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From Passive Acceptance to Active Integration: A Multi-Stage Model of In-Service Secondary Vietnamese Teachers' AI Readiness

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Abstract

Aim/Purpose	This study aims to identify and explain the key factors influencing the artificial intelligence (AI) readiness of in-service secondary Vietnamese teachers, addressing the lack of empirical evidence on how teachers progress from initial acceptance to active instructional integration of AI.

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Background While AI is increasingly promoted in education policy and practice, teachers' readiness to adopt and integrate AI remains uneven and underexplored in developing countries. Existing studies often conceptualize AI readiness as a single construct, overlooking its developmental nature.

Methodology The study employed a quantitative approach and collected survey data from 1,145 in-service secondary school teachers in Vietnam. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the study developed and validated a theoretical model incorporating organizational factors (policy and organization support, professional development, collegial support), individual factors (confidence, perceived relevance), and social factors (subjective norms) as predictors of readiness stages (Accepting, Introducing, Teaching).

Contribution This research contributes to the literature by conceptualizing teachers' AI readiness as a progressive, multi-stage construct and empirically validating a comprehensive model that integrates organizational, professional, social, and individual factors in a developing-country context.

Findings The model demonstrated strong explanatory power and predictive relevance, with thirteen of fourteen hypotheses supported. Results indicate that AI confidence and perceived AI relevance significantly predict all stages of AI readiness. Subjective norms influence early stages of readiness but do not directly affect advanced teaching integration. Acceptance strongly predicts introduction, and introduction, in turn, is a powerful predictor of AI integration in teaching. Collegial support emerged as the strongest organizational predictor of subjective norms. Multi-group analysis revealed gender and regional differences, with professional development effects stronger for female teachers and perceived relevance influencing male teachers' integration intentions more substantially.

Recommendations for Practitioners Educational leaders should design staged professional development programs that build teachers' confidence, highlight the pedagogical relevance of AI, foster supportive collegial cultures, and provide clear institutional policies.

Recommendations for Researchers Future studies should adopt longitudinal designs to examine changes in AI readiness over time and extend the model to other subject areas and educational levels to enhance generalizability.

Impact on Society By clarifying how teachers develop readiness to integrate AI into teaching, this study supports more effective implementation of AI-driven educational reforms, contributing to improved teaching quality and equitable digital transformation in education.

Future Research Further research should explore causal mechanisms through mixed-methods approaches and investigate how student outcomes and ethical considerations interact with teachers' AI readiness across diverse educational contexts.

Keywords AI, readiness, teacher, PLS-SEM

INTRODUCTION

Artificial intelligence (AI) has rapidly penetrated the education sector and is expected to have a profound impact on its future development (Nedungadi et al., 2024; Qu et al., 2022). As modern AI technology gains popularity, teachers can automate daily classroom tasks and interact more efficiently with students (Baidoo-anu & Owusu Ansah, 2023; Opesemowo & Ndlovu, 2024) without manual programming (Akpan et al., 2025). Studies by Hwang et al. (2020) and Jian (2023) show that advances in AI enable adaptive, personalized teaching strategies that prioritize human-centeredness. These tools enhance learning efficiency, creativity, and decision-making. According to the Vietnamese Ministry of Education and Training (2025), the "Application of Artificial Intelligence" is one of the six competency domains to be developed in the Digital Competency Framework. The inclusion of artificial intelligence in the Digital Competency Framework reflects the education sector's vision for preparing a quality workforce for the future. AI's long-term impact can completely restructure the Vietnamese education system. It improves the traditional one-way education model, reshapes the approach to knowledge, and the way learners are tested (Vinh & Ngoc, 2024).

In mathematics teaching and learning, AI has become a widely adopted tool worldwide. The majority of countries incorporate AI into their curricula to enhance educational standards (Göktepe Yıldız & Göktepe Körpeoğlu, 2025). The potential of AI to solve mathematical problems is enormous. Teachers can guide students to use natural language to quickly ask questions, thereby aiding their understanding of complex mathematical formulas and concepts (Wardat et al., 2023). The new generation of artificial intelligence uses algorithms that generate synthetic outputs by analyzing and learning from available digital content. AI can assist math teachers in identifying practical connections to math topics, helping students understand the meaning behind math problems, and creating classroom teaching materials relevant to specific student audiences (Egara & Mosimege, 2024; Le et al., 2025).

According to Norberg et al. (2025), using GPT-4 to rewrite math problems into text improves reading comprehension among middle school students, with an effect comparable to that of humans. Many studies have examined the use of ChatGPT in math teaching, showing the potential of this generative AI to be combined with geometry software (Uygun et al., 2025; Yunianto et al., 2024), simulate dialogue (Galiç et al., 2025; Torres-Peña et al., 2024), and strengthen learners' critical thinking (Barana et al., 2023). Overall, these studies demonstrate that AI has significant potential to transform mathematics teaching, student engagement, and instructional effectiveness when appropriately integrated into educational practices.

As AI becomes increasingly embedded in classrooms, teachers play a pivotal role as active pedagogical gatekeepers, not simply adopting tools but deliberately selecting, guiding, and scrutinizing their use so that AI supports learning goals rather than steers them. However, this responsibility also exposes a key tension between passive use (over-trusting AI outputs, relying on it to explain or decide) and active use (setting instructional constraints, verifying accuracy, and integrating AI strategically), which raises several challenges.

There are concerns about the reliability of AI in producing accurate solutions. For example, advanced versions such as GPT-4o and GPT-4 have high success rates (87% and 82%, respectively), but AI still generates incorrect solutions (Ergene & Ergene, 2025). Without proper pedagogical constraints, explanations may be inaccurate, oversimplify complex concepts, or become rambling (C. Li & Lyu, 2025). Additionally, the target group selected for AI intervention programs in education is unevenly distributed across school levels. One reason Hwang and Tu (2021) give is that primary school teachers are often more receptive to new learning methods than teachers of other subjects, as they do not have to worry about entrance exams, especially in Asian countries. Moreover, some content does not benefit from AI, so teachers need to be cautious and use this type of technology appropriately under the right conditions (Yi et al., 2025).

So far, there is a growing consensus that it is necessary to equip teachers with the essential technical, ethical, and pedagogical aspects to use AI effectively. For example, UNESCO (2024) has issued the AI Competency Framework for Teachers, designed to guide its localization and to build a teacher workforce with comprehensive digital competencies. In line with the significant transformation of the world under the influence of AI, in Vietnam, teachers are considered an irreplaceable central factor (Vinh & Ngoc, 2024), a core force in the application and dissemination of this technology in education. However, the reality shows that teachers are still not fully equipped with the necessary skills and knowledge to meet this requirement. Tuan et al. (2025) underscore the urgency of developing AI competencies for teachers. Moreover, Giam et al. (2022) found that teachers who lack access to many advanced teaching technologies highly appreciate the use of AI in teaching.

To overcome barriers and successfully implement AI in education, teacher readiness is key. Technology readiness refers to the degree to which an individual is psychologically prepared, capable, and conditioned to effectively receive, use, and exploit new technology (Leung & Cheung, 2025). AI readiness has a significant positive effect on behavioral intent to teach AI (Ayanwale et al., 2022). According to previous studies, higher readiness improves work efficiency and increases teachers' professional satisfaction. Teachers who demonstrate a strong willingness to apply artificial intelligence often possess the abilities and understanding to enhance professional performance by exploring and adapting to AI-generated opportunities (Luckin et al., 2022; X. Wang et al., 2023).

In contrast, individuals with low readiness are more likely to feel insecure and shy away from interacting with AI-based technologies (Chounta et al., 2022). Furthermore, Luckin (2018) emphasizes the need for ethical and regulatory mechanisms to understand and address the impacts of AI systems. This suggests that when clear guidelines are in place, such as those related to student data privacy, user accountability, and transparency in assessments, teachers tend to be more confident in technology and more willing to test AI applications in the classroom, rather than being concerned about potential ethical or legal risks.

