.215$), presenting only the aggregate coefficient conceals an important behavioral divergence. To uncover subgroup-specific dynamics, a multi-group analysis (MGA) was conducted comparing students and lecturers.

Table 5: Multi-group analysis results (Students vs. Lecturers)

Path	Beta (Students)		Beta (Lecturers)	Difference	p-value	Conclusion
AIC →INT	0.156		0.345	0.189	0.021	Significant difference
PU →INT	0.489		0.312	0.177	0.035	Significant difference

The MGA results reveal statistically significant differences in behavioral drivers between students and lecturers. Among lecturers, AI Competence has a particularly strong influence on Intention to Use (β = 0.345). In contrast, for students, this effect is comparatively modest (β = 0.156). The p-value of 0.021 confirms that this difference is statistically significant.

This unexpected outcome suggests a "professional vulnerability" phenomenon. Lecturers operate within strict academic accountability structures and may be reluctant to integrate AI into their teaching unless they possess substantial digital competence owing to concerns about pedagogical errors or diminished professional authority. Students, by contrast, often described as digital natives, demonstrate "fearless adoption." They are willing to experiment with AI tools regardless of their foundational technical knowledge, with their behavior driven primarily by Perceived Usefulness ($\beta = 0.489$ for students versus $\beta = 0.312$for lecturers).

Table 6: Specific indirect effects analysis (Mediation)

Indirect Path	Effect (β)	t-statistics	p-values	Confidence Interval [2.5%; 97.5%]
TRI →PU →INT	0.186	5.432	0.000	[0.125; 0.254]
TRI →PEOU →INT	0.111	3.890	0.000	[0.065; 0.165]

The indirect effects analysis demonstrates that Technology Readiness does not directly initiate AI usage behavior. Instead, its influence operates entirely through the mediating constructs Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). This finding carries an important practical implication: simply recruiting innovative individuals is insufficient to ensure AI adoption. University administrators must clearly demonstrate how AI tools generate concrete value in specific academic tasks in order to transform natural optimism into actual technology usage behavior.

4.3 Effects of AI Usage on the Innovation of Lecturers' Pedagogical Practices and Students' Actual Learning Outcomes (Objective 2)

Extending beyond psychological intention toward AI usage, the second research objective examines the concrete educational outcomes resulting from AI integration within the higher education environment.

Table 7: Hypothesis testing results for educational outcomes

Hypothesis	Path (Relationship)	Beta (β)	t-statistics	p-values	Conclusion
H6 (Lecturers)	INT →PED	0.582	11.230	0.000	Supported
H7 (Students)	INT →LO	0.495	10.451	0.000	Supported

Both hypotheses concerning educational outcomes receive strong empirical support. For lecturers (H6), Intention to Use AI significantly predicts Pedagogical Practices, with a substantial effect size ($\beta = 0.582$, $p < 0.001$). This represents the strongest direct relationship observed within the entire structural model. From a practical standpoint, this suggests that AI adoption in Vietnamese higher education is not merely symbolic or superficial. Lecturers who actively intend to use AI are fundamentally transforming their instructional approaches—shifting from conventional one-directional lecturing toward interactive, data-driven, and personalized teaching and assessment strategies.

For students (H7), Intention to Use AI also demonstrates a strong positive impact on learning outcomes ($\beta = 0.495$, $p < 0.001$). The statistical evidence confirms that students who integrate AI tools into their learning processes achieve measurably improved academic outcomes. This improvement is likely attributable to AI-enabled personalized pacing, adaptive support, and real-time feedback mechanisms.

4.3.1 Explanatory Power (R^2) and Effect Size (f^2)

Although p-values establish statistical significance, they do not reflect the practical magnitude of the relationships. Therefore, the coefficient of determination (R^2) and effect size (f^2) were calculated to evaluate the model's explanatory strength and substantive impact.

Table 8: Explanatory power (R^2) and effect size (f^2)

Dependent Variable	R^2	Model Predictive Strength	Independent Variable with Highest f^2	Effect Size Meaning
INT	0.678	High	Perceived Usefulness (PU)	$f^2 = 0.41$(Large effect)
PED (Lecturers)	0.542	Moderate to High	Intention to Use (INT)	$f^2 = 0.55$(Very large effect)
LO (Students)	0.489	Moderate	Intention to Use (INT)	$f^2 = 0.48$(Large effect)

The structural model explains 67.8% of the variance in Intention to Use ($R^2 = 0.678$), indicating high predictive accuracy within behavioral research standards. More importantly, the effect sizes (f^2) provide insight into the substantive magnitude of the relationships. According to Cohen's benchmarks, an f^2value greater than 0.35 is classified as a large effect. In this study, Intention to Use AI exerts exceptionally strong practical impacts on both Pedagogical Practices ($f^2 = 0.55$) and Learning Outcomes ($f^2 = 0.48$). These findings confirm that strategies promoting AI adoption yield substantial and measurable improvements in educational quality, extending well beyond mere statistical significance.

4.4 Assessment of Potential Biases and Data Limitations

Although the statistical results present a highly positive portrayal of AI integration, it is essential to recognize potential anomalies and methodological constraints to maintain scientific objectivity and balance.

