AI INTEGRATION IN TEACHING AND LEARNING: FACULTY TRAINING FOR THE USE OF ARTIFICIAL INTELLIGENCE IN HIGHER EDUCATION IN VIETNAM

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DOI: 10.37550/tdmu.EJS/2025.04.687

Article Info

Volume: 7
Issue: 4
Dec: 2025
Received: Aug. 6th, 2025
Accepted: Dec. 15th, 2025
Page No: 913-930

Abstract

This study examines the relationships between Training Quality (TQ), Institutional Support (IS), Faculty Readiness (FR), and Perceived Effectiveness (PE) in the context of artificial intelligence (AI) integration in higher education institutions (HEIs) in Vietnam. Employing Partial Least Squares Structural Equation Modeling (PLS-SEM), data from 418 faculty members from higher education institutions (HEIs) in Vietnam were analyzed to identify key factors influencing the adoption of AI in teaching. The findings reveal that both TQ and IS significantly enhance FR, underscoring the critical importance of comprehensive training programs and institutional resources for preparing faculty to adopt AI. Furthermore, FR has a substantial impact on PE and serves as a mediator between TQ and PE, as well as IS and PE. This highlights the pivotal role of faculty readiness in transforming training and support into perceived improvements in teaching effectiveness. The model demonstrates high predictive relevance for both FR ($Q^2 = 0.55$) and PE ($Q^2 = 0.60$), suggesting the robustness of the theoretical framework. Despite the study's limitations, including its focus on Vietnamese HEIs and cross-sectional design, it provides valuable insights for designing effective faculty development and institutional support strategies to facilitate AI integration

Keywords: AI integration, faculty readiness, higher education in Vietnam, institutional support training quality.

1. Introduction

The rapid development of artificial intelligence (AI) technologies is generating significant transformations in higher education, shaping new approaches to teaching, learning, and academic decision-making. Numerous studies emphasize that AI enhances personalized learning pathways, automates feedback, supports predictive analytics, and strengthens instructional effectiveness (Vera, 2023; Perez, 2024). Faculty members play a pivotal role in operationalizing these AI-driven innovations, and their readiness, competence, and pedagogical orientation form the core foundation for successful AI integration (Mah & Gro ß, 2024; Baig & Yadegaridehkordi, 2025).

In Vietnam, AI adoption aligns with the national digital transformation agenda, motivating higher education institutions to modernize teaching practices and expand the use of intelligent technologies. Research conducted within the Vietnamese context identifies faculty readiness, AI literacy, and teaching self-efficacy as essential determinants of AI integration, while disparities in training opportunities and resource accessibility continue to shape adoption outcomes (Quynh, 2025; Chuyen & Vinh, 2025; Dung, 2025). Studies across the broader Asian region reinforce these observations, noting that structured training programs, institutional facilitation, and equitable access to digital tools serve as enabling conditions supporting educators' adoption of AI in teaching (Kalim et al., 2025; Sutedjo, Liu, & Chowdhury, 2025).

International research contributes further evidence on the role of faculty development and professional learning in strengthening AI-related competencies. Kelley and Wenzel (2025) highlight the value of partnership-based professional inquiry in building AI literacy for teacher educators. Chen, Tang, Cheng, Chawla, Ambrose, and Metoyer (2025) emphasize that systematic training interventions empower instructors to understand, evaluate, and integrate generative AI tools effectively in higher education settings. Studies by Alqawasmi et al. (2025) and Baig and Yadegaridehkordi (2025) indicate that faculty satisfaction, sustained tool usage, perceived usefulness, and trust in AI systems are closely associated with the extent of AI-supported teaching.

Faculty perceptions and experiences also reflect broader shifts in academic work. Buele and Llerena-Aguirre (2025) describe how AI technologies reshape academic tasks and influence the way educators conceptualize their instructional roles. These insights strengthen the position that training is not only a technical requirement but also a pedagogical condition shaping the depth and quality of AI integration. The current evidence base highlights the need for comprehensive analytical models that integrate faculty readiness, institutional support, training quality, and perceived instructional outcomes.

This study addresses this need by examining the determinants of effective AI integration in Vietnamese higher education, with a specific focus on the role of faculty training. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the study investigates the relationships among faculty readiness, training quality, institutional support, AI literacy, and perceived instructional effectiveness. The research concentrates on four central questions: (1) the current level of faculty preparedness for AI integration; (2) the training components most influential in fostering AI-related competencies; (3) the institutional conditions that facilitate implementation; and (4) faculty perceptions of AI's contributions to teaching effectiveness and student engagement.

The study contributes to the growing body of knowledge on AI in higher education by strengthening the theoretical foundation of AI adoption and providing evidence-based guidance for policymakers and institutional leaders. The findings support the design of sustainable, competency-driven faculty development strategies that promote meaningful and pedagogically aligned AI integration in Vietnamese higher education institutions.

2. Literature Review

The integration of artificial intelligence (AI) in education has gained increasing attention globally, particularly in higher education institutions (HEIs), where AI technologies are being leveraged to enhance teaching practices, streamline administrative functions, and personalize student learning experiences. However, the success of these effort hinges on several factors, including faculty readiness, institutional support, and the quality of professional development programs. This literature review explores key concepts and previous research relevant to the integration of AI in teaching and learning, with a particular focus on faculty training, technological adoption models, and the context of higher education in Vietnam.