Several studies worldwide are examining the factors that influence teachers' AI readiness. Ayanwale et al. (2022) employed the PLS-SEM model to examine the factors influencing the readiness of 368 K-12 teachers in Nigeria to teach AI. The two factors, AI Relevance and Confidence in Teaching AI, significantly predicted teachers' willingness to adopt AI education. Fundi et al. (2024) assessed the readiness of 308 in-service teachers in Kenya to integrate AI into the Competency-Based Curriculum. The study examined five hypotheses and found a direct relationship between exogenous variables and AI Readiness (the endogenous variable). Three of the five hypotheses were confirmed, indicating that AI Ethics, Confidence in AI, and Subjective Norms significantly influence teachers' willingness to integrate AI in the Competency-Based Curriculum. Attitude toward AI, on the other hand, did not significantly affect AI teaching readiness, suggesting that attitude may not always predict readiness.

Additionally, Perceived Threats did not predict readiness, either because most participants were in older age groups or because AI is increasingly prevalent in Kenya. In the Vietnamese context, Viet Quynh (2025) examined the factors affecting the readiness of 468 pre-service educators at Hanoi Metropolitan University to use AI in lesson plan design. These results show that Performance Expectancy (the belief that AI will improve the quality of planning, save time, etc.) and Skills in using AI are the most significant predictors of readiness, consistent with classical models such as the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology. Support from lecturers and the teacher education institution, technological infrastructure and learning environment, and ethical and legal understanding of AI in education were identified as essential support conditions.

Initiatives to integrate artificial intelligence into K-12 teaching in Vietnam are still in their infancy and are being explored step by step. Because teachers play a pivotal role in translating these AI initiatives into classroom practice, determining whether they are ready to integrate AI is critical for effective, sustainable implementation. Research on AI readiness among Vietnamese teachers aligns with the national digital transformation trend and is necessary to inform strategies for teacher training, support, and professional development. However, no studies have examined the factors that determine AI readiness among secondary teachers in Vietnam, leaving a research gap. To address this, our study conceptualizes teachers' AI readiness as a multi-level construct shaped by organizational, professional, and individual factors. Based on the stated objectives, the following research question guided our study: "What factors influence the AI readiness of in-service secondary Vietnamese teachers?"

To address these research gaps, this study develops a conceptual model grounded in the Theory of Planned Behavior and extended with a multi-stage conceptualization of AI readiness. The following section reviews relevant literature to establish the theoretical foundation for each construct and to justify the proposed research model.

THEORETICAL FRAMEWORK

This section synthesizes prior research to establish the theoretical foundation of the proposed model. Each subsection corresponds to a core construct in the research framework and directly informs the development of the hypotheses.

Confidence is understood as an individual's belief in their ability to complete specific tasks, significantly influencing professional development, teaching options, and overall teaching effectiveness (Zonoubi et al., 2017). In defining teachers' readiness, Arhin et al. (2024) note that confidence is an important factor and an integral part of assessing their willingness to integrate information technology into mathematics teaching. Fundi et al. (2024) assert that confidence is an important predictor of teachers' willingness to teach AI. The authors also added that the more confident teachers are, the more ready they are. A study by Ayanwale et al. (2022) found that confidence in AI influences teacher readiness. In the researchers' view, confidence levels reflect teachers' beliefs in their self-efficacy. It can promote or limit the willingness to engage in AI-related activities. Prior studies have examined the relationship between AI confidence (CA) and readiness (RE), leading to the first hypothesis.

H1: CA has a positive and significant effect on RE.

Awareness of AI relevance has important implications for teaching readiness (Ayanwale et al., 2022). Yue et al. (2024) found that perceptions of AI's importance as an academic field can influence teachers' attitudes towards AI education. Similarly, Jatileni et al. (2024) emphasize that understanding AI's relevance to teachers clarifies perspectives on the possibility and necessity of integrating AI into the teaching process. Their findings indicate that AI relevance is a key factor in developing AI-enabled education policies and programs in Namibia. Therefore, to determine whether AI relevance (RA) predicts Vietnamese teachers' readiness (RE), we formulate the second hypothesis.

H2: RA has a positive and significant effect on RE.

In the Theory of Planned Behavior, subjective norms refer to an individual's perception of pressure from important people or groups. It reflects the extent to which they believe others expect them to exhibit or refrain from a particular behavior (Ajzen, 2020). Fundi et al. (2024) and Teo (2015) have demonstrated that subjective norms influence the extent to which teachers engage in preparatory behavior and intention to use technology. This is especially true as AI gradually becomes a powerful supporting tool for pedagogical innovation, while still facing numerous barriers related to trust, perception, and organizational culture (Zhang et al., 2025). Teachers tend to adjust their behavior, including their willingness to adopt, introduce, and integrate AI technology into teaching, based on perceptions of subjective norms within the educational community. Therefore, we examine the subjective norms (SN) of in-service teachers and their effect on AI readiness (RE) using the third hypothesis.

H3: SN has a positive and significant effect on RE.

In this study, subjective norms refer to the social pressure a teacher perceives from others, such as the government, schools, or colleagues. Even though teachers serve as key decision-makers in teaching and learning with AI, social pressures significantly influence how and to what extent they integrate technologies into their teaching practices (Teo, 2015). For example, research by Sun et al. (2025) indicates that participants who feel supported and respected by their peers when using smart devices tend to have relatively high subjective norms. Y. Li (2023) reported that people aware of institutional support are less likely to feel threatened by technological developments. We therefore make three hypotheses:

H4: AI policy and organization support (PO) has a positive and significant effect on SN.

H5. AI professional development (PD) has a positive and significant effect on SN.

H6. AI collegial support (CS) has a positive and significant effect on SN.

Extending a model's structure by adding or refining component variables is necessary to improve prediction accuracy (Tian & Yang, 2024). Therefore, instead of treating AI readiness as a single endogenous construct, as in previous studies (Fundi et al., 2024; Viet Quynh, 2025), we conceptualize it as a multi-stage construct comprising three progressively advanced levels: AI Readiness–Accepting (REA), AI Readiness–Introducing (REI), and AI Readiness–Teaching (RET).

To preserve conceptual coherence, all three stages are labeled with the common prefix "RE" to denote readiness, while the suffixes "A", "I", and "T" capture their developmental progression from Accepting to Introducing to Teaching. This notation is intended to reflect a unified continuum of AI readiness rather than a set of unrelated constructs. Although the similarity of the abbreviations may require initial attention from readers, the naming convention strengthens theoretical consistency and makes the hierarchical relationship among the three stages explicit.

The first stage, REA, refers to teachers' willingness to allow students to use AI tools for learning. This foundational level reflects openness to AI's presence in educational settings without requiring teachers' active instructional engagement. The second stage, REI, denotes teachers' readiness to provide students with technical guidance on using AI tools. This stage presupposes basic technical competence and the ability to demonstrate AI-related functionalities. The third stage, RET, captures teachers' readiness to intentionally integrate AI into instructional practice, including designing learning activities that harness AI to support student understanding. Based on this conceptualization, we propose two hypotheses that express sequential relationships among the three readiness levels.

H7: REA has a positive and significant effect on REI.

H8: REI has a positive and significant effect on RET.

Additionally, we extend the original hypotheses H1, H2, H3 to examine how predictor variables CA, RA, SN influence each stage of readiness REA, REI, RET as follows:

H1a: AI confidence (CA) has a positive and significant effect on teachers' readiness to **A**ccept students' use of AI tools for learning (REA).

H1b: AI confidence (CA) has a positive and significant effect on teachers' readiness to provide students with technical guidance (**I**ntroduce) on using AI tools (REI).

H1c: AI confidence (CA) has a positive and significant effect on teachers' readiness to intentionally integrate (**T**each) AI into instructional practice (RET).