First, concerning data anomalies, while overall learning outcomes among students demonstrated substantial improvement ($\beta = 0.495$), a more detailed examination of the outer loadings for the LO construct indicates that indicators directly associated with academic grades exhibited stronger loadings than those related to peer-to-peer engagement. This discrepancy suggests a possible latent downside: enhanced efficiency in human–machine interaction may unintentionally diminish human-to-human collaboration, thereby raising concerns about potential social isolation in AI-intensive learning environments.

Second, regarding methodological limitations, although the sample size of 630 respondents is statistically robust and substantially reduces random sampling error, the dataset may still be affected by self-selection bias. Since the survey was administered online through LMS platforms, individuals who voluntarily participated may already possess relatively higher levels of digital literacy compared to the general population. As a result, the relatively high R^2values may somewhat overstate the degree of technological optimism among the broader Vietnamese student body.

Finally, the study relies on self-reported measures rather than objective institutional grade records or independent pedagogical observations. While anonymity and confidentiality procedures were implemented to mitigate social desirability bias, self-reported learning outcomes inherently involve a degree of subjectivity. Additionally, the cross-sectional design captures a single temporal snapshot (early 2025). Therefore, although the PLS-SEM structural relationships strongly suggest causal directionality, definitive longitudinal causality cannot be conclusively established without tracking the same cohorts across multiple academic periods.

Despite these limitations, the consistently strong t-statistics and substantial effect sizes support the reliability and robustness of the primary findings, thereby providing a solid empirical basis for educational policy formulation and strategic decision-making.

5. Discussion

5.1 The Psychological Foundations of AI Adoption: Mindset Over Infrastructure

Addressing the first sequence of the findings regarding behavioral antecedents, the structural model strongly confirmed that Technology Readiness (optimism and innovativeness) serves as a critical, foundational catalyst for AI acceptance. The robust positive effects of TRI on both Perceived Usefulness and Perceived Ease of Use align seamlessly with the foundational assertions of Parasuraman and Colby (2015) and empirical validations by Walczuch et al. (2007) and Godoe and Johansen (2012) in broader technological contexts.

Contribution and Implication: This finding contributes a vital insight to the current body of knowledge regarding AI in developing nations: the primary barrier to digital transformation is not necessarily technical infrastructure, but psychological mindset. The indirect effects analysis demonstrated that technological optimism does not automatically trigger AI usage; it must be channeled through the recognition of tangible usefulness. For university leaders and policymakers, the implication is profound. Investments in expensive AI or IoT infrastructure will yield minimal returns unless they are accompanied by change-management initiatives designed to foster psychological readiness. Institutions must cultivate an institutional culture that celebrates digital innovativeness, shifting the narrative of AI from a "disruptive threat" to a "supportive co-pilot."

5.2 Pragmatism and the Divergence of Stakeholder Roles in AI Competence

Within the TAM framework, the data revealed that Perceived Usefulness exerts a substantially stronger influence on Intention to Use than Perceived Ease of Use. This corroborates recent findings by Anh and Ghi (2025) in the Vietnamese context, highlighting the extreme pragmatism of modern academic populations. Users are primarily motivated by performance enhancement such as time efficiency in research or grading rather than mere interface accessibility.

However, the most significant theoretical contribution of this study emerges from the multi-group analysis (MGA) regarding AI Competence. While the overall model supported the role of AI Competence, the MGA uncovered a stark behavioral divergence: AI Competence strongly dictates usage intention for lecturers, but has a comparatively weak influence on students. This builds upon and refines the findings of Du et al. (2024) and Delcker et al. (2024), who studied AI literacy as a generalized construct.

Contribution and Implication: The concept of "professional vulnerability" has been introduced to the body of educational technology literature. Lecturers in Vietnamese universities, operating within a culture that highly reveres pedagogical authority, are deeply hesitant to integrate AI unless they possess absolute mastery over it. They fear that algorithmic errors (hallucinations) or over-reliance on generative AI could undermine their professional credibility. Conversely, students function as "fearless adopters," willing to experiment with AI tools for immediate academic gain regardless of their foundational understanding of how the algorithms actually work.

The implication of this divergence is critical for strategic management. Faculty development programs cannot simply offer generic "how-to" tutorials. Training must explicitly focus on elevating lecturers' comprehensive digital pedagogical competence, providing them with the authoritative confidence needed to integrate, critique, and guide AI usage safely in their classrooms. Without this targeted upskilling, an asymmetric adoption curve will emerge, where students outpace their instructors technologically, fundamentally destabilizing the traditional academic hierarchy.

5.3 Transforming Pedagogical Practices: AI as an Agent of Change

Transitioning to the educational outcomes of AI usage (the second core objective), the strongest relationship in the entire structural model was found between the intention to use AI and innovation in pedagogical practices among lecturers. This massive effect size signifies that AI is not being utilized merely as an administrative add-on; it is fundamentally restructuring instructional methodologies.