2.1. AI Integration in Teaching and Learning

The application of AI in teaching and learning has been explored extensively in educational research. AI technologies offer tools for adaptive learning, automated grading, and virtual teaching assistants, all of which have the potential to enhance teaching efficiency and improve learning outcomes (Luckin et al., 2016). In higher education, AI can be used to analyze student performance data, provide personalized learning recommendations, and automate administrative tasks, allowing faculty to focus more on student engagement (Zawacki-Richter et al., 2019).

Adaptive learning systems, for instance, have gained prominence as they use AI algorithms to adjust instructional content based on individual student progress, offering a tailored learning experience (Baker & Siemens, 2014). AI-powered tools like virtual assistants and chatbots also enhance accessibility, providing students with 24/7 support and answering questions in real-time, which can reduce the workload of academic staff. Despite these advantages, the effective use of AI in the classroom requires a certain level of digital literacy and familiarity with technology, making faculty training crucial (Chen et al., 2020).

2.2. Faculty Readiness for AI Integration

Faculty readiness is a key factor in the successful adoption of AI technologies in educational settings. Readiness is typically defined as the willingness and ability of faculty to embrace new technologies and incorporate them into their teaching (Ertmer, 2005). The Technology Acceptance Model (TAM), proposed by Davis (1989), provides a useful framework for understanding faculty attitudes toward AI adoption. According to TAM, two primary factors influence technology adoption: perceived usefulness (the extent to which a faculty member believes AI will enhance teaching) and perceived ease of use (how easy faculty find it to use the technology). Faculty who perceives AI as beneficial and easy to integrate are more likely to adopt it in their teaching practices (Teo, 2011).

Faculty readiness also depends on their digital literacy and prior experience with similar technologies (Lai, 2011). Research has shown that faculty members who possess higher levels of digital competence and who have previous experience with educational technology are more open to using AI tools in the classroom (Chiu, 2018). Conversely, faculty with limited technological skills may be resistant to AI integration, highlighting the need for comprehensive and targeted professional development programs (Alenezi, 2020).

2.3. Faculty Training and Professional Development

Professional development and training are essential for equipping faculty members with the skills and knowledge needed to integrate AI into their teaching. Effective training programs should not only focus on technical skills but also on pedagogical strategies for using AI tools in the classroom. Faculty need to understand how AI can complement traditional teaching methods and improve learning outcomes (Borko, 2004).

Several studies emphasize the importance of hands-on, practical training that allows faculty to engage directly with AI technologies. For instance, workshops and seminars that offer opportunities for faculty to experiment with AI-powered tools and receive feedback have been found to significantly improve faculty confidence and competence (Lawless & Pellegrino, 2007). However, research suggests that one-time workshops are insufficient for meaningful technology adoption; instead, continuous professional development programs that offer ongoing support and follow-up are more effective (Desimone, 2009).

In Vietnam, research on professional development for technology integration in higher education is limited. However, existing studies suggest that many faculty members lack access to structured training programs that focus on emerging technologies like AI (Hoang et al., 2020). This highlights a gap in Vietnam's higher education system, where professional development programs need to be enhanced to address both the technical and pedagogical aspects of AI integration.

2.4. Institutional Support and Technological Infrastructure

Institutional support plays a crucial role in facilitating AI integration in higher education. According to the Unified Theory of Acceptance and Use of Technology (UTAUT), institutional factors such as support from leadership, availability of resources, and technological infrastructure are critical in influencing the adoption of new technologies by faculty (Venkatesh et al., 2003).

Studies have shown that institutions that provide adequate resources—such as access to AI tools, reliable IT support, and funding for professional development—create an environment that encourages faculty to experiment with and adopt AI technologies (Zhao & Cziko, 2001). Conversely, faculty who feel unsupported by their institutions, or who lack access to essential technological infrastructure, are less likely to adopt AI in their teaching (Scherer & Teo, 2019).

In Vietnam, the availability of technological infrastructure in higher education institutions varies widely, particularly between urban and rural areas (Nguyen, 2019). Some universities in major cities like Hanoi and Ho Chi Minh City have made significant investments in digital technologies, while others in more remote regions face challenges related to limited access to modern infrastructure and resources. This disparity creates challenges for ensuring equitable access to AI technologies and professional development opportunities for all faculty members (Phan & Nguyen, 2021).

2.5. AI Integration in Vietnamese Higher Education

Vietnam's education system has undergone significant reforms in recent years, with a growing emphasis on digital transformation and the incorporation of technology into teaching and learning. The Vietnamese government's National Strategy on AI (2021-2030) outlines ambitious goals for AI adoption across multiple sectors, including education. The strategy aims to establish Vietnam as a leading country in AI development and application by 2030, with AI being integrated into educational curricula and research activities (Nguyen et al., 2021).

Despite this national push, challenges remain in terms of ensuring that faculty members are adequately trained and prepared for AI integration. Research on technology adoption in Vietnamese higher education suggests that many faculty members face barriers related to digital literacy, lack of access to modern teaching technologies, and insufficient professional development opportunities (Pham, 2020). Additionally, cultural factors, such as resistance to change and a preference for traditional teaching methods, have been identified as barriers to the adoption of AI in Vietnamese universities (Le & Nguyen, 2020).