H2a: AI relevance (RA) has a positive and significant effect on teachers' readiness to **A**ccept students' use of AI tools for learning (REA).

H2b: AI relevance (RA) has a positive and significant effect on teachers' readiness to provide students with technical guidance (**I**ntroduce) on using AI tools (REI).

H2c: AI relevance (RA) has a positive and significant effect on teachers' readiness to intentionally integrate (**T**each) AI into instructional practice (RET).

H3a: Subjective norms (SN) have a positive and significant effect on teachers' readiness to **A**ccept students' use of AI tools for learning (REA).

H3b: Subjective norms (SN) have a positive and significant effect on teachers' readiness to provide students with technical guidance (**I**ntroduce) on using AI tools (REI).

H3c: Subjective norms (SN) have a positive and significant effect on teachers' readiness to intentionally integrate (**T**each) AI into instructional practice (RET).

Finally, the research model integrates all exogenous and endogenous constructs into a unified framework. Together, these hypotheses operationalize the proposed model and provide a structured basis to examine how individual, social, and institutional factors influence teachers' AI readiness across its progressive developmental stages. In particular, the model captures both direct effects and the sequential progression of readiness from acceptance to instructional integration (Figure 1).

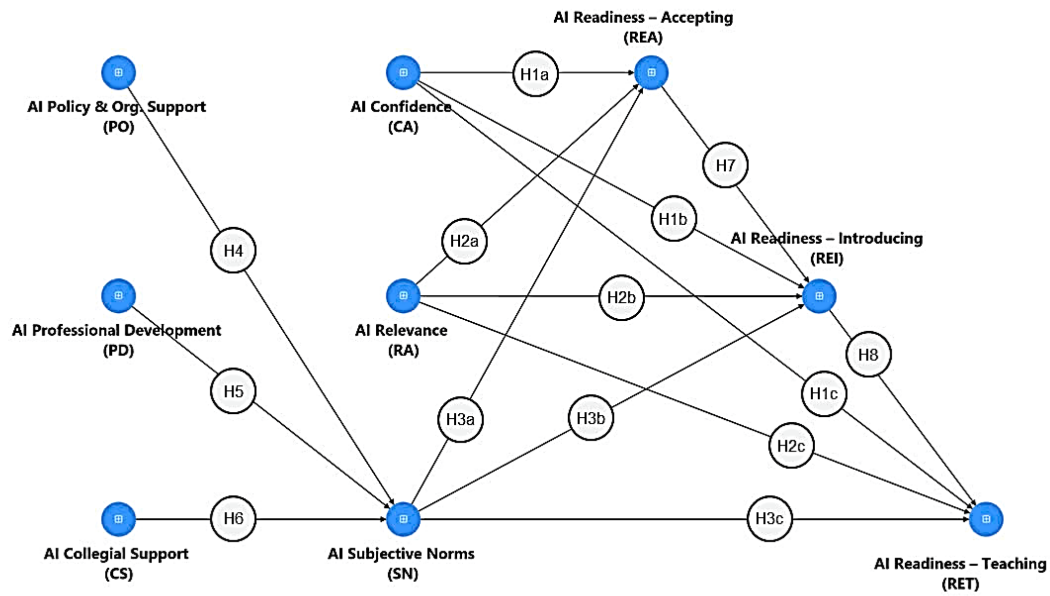

Figure 1. Theoretical model of secondary school teachers' AI readiness

METHOD

RESEARCH PROCEDURE

This study adopted a two-stage instrument development and validation design to create and test a measurement model of teachers' AI readiness in the Vietnamese secondary education context.

Stage 1. Instrument development

To develop the measurement items, we first reviewed relevant institutional and behavioral adoption frameworks, as well as recent studies on AI in education (Ayanwale et al., 2022; Fundi et al., 2024). The constructs and several measurement items used in this study were adapted from these prior studies to ensure theoretical grounding and relevance to AI adoption in education. Based on this review, an initial set of survey items was generated. The draft scale was then refined through two stages of qualitative feedback. Initially, four experts in educational technology and psychometrics evaluated the items to assess their content validity and alignment with the theoretical framework. Subsequently, focus group discussions were conducted with experienced teacher trainers to examine the clarity and practical relevance of the items in the context of Vietnamese secondary education. Their feedback helped clarify the meaning of several constructs, improve the wording of the items, and ensure that the instrument was culturally appropriate. As a result, unclear items were revised, and overlapping indicators were removed before the survey instrument was finalized for the pilot study.

Stage 2. Instrument validation

The finalized questionnaire used a six-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = slightly disagree, 4 = slightly agree, 5 = agree, 6 = strongly agree) to increase variance and avoid a neutral midpoint, which is suitable for behavioral intention and self-efficacy measures (Montaño & Kasprzyk, 2008). Demographic questions (e.g., gender, school location, teaching experience) were also included. A pilot test with 10 secondary teachers evaluated clarity, internal consistency, and completion time; minor adjustments to wording and ordering were made.

The main survey was administered online between October 2024 and August 2025 through professional teacher networks and educational forums. Participants were secondary school teachers representing diverse urban and rural contexts in Vietnam. Respondents were required to have prior exposure to AI-based tools or training to ensure contextual validity. Regarding practical experience, respondents were required to have at least 3 months of active, ongoing engagement with an AI platform, such as ChatGPT. Regarding formal proficiency, candidates were eligible if they had completed at least 3 hours of structured AI competency training or professional development workshops. A total of 1,145 valid responses were collected.

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS v4.1.1.4, following two sequential steps: (1) assessment of the measurement model (reliability, convergent and discriminant validity) and (2) evaluation of the structural model (multicollinearity, model fit, explained variance, predictive relevance, effect sizes, and hypothesis testing via bootstrapping with 5,000 subsamples).

All research activities were conducted in accordance with ethical guidelines for educational research and were approved by the institutional ethics review board of Ho Chi Minh City University of Education. Participation was entirely voluntary, with informed consent obtained from all respondents before survey completion, and no personally identifiable information was collected.

Data Analysis Method

Measurement model assessment

Reliability and validity were examined before hypothesis testing. Internal consistency was evaluated using Cronbach's alpha (CA) and Composite Reliability (CR), with values above 0.70 indicating satisfactory reliability (DeVellis & Thorpe, 2022; Nunnally & Bernstein, 1994). Indicator reliability was assessed using outer loadings, with values above 0.70 preferred and values between 0.40 and 0.70 retained only if they improved CR or the Average Variance Extracted (AVE) (Hair et al., 2021). Convergent validity was supported when AVE exceeded 0.50 (Fornell & Larcker, 1981). Discriminant validity was assessed using the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT), with HTMT < 0.85 indicating adequate discriminant validity (Henseler et al., 2015). Model fit was evaluated using the Standardized Root Mean Square Residual (SRMR), with values below 0.08 indicating good fit (Henseler et al., 2016; Hu & Bentler, 1998). Multicollinearity was examined using the Variance Inflation Factor (VIF), with a conservative threshold of 5 or lower (Hair et al., 2021).

Structural model assessment

The structural model's explanatory and predictive power was evaluated using the coefficient of determination (R^2), with values of 0.25, 0.50, and 0.75 indicating weak, moderate, and substantial explanatory power, respectively (Hair et al., 2021). Predictive relevance (Q^2) was estimated via blindfolding; $Q^2 > 0$ indicates predictive capability, with 0.02, 0.15, and 0.35 representing small, medium, and large predictive relevance (Chin, 2010; Shmueli et al., 2016). Effect size (f^2) was reported using Cohen's (2009) benchmarks (0.02 is small, 0.15 is medium, 0.35 is large). Path coefficients (β) were estimated, and their significance was assessed using non-parametric bootstrapping with 5,000 resamples, applying thresholds of $t \geq 1.96$ and $p < 0.05$.