This finding provides robust empirical support for Dimitriadou and Lanitis (2023) and Nguyen et al. (2022), who theorized the shift toward "smart classrooms." By automating repetitive tasks such as basic grading and plagiarism detection, AI acts as a liberator. It affords lecturers the temporal and cognitive bandwidth to transition from being unidirectional "transmitters of knowledge" to interactive "designers of learning experiences."

Contribution and Implication: This outcome enriches the literature on human-centered learning analytics (Alfredo et al., 2024) by proving that AI integration actually increases the capacity for high-value human mentorship, provided the educator embraces the technology. The managerial implication here is that university assessment metrics must evolve. Administrators should no longer evaluate teaching effectiveness based purely on traditional lecturing hours, but rather on the educator's ability to orchestrate AI-enhanced, personalized learning pathways that nurture higher-order critical thinking.

5.4 The Paradox of Learning Outcomes: Academic Efficiency vs. Digital Isolation

Finally, for the student demographic, the model confirmed a highly significant positive relationship between AI usage intention and actual learning outcomes. This strongly aligns with Xu et al. (2024) and Silva et al. (2024), validating the premise that hyper-personalized AI interventions such as adaptive pacing and real-time corrective feedback directly enhance academic performance.

However, a critical review of the data anomalies introduces a profound caveat to this success story. While academic performance metrics surged, the underlying indicators related to collaborative engagement and human-to-human interaction demonstrated weaker correlations. This exposes a hidden, yet dangerous, paradox of digital efficiency, providing stark empirical validation for Crawford et al. (2024) regarding the "cost of loneliness" in AI-driven higher education.

Contribution and Implication: This study contributes a crucial warning to the overly optimistic body of knowledge surrounding AIEd. As students retreat into algorithmic "bubbles" finding it more efficient to debate a chatbot or seek answers from a large language model than to engage with peers or professors, there is a latent risk of socio-emotional erosion. The implication of this finding cannot be overstated. While AI excels at knowledge transmission, it cannot replicate the complex social negotiations, empathy, and collaborative friction necessary for holistic human development.

Therefore, educational policymakers and curriculum designers face an urgent mandate. The integration of AI must be explicitly bounded by "human-centric" pedagogical constraints. Universities must intentionally design curriculum assessments that *cannot* be solved purely by interacting with a machine. Group projects, oral defenses, and collaborative physical workshops must be structurally reinforced to ensure that while students leverage AI for cognitive efficiency, they remain deeply anchored in the human community, preserving the essential social fabric of the university experience.

In summary, the findings prove that AI in Vietnamese higher education is a powerful, double-edged sword. Its successful implementation requires moving beyond mere technological deployment to fundamentally managing psychological readiness, empowering educator competence, and rigorously defending the socio-emotional dimensions of learning against the isolating efficiency of algorithms.

6. Conclusion

In the context of rapid digital transformation, this study addressed the pressing imperative to understand the multidimensional impacts of AI on higher education in Vietnam, moving beyond mere technological deployment to decode the underlying psychological and behavioral mechanisms driving its adoption. By validating an integrated theoretical framework combining the TAM, the TRI, and AI Competence through a robust PLS-SEM analysis of 630 stakeholders, the research yielded profound insights. The findings unequivocally demonstrate that individual psychological readiness, specifically optimism and innovativeness, serves as the foundational catalyst for recognizing AI's usefulness.

More importantly, the study exposed a critical behavioral divergence: while students pragmatically utilize AI to significantly enhance their personalized learning outcomes and academic efficiency, lecturers require a robust degree of digital pedagogical competence to overhaul their teaching practices confidently without experiencing professional vulnerability. Consequently, when properly embraced, AI acts as a transformative agent, transitioning traditional classrooms into smart, data-driven environments. However, the data also illuminated a latent paradox, warning that an over-reliance on algorithmic efficiency threatens to erode essential human-to-human collaboration and social connectivity among learners.

Ultimately, the paramount takeaway for policymakers and university leaders is that the future of digital education cannot be strictly algorithm-driven. To ensure sustainable educational quality, institutions must pivot toward a rigorously "human-centric" AI strategy. This necessitates moving beyond basic software training to invest deeply in faculty pedagogical upskilling, alongside the intentional design of collaborative curricula that utilize AI as a supportive co-pilot rather than a human replacement. By consciously balancing computational efficiency with the preservation of the socio-emotional dimensions of learning, Vietnamese higher education can harness the full revolutionary potential of AI without sacrificing the core humanistic values that define the university experience.

7. Limitations and Directions for Future Research

Despite its contributions, this study has several limitations. In terms of scope, the sample (N = 630) is concentrated in major universities in Hanoi and Ho Chi Minh City. As a result, the generalizability of findings to universities in rural areas or smaller provinces where infrastructure conditions and technology readiness differ remains limited. Methodologically, the study employs a cross-sectional design, capturing data at a single point in time. Future research should expand the geographic scope to provide a more comprehensive picture of the national digital divide. In addition, longitudinal designs are needed to examine the long-term effects of AI use on students' social skill development and mental health across academic years.

8. Conflict of Interest

The authors declare no financial, commercial, institutional, or personal conflicts of interest. The study was conducted independently, without funding or contractual relationships that could influence its design, analysis, or conclusions, including any affiliation with artificial intelligence tool providers.

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