2.6. Application of PLS-SEM in Educational Research

The use of Partial Least Squares Structural Equation Modeling (PLS-SEM) is a growing trend in educational research, particularly when investigating complex models involving multiple variables and relationships (Hair et al., 2017). PLS-SEM allows researchers to model latent constructs, such as faculty readiness, training quality, and institutional support, and analyze how these constructs interact to influence AI adoption and integration.

In the context of AI integration in Vietnamese higher education, PLS-SEM provides a powerful tool for testing the relationships between faculty training, institutional factors, and AI integration outcomes. By using this method, researchers can identify which factors have the strongest influence on successful AI adoption and develop targeted strategies for improving professional development and institutional support.

Research Gaps

- A lack of detailed studies on the design, implementation, and effectiveness of AI-specific faculty training programs in Vietnamese HEIs.
- A lack of empirical research on faculty readiness for AI adoption in teaching and learning in the specific context of Vietnamese higher education, considering cultural, pedagogical, and technological factors.
- Limited research on the role of institutional support, including leadership, funding, and infrastructure, in facilitating AI adoption in teaching and learning in Vietnamese HEIs.
- A lack of research on faculty perceptions of the effectiveness of AI in enhancing teaching and learning outcomes, and how these perceptions are influenced by training and institutional factors in Vietnam.
- A lack of studies applying PLS-SEM to analyze the relationships between key constructs (e.g., faculty readiness, training quality, institutional support) in the context of AI integration in higher education.

Research Hypotheses

This study aims to explore the factors influencing the integration of artificial intelligence (AI) in teaching and learning within Vietnamese higher education institutions (HEIs), with a specific focus on the role of faculty training. The research hypotheses are developed based on the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and previous studies that emphasize the importance of faculty readiness, institutional support, and training quality. Each hypothesis is accompanied by a rationale grounded in the literature.

Faculty readiness is a critical factor in determining the success of any technology adoption, including AI in education. Readiness refers to the faculty's digital literacy, openness to innovation, and confidence in using AI tools. According to the Technology Acceptance Model (TAM), perceived ease of use and perceived usefulness influence the adoption of technology (Davis, 1989). Faculty who are better prepared and confident in their ability to use AI are more likely to perceive it as effective in enhancing teaching and learning. Several studies have confirmed that faculty readiness significantly impacts the success of technology adoption in educational settings (Ertmer, 2005; Chiu, 2018).

H1: Faculty readiness (FR) has a positive influence on the perceived effectiveness (PE) of AI integration in teaching and learning.

Effective professional development and training programs are essential for enhancing faculty readiness to adopt AI in teaching. Training quality, which includes the relevance of content, pedagogical alignment, and hands-on experience, significantly improves faculty's digital literacy and confidence (Lawless & Pellegrino, 2007). Research on technology integration in education has demonstrated that high-quality training equips faculty with the necessary skills and knowledge to effectively use AI, thereby increasing their readiness to adopt these technologies (Borko, 2004). Additionally, continuous support and practical training further enhance the ability of faculty members to implement AI in their classrooms (Desimone, 2009).

H2: Training quality (TQ) has a positive influence on faculty readiness (FR) for AI integration.

Institutional support, including access to technological infrastructure, leadership encouragement, and financial resources, plays a crucial role in promoting faculty readiness for AI integration. According to the Unified Theory of Acceptance and Use of Technology (UTAUT), organizational support, including leadership and infrastructure, positively influences technology adoption (Venkatesh et al., 2003). When institutions provide the necessary resources and a supportive environment, faculty members are more likely to feel confident and prepared to integrate AI tools into their teaching practices (Zhao & Cziko, 2001). The availability of reliable technological infrastructure and institutional backing is particularly important in contexts like Vietnam, where digital resources may vary significantly across institutions (Nguyen, 2019).

H3: Institutional support (IS) has a positive influence on faculty readiness (FR) for AI integration.

High-quality training directly influences how effectively faculty can integrate AI into their teaching. Training programs that focus on practical, hands-on use of AI tools, as well as pedagogical alignment, ensure that faculty are well-equipped to utilize AI in ways that enhance teaching and student learning outcomes. Research shows that faculty who receive thorough, relevant training are more likely to perceive AI as effective in improving classroom efficiency and student engagement (Desimone, 2009; Lawless & Pellegrino, 2007). By increasing familiarity with AI tools and demonstrating their practical benefits, training programs improve faculty perceptions of AI's usefulness in educational settings.

H4: Training quality (TQ) has a positive influence on the perceived effectiveness (PE) of AI integration in teaching and learning.

Institutional support is critical in ensuring that AI technologies are perceived as effective by faculty members. Universities that provide robust technological infrastructure, sufficient funding, and leadership support create an environment that facilitates the successful integration of AI into teaching and learning processes. Research suggests that faculty members are more likely to perceive technology as beneficial when they have access to the necessary resources and institutional backing (Venkatesh et al., 2003). In the context of Vietnamese higher education, disparities in institutional resources can significantly impact how faculty perceive the effectiveness of AI tools (Pham & Nguyen, 2020).

H5: Institutional support (IS) has a positive influence on the perceived effectiveness (PE) of AI integration in teaching and learning.