Sample

Sample size and characteristics

According to Hair et al. (2021), the minimum sample size for Partial Least Squares Structural Equation Modeling (PLS-SEM) can be determined using the 10-times rule: at least 10 times the maximum number of indicators for any single latent construct or the maximum number of structural paths pointing to any latent construct. In this study, the construct with the most indicators had nine, requiring at least $10 \times 9 = 90$ respondents. The most complex endogenous construct had four incoming paths, requiring at least $10 \times 4 = 40$ respondents. Thus, a sample size of 90 or more was considered methodologically adequate.

Data were collected through convenience sampling among secondary school teachers participating in AI-related training programs and professional forums. The survey link was distributed through school networks, district and provincial Departments of Education and Training, and teacher communities across five Vietnamese localities: Ho Chi Minh City, Can Tho City, Tay Ninh Province, Dong Thap Province, and An Giang Province. Respondents were eligible if they provided voluntary consent, had prior exposure to AI-based tools or training, and completed all survey items without missing data. A total of 1,145 valid responses were retained for analysis (mean teaching experience is 16.24 ± 0.22 years, SD = 7.3), exceeding the minimum sample size requirement and providing robust statistical power for PLS-SEM analyses. Descriptive statistics for the sample are presented in Table 1.

Table 1. Descriptive statistics of the sample

Factor	Category	Frequency	Percentage (%)
Gender	Female	481	42.0
	Male	664	58.0
Region	Urban	463	40.4
	Rural / Mountainous / Island	682	59.6
Province/City	Ho Chi Minh City	253	22.1
	Can Tho City	190	16.6
	Tay Ninh Province	284	24.8
	Dong Thap Province	334	29.2
	An Giang Province	84	7.3
Total		1,145	100.0

Data distribution

To evaluate the dataset's distributional characteristics, skewness and kurtosis were examined as indicators of univariate normality. Skewness captures the degree of asymmetry in the distribution, whereas kurtosis reflects the relative peakedness and tail heaviness compared with a normal distribution.

As shown in Table 2, the mean and median values of all items are closely aligned, indicating generally symmetrical response patterns. The majority of skewness and kurtosis values fall within the commonly accepted threshold of ±2 (Dash & Paul, 2021), supporting the assumption of approximate normality. Nevertheless, a small number of items exhibit kurtosis values slightly exceeding this threshold (e.g., RE3 = 2.62). These deviations suggest mild departures from normality rather than severe violations of distributional assumptions. In large samples, such levels of kurtosis are typically considered acceptable and are unlikely to substantially bias parameter estimates.

Importantly, the use of PLS-SEM further mitigates concerns about non-normality, as this method does not require multivariate normality and has been shown to be robust to moderate skewness and kurtosis. Therefore, the observed distributional properties do not pose a substantive threat to the reliability or validity of the measurement and structural model estimations.

Table 2. Normality assessment of the study variables

Name	Mean	Median	Standard deviation	Excess kurtosis	Skewness
RE1	4.92	5.00	0.97	1.76	-1.10
RE2	5.02	5.00	0.91	2.21	-1.19
RE3	5.11	5.00	0.87	2.62	-1.21
RE4	4.99	5.00	0.91	2.26	-1.16
RE5	5.01	5.00	0.93	2.25	-1.19
RE6	4.93	5.00	0.98	1.46	-1.07
RE7	4.90	5.00	0.99	1.31	-1.03
RE8	4.84	5.00	0.99	1.13	-0.95
RE9	5.00	5.00	0.94	1.85	-1.15
RE10	5.06	5.00	0.87	2.09	-1.10
RE11	5.13	5.00	0.81	2.15	-1.07
RE12	5.04	5.00	0.87	2.39	-1.14
RE13	4.77	5.00	1.02	1.13	-0.98
RE14	4.98	5.00	0.88	1.83	-0.99
RE15	4.90	5.00	0.92	1.50	-0.99
RE16	4.96	5.00	0.90	1.84	-1.05
CA1	4.81	5.00	0.99	1.40	-1.00
CA2	4.69	5.00	1.06	0.81	-0.91
CA3	4.63	5.00	1.09	0.45	-0.82
CA4	4.73	5.00	1.04	0.93	-0.93
CA5	4.65	5.00	1.09	0.58	-0.86
CA6	4.72	5.00	1.03	0.78	-0.92
SN1	4.77	5.00	0.96	0.92	-0.87
SN2	4.75	5.00	0.97	0.72	-0.82
SN3	4.81	5.00	0.94	1.19	-0.89
SN4	4.83	5.00	0.95	1.35	-0.97
RA1	5.01	5.00	0.84	1.22	-0.88
RA2	4.94	5.00	0.84	0.90	-0.76
RA3	4.94	5.00	0.87	0.82	-0.77
RA4	5.00	5.00	0.84	1.26	-0.85
RA5	4.98	5.00	0.90	2.15	-1.09
CS1	4.78	5.00	0.93	1.25	-0.85
CS2	4.79	5.00	0.92	0.73	-0.72
CS3	4.77	5.00	0.94	1.19	-0.85
CS4	4.78	5.00	0.96	1.28	-0.90
PO1	4.70	5.00	1.04	1.05	-0.96
PO2	4.74	5.00	1.02	1.05	-0.94
PO3	4.73	5.00	1.05	0.74	-0.90
PO4	4.76	5.00	1.04	1.09	-1.00
PD1	4.65	5.00	1.13	0.78	-0.99
PD2	4.78	5.00	1.05	1.35	-1.09
PD3	4.78	5.00	1.11	1.40	-1.17
PD4	4.81	5.00	1.05	1.46	-1.13

Notably, the median value for most constructs is 5 on the 6-point Likert scale, indicating a generally favorable orientation toward AI readiness among respondents. While this pattern may initially suggest response bias (e.g., acquiescence or social desirability), it is theoretically plausible in the present context. Specifically, the strong national emphasis on digital transformation in education, along with greater exposure to AI-related professional development, may contribute to more positive perceptions among teachers. Accordingly, these high central tendency values are interpreted as reflecting perceived readiness rather than objective implementation outcomes.

Finally, it should be acknowledged that convenience sampling enabled the collection of a large and diverse dataset; however, it may limit the generalisability of the findings beyond the sampled population. Future research is therefore encouraged to adopt stratified or probability-based sampling approaches to improve representativeness across regions, school types, and teacher demographics.

RESULTS

MEASUREMENT MODEL ASSESSMENT

Reliability and convergent validity

As shown in Table 3, all constructs exhibited excellent measurement quality. Indicator outer loadings ranged from 0.858 to 0.969, well above the recommended threshold of 0.70 (Hair et al., 2021). Cronbach's alpha coefficients ranged from 0.915 to 0.973, and Composite Reliability (CR) values ranged from 0.940 to 0.980, surpassing the minimum recommended level of 0.70 and indicating high internal consistency. The Average Variance Extracted (AVE) values ranged from 0.789 to 0.925, exceeding the 0.50 benchmark and confirming strong convergent validity for all latent constructs.