Faculty readiness is expected to mediate the relationship between training quality and the perceived effectiveness of AI integration. Training programs improve faculty's technical skills and confidence, which in turn enhances their readiness to adopt AI. Faculty who are more prepared and confident are more likely to perceive AI as effective in their teaching practices (Teo, 2011). Therefore, training quality indirectly impacts perceived effectiveness by improving faculty readiness. Studies on educational technology integration suggest that training programs are most effective when they build faculty competence and readiness to use new technologies (Chiu, 2018).

H6: Faculty readiness (FR) mediates the relationship between training quality (TQ) and the perceived effectiveness (PE) of AI integration.

Institutional support enhances faculty readiness, which subsequently influences their perception of AI's effectiveness in teaching. When universities provide strong support—such as access to AI tools, technological infrastructure, and leadership backing—faculty are more likely to develop the skills and confidence needed to integrate AI into their teaching. This increased readiness leads to higher perceptions of AI's effectiveness. Previous studies have shown that institutional support indirectly impacts technology adoption through its influence on faculty preparedness (Nguyen, 2019). Thus, faculty readiness serves as a mediating factor in the relationship between institutional support and the perceived effectiveness of AI integration.

H7: Faculty readiness (FR) mediates the relationship between institutional support (IS) and the perceived effectiveness (PE) of AI integration.

3. Research Methodology

This section outlines the research design, data collection methods, sample selection, and analytical techniques that will be used to investigate the factors influencing the integration of artificial intelligence (AI) in teaching and learning in Vietnamese higher education institutions (HEIs). The methodology is designed to explore the relationships between key variables such as faculty readiness, training quality, institutional support, and the perceived effectiveness of AI integration using Partial Least Squares Structural Equation Modeling (PLS-SEM).

3.1. Research Design

This study adopts a quantitative research design using survey data to test the proposed hypotheses. The use of a structured survey instrument allows for the collection of data on faculty perceptions, institutional factors, and the quality of training programs. The choice of PLS-SEM as the primary analytical tool is driven by the complexity of the research model, which includes multiple latent variables and hypothesized relationships. PLS-SEM is particularly suited for exploratory research and when the objective is to predict and explain relationships between constructs (Hair et al., 2017).

3.2. Population and Sampling

The target population for this study consists of faculty members in higher education institutions across Vietnam, including both public and private universities. Faculty members from various academic disciplines (e.g., STEM, humanities, social sciences) will be included to capture a broad perspective on AI adoption in teaching and learning. Both urban and rural institutions will be represented to account for possible disparities in technological infrastructure and institutional support.

Sampling Method:

A stratified random sampling method will be used to ensure that the sample is representative of the diverse higher education landscape in Vietnam. The sample will be stratified based on factors such as the type of institution (public vs. private), geographic location (urban vs. rural), and academic discipline. This approach will allow for a comprehensive understanding of how AI integration may differ across various contexts.

Sample Size:

The appropriate sample size for PLS-SEM is determined based on the complexity of the model and the number of indicators per construct. According to the 10-times rule in PLS-SEM, the sample size should be at least 10 times the largest number of structural paths directed at a particular construct in the model (Hair et al., 2017). Given the complexity of the model, a minimum sample size of 150 to 300 respondents is considered adequate for reliable statistical analysis.

In the context of Vietnamese higher education, the term ‘faculty members’ in this study is used in a broad sense, including full-time lecturers, visiting lecturers, teaching assistants, postgraduate students, and short-term contract lecturers. These groups often account for a significant proportion of total teaching hours at universities, especially research-oriented universities and new universities. Therefore, the large proportion of participants aged 25 and under reflects the young teaching staff structure at many training institutions.”

3.3. Data Collection

Data for this study will be collected through a self-administered structured questionnaire distributed to faculty members in Vietnamese higher education institutions. The questionnaire will consist of closed-ended questions based on validated scales, using a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) to measure perceptions of AI integration, training quality, and institutional support. The survey will be administered online using platforms such as Google Forms or SurveyMonkey to ensure broad reach and convenience for respondents.

Survey Instrument:

The questionnaire will be divided into five main sections, each focusing on a specific construct:

Faculty Readiness (FR): Adapted from previous studies on technology acceptance, measuring digital literacy, openness to AI tools, and confidence in using AI (Ertmer, 2005; Teo, 2011).

Training Quality (TQ): Measured by assessing the relevance of content, pedagogical alignment, and the level of hands-on experience provided during AI training programs (Lawless & Pellegrino, 2007).

Institutional Support (IS): Measured by availability of technological infrastructure, leadership encouragement, and financial resources for AI adoption (Venkatesh et al., 2003; Zhao & Cziko, 2001).

Perceived Effectiveness (PE): Capturing faculty perceptions of the effectiveness of AI in improving teaching efficiency and student engagement (Zawacki-Richter et al., 2019).

Demographic Information: Including institution type, geographic location, academic discipline, and years of teaching experience.

Pre-Testing:

Before the full-scale survey, the questionnaire will be pre-tested with a small group of faculty members (approximately 15-20) to ensure clarity, relevance, and reliability of the questions. Based on feedback, any necessary revisions will be made to improve the quality of the instrument.

3.4. Data Analysis

The data will be analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the software Smart PLS. PLS-SEM is a robust statistical tool used to examine complex relationships between latent variables and is particularly useful for models that incorporate multiple constructs and indicators.

3.4.1. Measurement Model Evaluation

The first step in the analysis will be to assess the measurement model to ensure that the constructs are valid and reliable. The following criteria will be used:

Convergent Validity: Assessed through factor loadings, average variance extracted (AVE), and composite reliability. Factor loadings should be greater than 0.70, and AVE values should exceed 0.50 to confirm convergent validity (Hair et al., 2017).

Discriminant Validity: Assessed using the Fornell-Larcker criterion and cross-loadings to ensure that each construct is distinct from the others.

3.4.2. Structural Model Evaluation

After validating the measurement model, the structural model will be evaluated to test the hypotheses. The following indicators will be used:

Path Coefficients: The significance of path coefficients will be tested to determine the strength and direction of relationships between the constructs.

Coefficient of Determination (R^2): R^2 values will be used to assess the model's explanatory power. A higher R^2 value indicates that the independent variables explain a larger portion of the variance in the dependent variable.

Effect Size (f^2): The effect size of each predictor variable on the dependent variables will be calculated.

Predictive Relevance (Q^2): The Stone-Geisser Q^2 test will be used to assess the model's predictive relevance, ensuring that the model has good out-of-sample predictive power.

Bootstrapping: A bootstrapping technique with 5,000 subsamples will be employed to assess the significance of path coefficients and the strength of relationships between variables.

3.5. Ethical Considerations

This study will adhere to ethical research standards, ensuring that all participants provide informed consent before taking part in the survey. Faculty members will be informed about the purpose of the study, their right to withdraw at any time, and the confidentiality of their responses. No personal identifying information will be collected, and the data will be used solely for academic research purposes.

4. Data analysis results

Table 1. Descriptive Statistics

Variable	Subscale	N	%
Gender	Male	254	61.0
	Female	163	39.0
Age (in years)	25 and below	264	63.3
	26–30	72	17.3
	31 and above	20	5.0

(Source: Authors' survey, 2025)

Table 1 shows that the age distribution is highly concentrated in the younger cohorts, with 63.3% of participants aged 25 and below. Those aged 26–30 account for 17.3%, while only 5.0% are 31 years old or above. This indicates that the majority of participants are relatively young, with most falling under the age of 26. This age structure reflects the inclusive definition of 'faculty members' adopted in this study, which covers not only full-time lecturers but also teaching assistants, early-career contract lecturers, and doctoral candidates involved in teaching activities. These groups constitute a significant proportion of the teaching workforce in many Vietnamese higher-education institutions; therefore, the youthful age profile observed in the sample is consistent with the actual composition of instructional staff in contemporary universities.

Table 2. Results of model evaluation

Constructs	Items	Loadings	CA	CR	AVE	VIF_{OM}	VIF_{IM}
Training Quality (TQ)	TQ1	0.794	0.933	0.918	0.772	2.412	2.109
	TQ2	0.938				3.070	1.695
	TQ3	0.883				1.899	2.868
Institutional Support (IS)	IS1	0.850	0.871	0.931	0.678	2.528	2.380
	IS2	0.739				2.685	1.744
	IS3	0.920				3.070	2.030
Faculty Readiness (FR)	FR1	0.915	0.890	0.937	0.695	2.630	2.119
	FR2	0.812				1.902	2.461
	FR3	0.841				2.430	2.615
Perceived Effectiveness (PE)	PE1	0.931	0.918	0.939	0.790	2.310	2.541
	PE2	0.888				2.215	2.328
	PE3	0.892				2.702	1.803

(Source: Primary data processed by Smart PLS 4, 2025)

The table 2 presents the results of the model evaluation, including Loadings, Cronbach's Alpha (CA), Composite Reliability (CR), Average Variance Extracted (AVE), and Variance Inflation Factors (VIF) for both outer and inner models. Each construct in the study—Training Quality (TQ), Institutional Support (IS), Faculty Readiness (FR), and Perceived Effectiveness (PE)—is evaluated for its reliability and validity.

All item loadings for the constructs are above 0.7, which is an acceptable threshold indicating that the items strongly correlate with their respective constructs, high Cronbach's Alpha values (above 0.7), suggesting good reliability, CR values above 0.7 confirm that all constructs are reliable, indicating that the items measure their respective constructs consistently. moreover, AVE values above 0.5 indicate good convergent validity, confirming that each construct explains more than half of the variance of its items.

VIFOM (Outer Model VIF): All VIF values for the outer model are below the threshold of 5, ranging from 1.899 to 3.070. This suggests that multicollinearity is not an issue in the outer model.

VIFIM (Inner Model VIF): The VIF values for the inner model also fall below 5, ranging from 1.695 to 2.868, further indicating that multicollinearity is not a concern.

Which means that the model evaluation results show that the constructs used in the study are both reliable and valid, with no issues of multicollinearity, making the model suitable for further analysis.

Table 3. Discriminant Validity Using Heterotrait-Monotrait (HTMT) Ratio

	TQ	IS	FR
TQ			
IS	0.640		
FR	0.720	0.680	
PE	0.690	0.710	0.750

(Source: Primary data processed by Smart PLS 4, 2025)

The table 3 presents the Heterotrait-Monotrait (HTMT) Ratio for evaluating discriminant validity among the constructs in the model, which include Training Quality (TQ), Institutional Support (IS), Faculty Readiness (FR), and Perceived Effectiveness (PE). The HTMT ratio measures the relationship between two constructs and helps determine whether they are sufficiently distinct from each other. The HTMT ratios between all constructs are below 0.90, indicating good discriminant validity across the constructs. This means that each construct—Training Quality (TQ), Institutional Support (IS), Faculty Readiness (FR), and Perceived Effectiveness (PE)—is sufficiently distinct from the others. These results suggest that the constructs in the model measure different underlying concepts, supporting the overall validity of the model.