Table 3. Reliability and convergent validity of the measurement model

Variable	Item	Outer loading	Cronbach's alpha	Composite reliability	AVE
REI	RE1	0.875	0.917	0.948	0.858
	RE2	0.891			
	RE3	0.864			
	RE4	0.895			
	RE5	0.911			
	RE6	0.906			
	RE8	0.867			
	RE9	0.895			
REA	RE10	0.929	0.915	0.940	0.796
	RE11	0.915			
	RE12	0.935			
RET	RE13	0.858	0.962	0.968	0.789
	RE14	0.885			
	RE15	0.921			
	RE16	0.905			
CA	CA1	0.859	0.961	0.968	0.836
	CA2	0.925			
	CA3	0.944			
	CA4	0.919			
	CA5	0.931			
	CA6	0.905			
SN	SN1	0.917	0.947	0.962	0.863
	SN2	0.934			

Variable	Item	Outer loading	Cronbach's alpha	Composite reliability	AVE
	SN3	0.936			
	SN4	0.929			
RA	RA1	0.902	0.948	0.960	0.828
	RA2	0.917			
	RA3	0.931			
	RA4	0.932			
	RA5	0.867			
PO	PO1	0.952	0.973	0.980	0.925
	PO2	0.969			
	PO3	0.962			
	PO4	0.963			
PD	PD1	0.940	0.960	0.971	0.892
	PD2	0.951			
	PD3	0.947			
	PD4	0.939			
CS	CS1	0.940	0.960	0.971	0.892

Discriminant validity

Discriminant validity was evaluated using the Fornell-Larcker criterion (Table 4) and the Heterotrait-Monotrait ratio (HTMT) (Table 5). In Table 4, the square roots of the AVEs (bold diagonal elements) exceeded the corresponding inter-construct correlations, and all correlations were below 0.85. The HTMT values ranged from 0.547 to 0.815, remaining below the conservative 0.85 threshold (Henseler et al., 2015). Collectively, these results confirm that the measurement model achieves excellent reliability, convergent validity, and discriminant validity, providing a robust foundation for subsequent structural model analysis.

Table 4. Discriminant validity assessment – Fornell-Larcker criterion

Variable	CS	CA	PO	PD	REA	REI	RET	RA	SN
CS	**0.944**								
CA	0.746	**0.914**							
PO	0.814	0.705	**0.962**						
PD	0.737	0.700	0.802	**0.945**					
REA	0.637	0.703	0.631	0.615	**0.892**				
REI	0.592	0.643	0.551	0.538	0.764	**0.926**			
RET	0.594	0.640	0.568	0.564	0.715	0.727	**0.888**		
RA	0.777	0.700	0.699	0.680	0.683	0.666	0.668	**0.910**	
SN	0.772	0.765	0.753	0.696	0.664	0.633	0.607	0.743	**0.929**

Note. Diagonal elements (bold) are the square roots of AVEs. Off-diagonal values are correlations among constructs.

Table 5. Discriminant validity assessment – Heterotrait-Monotrait (HTMT) ratio

Variable	CS	CA	PO	PD	REA	REI	RET	RA	SN
CS									
CA	0.776								
PO	0.843	0.729							
PD	0.768	0.727	0.829						

Variable	CS	CA	PO	PD	REA	REI	RET	RA	SN
REA	0.680	0.749	0.669	0.656					
REI	0.630	0.682	0.582	0.573	0.833				
RET	0.617	0.663	0.586	0.586	0.760	0.773			
RA	0.815	0.732	0.728	0.713	0.733	0.714	0.699		
SN	0.810	0.802	0.784	0.730	0.713	0.678	0.634	0.783	

Structural Model Assessment

Figure 2 presents the overall PLS-SEM model, with standardized loadings on the measurement paths and R^2 values for the endogenous constructs.

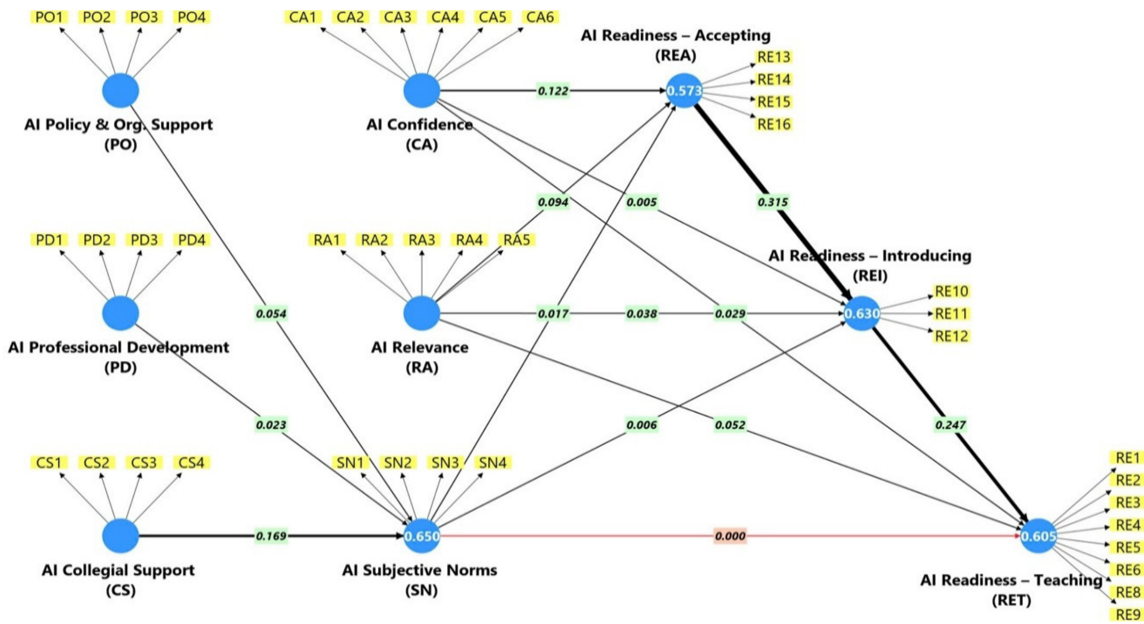

Figure 2. PLS-SEM model of secondary Vietnamese teachers' AI readiness

Notes. Blue nodes represent latent constructs; yellow boxes represent observed indicators. R^2 values are shown inside the blue latent construct circles (bold blue). Path coefficients are displayed on the connecting lines (green = significant; red = non-significant).

Multicollinearity diagnostics and model fit

Multicollinearity among predictor constructs was first assessed using the Variance Inflation Factor (VIF). As shown in Table 6, VIF values for all predictors ranged from 2.055 to 4.034. Although some predictors – such as AI Policy & Organizational Support (VIF = 4.034) and AI Collegial Support (VIF = 3.156) – exhibited moderate collinearity, all values remained well below the conservative cut-off of 5, indicating that multicollinearity is not a severe concern (Hair et al., 2021).

Table 6. Multicollinearity assessment – Variance Inflation Factor (VIF)

Predictor constructs	REA	REI	RET	SN
CA	2.659	2.982	2.808	
CS				3.156
PD				2.976
PO				4.034
RA	2.461	2.692	2.726	
REA		2.342		

Predictor constructs	REA	REI	RET	SN
REI			2.055	
SN	3.026	3.076	3.079	

Note. VIF < 5 indicates no severe multicollinearity.

Overall model fit was also examined using the Standardized Root Mean Square Residual (SRMR) and other global fit statistics. The SRMR for the estimated model was 0.047, below the recommended threshold of 0.08 and close to the saturated model (0.033), indicating a good fit (Hu & Bentler, 1998). Additional indices, including dULS (1.968 vs. 0.958 for the saturated model), dG (0.829 vs. 0.787), and the Normed Fit Index (NFI = 0.912), further support a good fit to the empirical data, with minimal discrepancy between the estimated and saturated models. Collectively, these results confirm that the structural model meets accepted criteria for good fit and is not affected by problematic multicollinearity, providing a reliable basis for testing the hypothesized structural relationships.

Coefficient of determination and predictive relevance

The structural model demonstrated satisfactory explanatory power (Table 7), accounting for 63% of the variance in REI, 60.5% in RET, 57.3% in REA, and 65% in SN, indicating moderate to substantial levels of explanatory power. Predictive relevance was also supported, with Q^2 values exceeding recommended thresholds (Q^2 values: REA = 0.567, REI = 0.497, RET = 0.502, SN = 0.645), and low prediction errors further confirming the model's predictive accuracy.