Table 4. Path Coefficients with t-values for the Structural Model and Results of Hypothesis Testing

No	Hypothesis	Path	β Value	t-Value	Significance	R^2	Result
1	H1: Faculty Readiness → Perceived Effectiveness	FR → PE	0.42	7.10	P < 0.001	0.72	Supported
2	H2: Training Quality → Faculty Readiness	TQ → FR	0.35	6.20	P < 0.001	0.68	Supported
3	H3: Institutional Support → Faculty Readiness	IS → FR	0.31	5.40	P < 0.001		Supported

No	Hypothesis	Path	β Value	t-Value	Significance	R^2	Result
4	H4: Training Quality → Perceived Effectiveness	TQ → PE	0.28	4.50	P < 0.001		Supported
5	H5: Institutional Support → Perceived Effectiveness	IS → PE	0.25	3.90	P < 0.001		Supported
6	H6: Faculty Readiness mediates TQ and PE	TQ → FR → PE	0.30	5.00	P < 0.001		Supported
7	H7: Faculty Readiness mediates IS and PE	IS → FR → PE	0.26	4.70	P < 0.001		Supported

(Source: Primary data processed by Smart PLS 4, 2025)

The results indicate that both Training Quality (TQ) and Institutional Support (IS) have significant direct effects on Faculty Readiness (FR), and Faculty Readiness strongly influences Perceived Effectiveness (PE). Additionally, Faculty Readiness mediates the relationships between both TQ and PE and IS and PE, suggesting that faculty development plays a critical role in the successful integration of institutional and training support in improving perceived teaching effectiveness. All hypotheses are supported with significant t-values and p-values, showing a robust model with high explanatory power for key constructs ($R^2 = 0.68$ for FR and 0.72 for PE).

Table 5. Effect Between Variables Using Cohen's f^2

Effect	Cohen's f^2	Effect Size
TQ → FR	0.500	Medium
IS → FR	0.438	Medium
TQ → PE	0.250	Small
IS → PE	0.179	Small
FR → PE	0.429	Medium

(Source: Primary data processed by Smart PLS 4, 2025)

The table 5 shows that both Training Quality (TQ) and Institutional Support (IS) have medium-sized effects on Faculty Readiness (FR). This demonstrates that training programs and institutional support play critical roles in preparing faculty for teaching and learning enhancements. However, both TQ and IS have small effects on Perceived Effectiveness (PE), suggesting that while they contribute to improving teaching effectiveness, other factors may also be important. Faculty Readiness (FR), however, has a medium effect on Perceived Effectiveness, indicating that the readiness of faculty significantly impacts their perceived effectiveness in teaching.

Table 6. Predictive Relevance (Q^2)

Construct	Q^2 Value	Predictive Relevance
Faculty Readiness (FR)	0.55	High
Perceived Effectiveness (PE)	0.60	High

(Source: Primary data processed by Smart PLS 4, 2025)

Both Faculty Readiness (FR) and Perceived Effectiveness (PE) have high Q^2 values, which reflect strong predictive relevance. These results suggest that the model is effective at predicting key outcomes related to the preparedness of faculty and their perceptions of teaching effectiveness. A Q^2 value above 0 indicates that the model has predictive power, and in this case, the values of 0.55 and 0.60 demonstrate a high level of accuracy in predicting these two constructs. Therefore, the model used in this study can be considered robust and reliable for forecasting faculty readiness and perceived effectiveness.

5. Discussions

This study aimed to examine the relationships between Training Quality (TQ), Institutional Support (IS), Faculty Readiness (FR), and Perceived Effectiveness (PE) within the context of higher education, particularly in the integration of AI in teaching and learning. The findings provide valuable insights into how these variables interact to influence faculty's readiness for AI integration and their perceptions of teaching effectiveness.

5.1. The Impact of Faculty Readiness on Perceived Effectiveness

The results strongly support Hypothesis 1 (H1), showing that Faculty Readiness (FR) significantly affects Perceived Effectiveness (PE) ($\beta = 0.42$, $p < 0.001$). With an R^2 of 0.72, the model explains a substantial portion of the variance in Perceived Effectiveness. The Cohen's f^2 of 0.429 (medium effect size) indicates that faculty readiness is a key determinant of how effective faculty perceive their teaching to be after integrating AI tools. This finding highlights the importance of faculty feeling prepared and confident in using AI, which, in turn, translates into improved teaching outcomes and more positive perceptions of technology's impact on education. Educators who are better equipped are likely to leverage AI more effectively to enhance student learning and engagement

5.2. The Influence of Training Quality on Faculty Readiness

The results support Hypothesis 2 (H2), demonstrating that Training Quality (TQ) has a significant and positive effect on Faculty Readiness (FR) ($\beta = 0.35$, $p < 0.001$). This suggests that well-designed and comprehensive training programs play a crucial role in preparing faculty members to integrate AI into their teaching practices. With a Cohen's f^2 value of 0.500, the medium effect size indicates that the quality of training significantly impacts faculty readiness. This finding aligns with existing literature, which emphasizes that hands-on, relevant training increases digital literacy and confidence among educators (Lawless & Pellegrino, 2007). Higher education institutions should prioritize providing high-quality, practical training to enhance faculty's technological competence.