Table 7. Coefficient of determination (R^2) and predictive relevance (Q^2) of the structural model

Dependent construct	R^2	R^2_{Adj}	Explanatory power*	Q^2	RMSE	MAE	Predictive power**
REA	0.573	0.572	Moderate	0.567	0.660	0.453	Strong
REI	0.630	0.629	Moderate to substantial	0.497	0.712	0.510	Strong
RET	0.605	0.603	Moderate to substantial	0.502	0.708	0.461	Strong
SN	0.650	0.649	Substantial	0.645	0.597	0.391	Strong

**Interpretation of R^2:* substantial ≥ 0.75; moderate 0.50-0.74; weak 0.25-0.49 (Hair et al., 2021)
***Interpretation of Q^2:* strong ≥ 0.35; moderate 0.15-0.34; weak 0.02-0.14 (Shmueli et al., 2016)

Hypothesis testing

To test the proposed hypotheses, the significance of the structural paths was assessed using a non-parametric bootstrapping procedure with 5,000 resamples and 1,145 valid observations. Path significance was evaluated using t-statistics and associated p-values, with 5% as the primary significance level. Effect sizes (f^2) were also examined to assess the practical importance of each relationship (Hair et al., 2021). The results are summarized in Table 8.

Table 8. Bootstrapping results for the structural model (direct effects)

Hyp.	Path	β	t	p	f^2	Result	Effect size
H1a	CA → REA	0.372	7.510	***	0.122	Supported	Small-Medium
H2a	RA → REA	0.314	6.522	***	0.094	Supported	Small-Medium
H3a	SN → REA	0.146	2.789	**	0.017	Supported	Very Small
H1b	CA → REI	0.075	2.001	*	0.005	Supported	Negligible
H2b	RA → REI	0.195	4.967	***	0.038	Supported	Small
H3b	SN → REI	0.084	2.134	*	0.006	Supported	Negligible
H1c	CA → RET	0.179	4.530	***	0.029	Supported	Small
H2c	RA → RET	0.237	5.522	***	0.052	Supported	Small-Medium

Hyp.	Path	β	t	p	f^2	Result	Effect size
H3c	SN → RET	0.011	0.290	ns	0.000	Not supported	None
H4	PO → SN	0.276	5.215	***	0.054	Supported	Small-Medium
H5	PD → SN	0.156	3.545	***	0.023	Supported	Small
H6	CS → SN	0.432	8.613	***	0.169	Supported	Medium
H7	REA → REI	0.523	13.294	***	0.315	Supported	Large
H8	REI → RET	0.448	9.742	***	0.247	Supported	Large

Note. p < .05; p < .01; p < .001; ns = not significant. Effect size interpretation: none (<0.02), small (0.02-0.14), medium (0.15-0.34), large (≥0.35) (Cohen, 2009; Hair et al., 2021).

At the organizational level, all three support-related factors significantly influenced SN, with CS showing the strongest effect (β = 0.432, p < .001), followed by PO and PD. This highlights the importance of institutional and peer environments in shaping perceived social expectations regarding AI use. At the individual level, both CA and RA emerged as consistent predictors across readiness stages. Both constructs significantly influenced REA (e.g., CA → REA: β = 0.372, p < .001), and continued to affect more advanced stages, although with varying strength. Notably, RA exerted a stronger influence on REI compared to CA, while the effect of CA on REI was relatively weak.

The results also support the sequential nature of AI readiness. REA strongly predicted REI (β = 0.523, p < .001, large effect), and REI, in turn, was the strongest predictor of RET (β = 0.448, p < .001), confirming a progressive pathway from acceptance to integration. For RET, both CA and RA maintained significant direct effects, indicating the continued importance of individual capability and perceived value in advanced stages. In contrast, SN did not significantly influence RET (β = 0.011, ns), suggesting that external expectations play a diminishing role as teachers move toward deeper instructional integration.

Multi-Group Analysis

To examine whether the structural relationships differ across subgroups, a multi-group analysis (MGA) was conducted simultaneously by gender (female vs. male) and by region (urban vs. rural/mountainous/disadvantaged). The results are summarized in Tables 9 and 10, which report standardized path coefficients (β), within-group p-values, between-group differences in coefficients (Δβ), Welch's t and p-values for cross-group comparisons, and significance levels (p < 0.05).

Most hypothesized structural paths remained statistically invariant across gender (Table 9) and regional subgroups (Table 10), supporting the overall robustness and generalizability of the proposed AI readiness model. Nevertheless, several meaningful moderating effects emerged.

Table 9. MGA of structural path coefficients by gender

Gender		Female (N=481)		Male (N=664)		Different			
Hyp.	**Path**	**β Female**	**p Female**	**β Male**	**p Male**	**Δβ (Male - Female)**	**Welch t**	**Welch p**	**Sig.**
H1a	CA → REA	0.305	***	0.449	***	0.144	1.446	0.149	ns
H2a	RA → REA	0.360	***	0.247	***	–0.114	1.177	0.240	ns
H3a	SN → REA	0.182	**	0.122	ns	–0.060	0.555	0.579	ns
H1b	CA → REI	0.049	ns	0.100	ns	0.051	0.662	0.508	ns
H2b	RA → REI	0.148	**	0.233	***	0.085	1.110	0.267	ns
H3b	SN → REI	0.109	*	0.051	ns	–0.058	0.740	0.460	ns
H1c	CA → RET	0.161	**	0.191	***	0.031	0.400	0.690	ns
H2c	RA → RET	0.148	**	0.326	***	0.178	2.074	0.039	*

Gender		Female (N=481)		Male (N=664)		Different			
Hyp.	Path	β Female	p Female	β Male	p Male	Δβ (Male - Female)	Welch t	Welch p	Sig.
H3c	SN → RET	0.014	ns	–0.011	ns	–0.025	0.350	0.727	ns
H4	PO → SN	0.265	***	0.284	***	0.019	0.182	0.856	ns
H5	PD → SN	0.239	***	0.059	ns	–0.179	2.116	0.035	*
H6	CS → SN	0.358	***	0.516	***	0.158	1.574	0.116	ns
H7	REA → REI	0.561	***	0.494	***	–0.067	0.879	0.380	ns
H8	REI → RET	0.541	***	0.366	***	–0.175	1.868	0.062	ns

Note. Significance levels: ***p < .001; **p < .01; *p < .05; ns = non-significant

Table 10. MGA of structural path coefficients by region

Region		Urban (N=463)		Rural (N=682)		Different			
Hyp.	Path	B Urban	p Urban	β Rural	p Rural	Δβ (Rural–Urban)	Welch t	Welch p	Sig.
H1a	CA → REA	0.342	***	0.407	***	0.064	0.681	0.496	ns
H2a	RA → REA	0.353	***	0.267	**	–0.086	0.891	0.373	ns
H3a	SN → REA	0.125	*	0.173	ns	0.048	0.452	0.651	ns
H1b	CA → REI	0.033	ns	0.129	*	0.096	1.266	0.206	ns
H2b	RA → REI	0.248	***	0.133	*	–0.115	1.477	0.140	ns
H3b	SN → REI	0.082	ns	0.090	ns	0.008	0.099	0.921	ns
H1c	CA → RET	0.140	**	0.203	**	0.063	0.809	0.419	ns
H2c	RA → RET	0.271	***	0.209	**	–0.062	0.750	0.454	ns
H3c	SN → RET	0.084	ns	–0.060	ns	–0.143	1.970	0.049	*
H4	PO → SN	0.258	***	0.292	**	0.034	0.315	0.753	ns
H5	PD → SN	0.253	***	0.067	ns	–0.186	2.063	0.040	*
H6	CS → SN	0.391	***	0.461	***	0.070	0.702	0.483	ns
H7	REA → REI	0.531	***	0.502	***	–0.029	0.367	0.714	ns
H8	REI → RET	0.418	***	0.475	***	0.056	0.627	0.531	ns

Note. Significance levels: ***p < .001; **p < .01; *p < .05; ns = non-significant

Regarding gender, the influence of PD → SN was significantly stronger among female teachers ($\beta = 0.239$, $p < .001$) than among male teachers ($\beta = 0.059$, $p = .272$; $\Delta\beta = –0.179$, Welch $p = .035$), indicating that structured AI training and upskilling have a more pronounced effect on women's perceived social support and normative pressure to adopt AI. In contrast, the pathway RA → RET was stronger for male teachers ($\beta = 0.326$, $p < .001$) than for female teachers ($\beta = 0.148$, $p = .015$; $\Delta\beta = +0.178$, Welch $p = .039$), suggesting that male teachers' decisions to integrate AI depend more heavily on perceiving its practical applicability to classroom practice.