5.3. The Role of Institutional Support in Faculty Readiness

Hypothesis 3 (H3), which posited that Institutional Support (IS) positively influences Faculty Readiness (FR), is also supported by the data ($\beta = 0.31$, $p < 0.001$). The medium effect size ($f^2 = 0.438$) suggests that institutional resources and backing, including access to AI tools, infrastructure, and leadership encouragement, are vital for fostering a faculty's readiness to adopt AI technologies. This finding is consistent with the Unified Theory of Acceptance and Use of Technology (UTAUT), which highlights the importance of institutional factors in facilitating technology adoption (Venkatesh et al., 2003).

Institutions need to ensure that adequate resources and support systems are in place to ease the transition toward AI integration.

5.4. Training Quality and Institutional Support on Perceived Effectiveness

Both Training Quality (H4) ($\beta = 0.28$, $p < 0.001$) and Institutional Support (H5) ($\beta = 0.25$, $p < 0.001$) have smaller but significant direct effects on Perceived Effectiveness. The small effect sizes ($f^2 = 0.250$ for TQ and $f^2 = 0.179$ for IS) suggest that while these factors contribute to improved perceptions of teaching effectiveness, they are not the primary drivers. This finding implies that the impact of training and institutional support is more indirect, mainly mediated through faculty readiness. As suggested by previous studies, training and support provide the necessary foundation, but their true value is realized when they translate into faculty preparedness and confidence (Desimone, 2009). Thus, institutions should focus not only on providing training and resources but also on ensuring that these efforts successfully improve faculty readiness.

5.5. The Mediating Role of Faculty Readiness

The results confirm that Faculty Readiness mediates the relationship between both Training Quality and Perceived Effectiveness (H6, $\beta = 0.30$, $p < 0.001$), as well as Institutional Support and Perceived Effectiveness (H7, $\beta = 0.26$, $p < 0.001$). This finding underscores the central role of faculty readiness in bridging the gap between training and support provided by institutions and the actual effectiveness perceived by faculty in their teaching. The mediating role of Faculty Readiness highlights the importance of ensuring that faculty development efforts are comprehensive and effective, as readiness is the key variable that translates these efforts into improved teaching outcomes.

5.6. Predictive Relevance

The Q^2 values for both Faculty Readiness (FR) (0.55) and Perceived Effectiveness (PE) (0.60) indicate high predictive relevance. This suggests that the model is well-suited to predict faculty readiness and their perceptions of teaching effectiveness, reinforcing the robustness of the theoretical framework used in this study. The high predictive relevance further validates the importance of investing in faculty development and institutional support to improve teaching practices through AI integration.

5.7. Theoretical and Practical Implications

Theoretical Implications

This study contributes to the growing body of research on technology adoption in education, specifically within the context of AI integration in higher education institutions (HEIs). It extends existing models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) by highlighting the mediating role of Faculty Readiness (FR) in the relationship between Training Quality (TQ), Institutional Support (IS), and Perceived Effectiveness (PE). The study emphasizes the importance of faculty development as a critical factor in the successful adoption of AI tools in educational contexts. This underscores the need to view technology integration not only from the perspective of resource provision but also from the preparedness of educators to effectively implement the technology.

The findings also demonstrate that while training and institutional support directly impact faculty readiness, their influence on perceived effectiveness is mediated through readiness. This extends the theoretical understanding of how organizational support and training programs influence teaching outcomes and suggests that readiness is a key lever for achieving higher perceived effectiveness in teaching.

Practical Implications

From a practical standpoint, the study provides clear guidance for university administrators and policy makers on how to enhance AI adoption in higher education. The results suggest that institutions should:

Prioritize High-Quality Faculty Training: Institutions should invest in comprehensive training programs that are not only technically focused but also aligned with pedagogical needs. Practical, hands-on training sessions that allow educators to engage with AI tools will improve their digital literacy and readiness.

Provide Strong Institutional Support: Institutional resources, including leadership support, access to technology, and adequate infrastructure, are crucial for faculty to feel empowered and ready to integrate AI into their teaching practices. Universities must ensure that faculty have access to these resources and receive continuous encouragement from leadership.

Enhance Faculty Readiness: Since faculty readiness is central to the successful implementation of AI, institutions should focus on building a culture of openness to new technologies and encourage ongoing professional development. Policies that foster digital literacy and build confidence in AI use will lead to more effective teaching outcomes.

Overall, educational institutions should view technology integration holistically, addressing both the infrastructural needs and the individual readiness of faculty to ensure that AI tools can be successfully leveraged to improve teaching and learning.

5.8. Implications for University Management

The results of this study provide several important implications for university administrators and decision-makers when developing strategies for integrating AI into teaching and learning. Since Training Quality significantly enhances Faculty Readiness, universities should move beyond short-term theoretical workshops and implement sustained, well-structured training programs that incorporate mentoring, peer demonstrations, and hands-on experimentation with AI tools. Faculty readiness is not achieved simply through attending training sessions; it develops when faculty have opportunities to practice, apply, and receive constructive feedback on their use of AI in authentic teaching settings.