For regional context, the influence of PD → SN was significantly stronger in urban schools ($\Delta\beta = –0.186$, Welch $p = .040$), suggesting that professional learning communities and resource-rich environments amplify the normative impact of training. Conversely, the direct effect of SN → RET was weaker and non-significant in rural and disadvantaged contexts ($\Delta\beta = –0.143$, Welch $p = .049$), indicating that social expectations alone may not translate into behavioral intention when infrastructural and collegial supports are limited. Other key psychological drivers, including CA → REI, RA →

REI, and SN → REI, remained stable across subgroups, suggesting that confidence and perceived relevance of AI operate consistently regardless of demographic or contextual differences.

DISCUSSION

The primary objective of our research is to identify and validate factors that influence the artificial intelligence readiness of secondary school teachers in Vietnam. Theoretically, this study developed a model comprising 14 hypotheses, which were subsequently tested. These hypotheses examine relationships among predictors at the organizational, professional, and individual levels, as well as across different stages of teachers' AI readiness. While previous studies have examined RE as a single variable (Ayanwale et al., 2022; Chuyen & Vinh, 2025; Fundi et al., 2024), we consider it to have a multi-level structure progressing through three successive stages. This stratified approach enables more accurate identification of the transition from students' implicit acceptance of AI techniques to teachers' teaching of AI techniques, and ultimately, the integration of AI into teaching. It explains the transition from an informal to a formal role, from a simple (technical) to an advanced (subject-specific) level. The results of this study were based on 1,145 responses, which were used in the bootstrapping procedure to test the hypotheses, providing strong support for the theoretical model. Specifically, 13 of 14 hypotheses showed a statistically significant, positive relationship. The only non-significant hypothesis, SN → RET, suggests that expectations from peers and the organization do not predict the extent of AI integration into teaching practices.

While most of the hypothesized relationships were supported and appear consistent with prior research, this should not be interpreted as merely expected or redundant. Rather, these findings confirm the robustness of established theoretical relationships within the specific context of Vietnamese in-service teachers, where empirical evidence remains limited. More importantly, the multi-stage conceptualization of AI readiness reveals meaningful differences in how predictors influence each stage. For instance, certain factors exert stronger effects in the early stages (e.g., REA), whereas others become more influential in the advanced stages (e.g., RET). These nuanced patterns extend beyond prior research, which typically conceptualizes readiness as a single construct.

Based on the measurable results, CA is an individual factor that promotes readiness and has a significant positive impact on all three stages of REA, REI, and RET. This finding aligns with research by Ayanwale et al. (2022), Fundi et al. (2024), and Liu (2025). This suggests that the more confident teachers are in AI technology, the more comfortable they are with its flexible classroom applications. Bui et al. (2025)'s t-test validation across participating groups reveals a strong, consistent association: higher confidence is linked to greater willingness to integrate AI. However, the strength of this effect varies with readiness, suggesting a shifting role for trust as teachers move from acceptance to integration. CA's impact on REA was strongest, indicating that teachers' confidence in their individual competence is crucial for achieving readiness for AI in education. This leads them to implicitly allow learners to use AI tools as part of the learning process, provided that use is directed toward the right purpose and does not violate ethical standards. The weakening of influence in the later stages implies that, although trust is necessary for initial acceptance, as onboarding and integration progress toward more complex activities, other factors, such as prior acceptance experience, play an increasingly significant role. Indeed, Ofem et al. (2025) state that when educators are confident that the technology is relevant to their teaching goals, they are more likely to perceive it as user-friendly (for teachers and students) and adaptable. These findings highlight an important predictor of confidence in RE, particularly REA. Choi et al. (2025) demonstrate that even self-motivated individuals may need greater confidence to translate their motivation into practical activities effectively.

A comparison of path coefficients and impact sizes shows that RA significantly influences all three readiness levels (REA, REI, RET), with the strongest effect at the acceptance stage (REA). This impact is justified because REA reflects a foundational teacher openness to AI in educational contexts, which does not require active instructional involvement. When teachers find AI truly relevant and valuable, they are significantly more willing to accept its presence in students' classrooms. Like CA, RA has its weakest impact on REI. This is because REI represents basic technical instruction to students on how to operate AI tools, which other factors in the model can more strongly influence (e.g., REA strongly influences REI). Notably, the impact of RA on RET is greater than on REI. It suggests that while introducing the technique may depend less on perceptions of relevance, achieving a deeper, more purposeful level of integration into teaching practice still requires that perceptions of AI's practical value and relevance play an ongoing role. Additionally, the RA → RET pathways were stronger for male teachers than for female teachers. The findings are consistent with those of a study by Fteiha et al. (2025), which showed that, while female teachers have more positive attitudes, cognitive familiarity with AI relevance has a greater impact on willingness to engage among males. It demonstrates that, for males, the decision to switch to AI-integrated teaching methods is primarily a pragmatic calculation; once they realize the practical value of AI in a classroom setting, they are more likely to translate that awareness directly into a readiness to teach. These relationships align with previous studies (Ayanwale et al., 2022; Sanusi et al., 2024), which have established that awareness of AI's relevance is important for teacher readiness. Hsu et al. (2025) strongly confirm the hypothesis that RA has explanatory implications for the RE of pre-service preschool teachers. More importantly, the authors clarify the essential intermediate role of AI literacy in linking RA to RE. AI literacy → RA → RE is statistically significant. Taken together, future teacher training programs should integrate modules that help learners not only understand AI but also clearly see its relevance to teaching and learning, thereby optimizing their readiness.

In this study, SN refers to the social pressure teachers feel from stakeholders, including governments, schools, or peers, that affects their willingness to accept and apply AI. The impact of SN on teacher readiness stages diminishes as AI application complexity increases, from initial acceptance to teaching integration within the subject. SN can stimulate teachers' motivation for AI by providing appropriate support resources, thereby enhancing their readiness (Liu, 2025). SN has a positive and significant effect on the REA, and this effect is reduced but still significant for the REI. However, the actual impact of SN on both REA and REI is negligible. Surprisingly, the H3c hypothesis was not supported; SN did not significantly predict the RET phase. This result is explained by the fact that SN related to AI integration may not be well established, thereby reducing their influence on teachers' behavioral readiness (Du et al., 2025). This contrasts with Fundi et al. (2024), who state that when subjective norms benefit teachers, they can support teachers' AI teaching-readiness journey. This difference suggests that although social norms and expectations from institutions or peers drive initial acceptance of students' use of AI and may encourage the introduction of basic AI tools, these factors are not robust enough to sustain or purposefully integrate AI into teaching practice. In other words, when teachers need to move from enabling or guiding techniques to designing learning activities that leverage AI capabilities, their readiness depends more on individual competencies (CA, RA) and internalized readiness than on external social pressures. On the other hand, the direct impact of SN → RET is weaker and less meaningful in rural and disadvantaged contexts, emphasizing that mere social expectations may not translate into a willingness to teach AI when infrastructure and peer support are limited. Guilen and Omolara (2025) point out that even if teachers are eager to integrate AI into their lessons, the lack of reliable technology infrastructures, such as hardware, software, and a stable internet connection, still creates a major barrier that prevents them from practicing integrating what they have learned. For teachers in underserved areas, RET is often seen as an additional burden rather than a support tool, especially when they are already exhausted by large class sizes and a lack of teaching aids.