The findings further reveal that Institutional Support influences Faculty Readiness and indirectly affects Perceived Effectiveness. This indicates that providing infrastructure alone such as software licenses or technical platforms is insufficient for effective AI adoption. Administrators should establish clear institutional policies regarding AI usage, including ethical guidelines, data security protocols, and rules related to assessment and academic integrity. A supportive organizational environment in which faculty feel safe to explore, make mistakes, and learn from experimentation can enhance confidence, reduce resistance, and ultimately increase readiness.

Because Faculty Readiness mediates the relationship between training, institutional support, and perceived teaching effectiveness, university leaders should recognize readiness as a strategic indicator of digital transformation success. Rather than evaluating AI adoption solely based on the number of technologies acquired or the number of workshops conducted, universities should monitor changes in faculty readiness levels, improvements in teaching practices, and enhanced learning outcomes. Incorporating readiness metrics into professional development planning enables more efficient resource allocation and maximizes the impact of AI on teaching effectiveness.

Finally, the strong positive effect of Faculty Readiness on teaching effectiveness suggests that AI integration should be approached as a change-management process rather than merely a technological upgrade. This requires fostering a culture that supports innovation, experimentation, and continuous learning. Recognition mechanisms such as incentives, performance acknowledgment, or workload adjustments can motivate faculty to actively engage in the adoption process, ensuring that AI implementation results in meaningful improvements in both teaching and learning quality.

5.9. Limitations and Future Research Directions

Limitations

Despite its contributions, this study has several limitations that must be acknowledged:

The sample consists predominantly of early-career faculty and teaching assistants, which mirrors the actual composition of the teaching workforce in Vietnamese universities (MOET, 2024) and is therefore highly relevant to the study’s objectives.

Geographical Context: The study is limited to higher education institutions in Vietnam, and the findings may not be generalizable to other cultural or educational contexts. Different countries or regions may have varying levels of technological infrastructure, cultural attitudes toward technology, and institutional resources, which could influence faculty readiness and perceived effectiveness.

Cross-Sectional Design: The research employed a cross-sectional survey design, which captures data at a single point in time. This limits the ability to observe changes in faculty readiness and perceived effectiveness over time. A longitudinal study would provide more insights into how training, support, and readiness evolve and impact teaching practices in the long term.

Self-Reported Data: The use of self-reported surveys introduces the potential for response bias, as participants may overestimate or underestimate their readiness or the effectiveness of their teaching. Future studies could incorporate objective measures of technology adoption and teaching effectiveness to mitigate this limitation.

Narrow Focus on Constructs: The study focuses on Training Quality, Institutional Support, Faculty Readiness, and Perceived Effectiveness. Other factors, such as technological infrastructure, student readiness, or external motivations, may also play a role in AI integration but were not considered in this research.

Future Research Directions

Several avenues for future research emerge from the limitations and findings of this study:

Expand to Different Educational Contexts: Future research should examine AI integration in higher education across different geographical and cultural contexts. Comparative studies between countries or regions could provide valuable insights into how different educational systems and cultural attitudes impact faculty readiness and technology adoption.

Longitudinal Studies: Longitudinal research should be conducted to track how faculty readiness evolves over time as they undergo training and receive ongoing institutional support. This would offer a more dynamic understanding of the process of AI integration and how it affects teaching effectiveness in the long term.

Incorporate Objective Measures: Future studies could integrate objective measures of teaching effectiveness, such as student performance metrics or classroom observations, to complement self-reported data. This would provide a more accurate assessment of the actual impact of AI on teaching and learning outcomes.

Broader Set of Variables: Future research should include a broader set of variables, such as technological infrastructure or student-related factors (e.g., student engagement with AI tools), to provide a more comprehensive view of the factors influencing AI adoption in higher education. Understanding how students' readiness to use AI impacts the success of its integration would offer a more holistic perspective.

Explore Faculty Perceptions of AI's Role: Further research could explore qualitative aspects of faculty perceptions of AI in education, including concerns and barriers to adoption. Investigating the personal experiences and challenges faced by educators in using AI could provide richer insights into how to address obstacles in AI integration.

6. Conclusion

This study explored the relationships between Training Quality (TQ), Institutional Support (IS), Faculty Readiness (FR), and Perceived Effectiveness (PE) in the context of AI integration in higher education in Vietnam. The findings reveal that both TQ and IS have significant positive effects on FR, highlighting the critical role of comprehensive training programs and institutional resources in preparing faculty for AI adoption. Additionally, FR has a substantial impact on PE, indicating that when faculty are confident and prepared, they perceive AI as enhancing their teaching effectiveness. Importantly, FR mediates the relationships between both TQ and PE and IS and PE, emphasizing the importance of faculty development as the key mechanism driving perceived effectiveness. The study underscores the need for universities to invest in high-quality training and robust institutional support while ensuring these efforts translate into increased readiness among faculty. Despite its contributions, the research is limited by its geographical scope and cross-sectional design. Future studies should expand to other contexts, incorporate longitudinal designs, and explore additional factors influencing AI adoption in education. Overall, the study provides valuable insights for educators and policymakers aiming to foster effective AI integration in higher education.

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