The structural model validated three organizational hypotheses: PO, PD, and CS all have a positive and significant influence on SN. Specifically, CS has the strongest impact on SN. Teachers who feel supported by their peers are more likely to take risks and try new teaching methods (Tang et al., 2025). Furthermore, when teachers observe their colleagues successfully using AI, they are inspired to follow suit. This contrasts with the results of Zhao and Huang (2025), which indicate that CS primarily influences behavioral attitudes rather than directly influencing subjective norms. This variation can be attributed to differences in organizational context and levels of professional autonomy between the two groups studied. Next, PO has a positive impact on SN, suggesting that, under the collective cultural context, teachers are more likely to be influenced by their superiors' policies and directives during technology adoption (Y. Wang et al., 2025). Moreover, teachers may feel unprepared to engage with AI technology without clear management policies and data regulations in schools (Batubara et al., 2025). International guiding frameworks, such as UNESCO's (2022) Recommendation on the Ethics of Artificial Intelligence, emphasize the importance of protecting user privacy, fairness, and transparency. Finally, PD also showed significance for SN, with a slight influence. UNESCO (2024) has guided national teacher-training programs to enhance AI capacity and address concerns arising from social pressures on educators. In terms of demographics, the impact of PD → SN was more substantial among female teachers than among male teachers, demonstrating that AI training and upskilling programs had a more pronounced effect on shaping women's perceptions of social support and the normative pressure to use AI. These findings underscore that well-structured AI policies, formal training opportunities, and an environment with strong peer support are critical in establishing social norms that encourage teachers to be ready for AI.

REA has a positive and significant impact on REI, as strongly supported, indicating that it is one of the relationships with a large impact in the model. This result suggests that initial acceptance provides a strong foundation, motivating teachers to take more proactive steps to introduce and guide the use of AI applications. In other words, overcoming the initial psychological barrier and accepting AI's role in student learning is an important prerequisite for teachers to develop their competence and willingness to provide technical instruction. Choi et al. (2025) argue that student preparation is a crucial regulatory factor that influences teachers' intrinsic motivation. When teachers have reached a certain level of confidence in instructing students technically – that is, in solving the "bottleneck" of technological competence – they tend to be more willing to implement high-level AI integration strategies in teaching. Indeed, REI is a powerful explanatory factor for RET and has been identified as the most influential predictor of RET. The importance of this relationship underscores that teachers' proficiency in guiding students to use AI is the most necessary and powerful stepping stone for them to transition into the design and implementation phases of more complex AI-based teaching strategies. The degree of correlation among REA → REI → RET clarifies the anxiety of Alagöz Hamzaj (2025), who expressed openness to AI acceptance, which may not fully explain the observed differences in participants' attitudes. Academically, by expanding the concept of RE with specific variables related to AI technology, the study significantly enriches the theoretical framework, providing a detailed understanding of the factors affecting each stage of the AI readiness process for teachers in Vietnam. This separation is not only theoretical but also helpful in designing practical interventions, as each group of teachers will require different forms of support to transition smoothly through the stages of RE.

This study contributes to the growing discussion on technology adoption in education by rethinking how teachers' AI readiness should be understood. Rather than seeing readiness as a single, fixed condition, the findings suggest that it develops gradually over time. Teachers move through several stages as they become more comfortable working with AI. At first, they may accept students' use of AI tools (REA). Over time, some begin to guide students in using these tools appropriately (REI). Only at a later stage do teachers intentionally incorporate AI more into their teaching practices (RET). The study also reveals that the factors shaping teachers' behavior differ across these stages. In the beginning, subject norms play an important role in encouraging teachers to accept students' use of AI. Our study can further complement and clarify previous research (Fundi et al., 2024; Liu, 2025) by identifying the specific impact of this factor during the early stage of readiness, rather than addressing readiness as a general construct. However, as teachers gain more experience, these external pressures appear to matter less. When teachers reach the stage of integrating AI into their teaching, their decisions seem to depend more on personal factors, particularly their confidence in using AI and their perceived relevance of AI to their work. In other words, there seems to be a point where teachers shift from responding mainly to external expectations to relying more on their own professional judgment. Another aspect highlighted by the model is the role of the institutional and professional environment in shaping these early social influences. Support from colleagues and guidance from school policies can help establish norms that encourage teachers to be more open to engaging with AI. It may be particularly important in developing-country contexts, where institutional signals and peer practices often strongly shape attitudes toward new technologies. Taken together, previous studies have largely treated readiness merely as a single explanatory factor in research models (Hsu et al., 2025; Jatileni et al., 2024; Liu, 2025; Sanusi et al., 2024; Sun et al., 2025). Our findings suggest that understanding AI adoption among teachers requires looking not only at whether teachers are ready, but also at how that readiness develops over time. By framing readiness as a staged process, the study offers a way to identify better where teachers may encounter difficulties and how their professional engagement with AI evolves as they move from initial acceptance to deeper instructional use.

These results underscore that while the core acceptance mechanism of AI readiness is broadly invariant, contextual inequities, particularly access to targeted professional development and an enabling school culture, moderate how social norms and perceived relevance translate into advanced integration readiness. This evidence informs the design of differentiated capacity-building policies, emphasizing gender-responsive training that reinforces norms for female teachers and showcases pragmatic instructional applications for male teachers, while also addressing structural barriers that limit the impact of social influence in rural and disadvantaged schools. Although this study provided a robust and reliable model for assessing the AI readiness of secondary school teachers in Vietnam, and the model met the criteria for reliability, convergence validity, and differentiation, the research still has certain limitations that need to be addressed in future work. The most obvious limitation is the reliance on convenience sampling to collect data from teachers participating in AI-related forums and training programs across five localities in Vietnam.

Although this approach facilitates access to a large and diverse group of teachers, it may limit the ability to generalize findings beyond the areas surveyed. Therefore, future studies are recommended to use stratified or randomized sampling to enhance representation across different types of schools and geographic areas. It is essential to acknowledge that the data rely on self-reported perception surveys. This methodology may introduce social desirability bias, as teachers might feel a professional obligation to report higher levels of readiness to align with national digital mandates. Future research should therefore complement these perceptual findings with objective behavioral data, such as classroom observations or digital logs of AI tool usage, to triangulate self-reported readiness with actual pedagogical practice. Additionally, the results of the multi-group analysis indicate that the effect of SN on RET is weak and not statistically significant in remote areas. Therefore, future studies should more deeply investigate structural barriers in low-resource environments to clearly identify the factors that prevent teachers from progressing from acceptance to the subsequent stages of readiness. Ultimately, the findings from this study inform the design of differentiated capacity-building policies, particularly the development of gender-responsive training programs that reinforce subjective norms for female teachers, highlight practical teaching applications, and underscore the relevance of AI for male teachers.

CONCLUSION

This study aimed to identify and explain the factors influencing the artificial intelligence readiness of secondary school teachers in Vietnam, conceptualizing readiness as a multi-stage process spanning from acceptance to instructional integration. The findings indicate that AI confidence and perceived AI relevance are consistent predictors across all readiness stages, as readiness progresses sequentially from acceptance to introduction and, finally, to teaching integration. Organizational factors, especially collegial support, significantly shape subjective norms, which influence early readiness but do not directly predict advanced instructional integration. For practitioners, the results highlight the importance of staged professional development that strengthens teachers' confidence, clarifies the pedagogical relevance of AI, and fosters supportive collegial environments. For researchers, this study contributes a validated multi-stage framework for examining teachers' AI readiness and provides a foundation for future longitudinal and cross-contextual investigations. At a broader societal level, the findings support more effective and equitable implementation of AI-driven educational reforms, thereby improving teaching quality and advancing sustainable digital transformation in education.

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