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A Structural Model of Factors Affecting Primary School Teachers' AI Competence in Northern Mountainous Vietnam

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Abstract. In the context of artificial intelligence (AI) increasingly shaping education, this study develops and validates a structural model of factors that influence primary school teachers' capacity to apply AI in teaching. Data were collected from 624 teachers in the mountainous northern region of Vietnam. The study employed generalized structured component analysis, a variance-based variant of structural equation modeling, to evaluate the proposed model. The model included six key components: knowledge, skills, ethical awareness, reflective thinking, attitude, and application behavior. The results show that knowledge serves as a foundational factor, directly influencing both skills and attitude. Skills and reflective thinking act as mediators that foster pedagogical competence, which subsequently leads to application behavior. A positive attitude emerged as the strongest predictor of AI usage in teaching. In contrast, ethical awareness contributes to overall competence but does not directly affect application behavior. These findings provide important implications for teacher training in the AI era. In particular, the findings highlight the need to strengthen foundational knowledge, integrate skill development into practice, promote reflective environments, and embed ethical considerations into technology education.

Keywords: Artificial intelligence (AI); primary school teachers; digital pedagogical competence; technology integration in teaching; generalized structured component analysis

1. Introduction

Artificial intelligence (AI) has emerged as a transformative technology capable of reshaping various aspects of human life, including education (Al-Tkhayneh et al., 2023). In educational contexts, AI holds significant potential to personalize

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learning experiences, support differentiated instruction, and enhance administrative efficiency by automating tasks such as grading and academic record management (Popenici & Kerr, 2017). Furthermore, AI enables early detection of students' learning patterns and socio-emotional difficulties, allowing timely pedagogical interventions to improve both academic performance and well-being (Ali, 2024). Collectively, these applications contribute to raising educational quality and enriching students' overall learning experiences.

Over the past decade, the integration of AI in education has become a prominent area of research, attracting increasing attention from scholars worldwide (Chuyen, 2024). Research has highlighted various trends, opportunities, and challenges of AI in teaching (AlDhaen, 2022; Li et al., 2024; Owoc et al., 2019; Xia et al., 2022). Several studies focus on analyzing the positive impacts of AI on students' attitudes and learning motivation (Deveci Topal et al., 2021; Huang, 2021), while others warn about ethical issues and the risk of overreliance on technology (Zawacki-Richter et al., 2019).

However, most existing studies only describe the benefits and risks, without delving deeply into the factors that directly affect teachers' capacity to apply AI—especially in areas lacking infrastructure and implementation conditions. In Vietnam, interest in AI in education is steadily increasing. The Ministry of Education and Training has emphasized digital transformation and innovation as core pillars in the national education development strategy, with AI being a vital tool to achieve these goals. Furthermore, digital transformation in education is recognized as a strategic driver for the country's overall development (Socialist Republic of Vietnam, 2024).

However, in practical implementation, a significant gap still exists between regions. In the mountainous areas of Northern Vietnam, limited technological infrastructure and lack of training opportunities for teachers have made AI integration particularly challenging. Recent reports indicate that these constraints considerably hinder the integration of technology into teaching and further exacerbate digital inequality in general education (Aravantinos et al., 2024). In this context, studying the components and driving factors of primary school teachers' capacity to apply AI has become essential both theoretically and practically.

A significant gap in current research is the lack of multi-component theoretical models to explain teachers' AI application behavior. Most previous studies have focused only on isolated factors such as knowledge, attitudes, or technological skills. In reality, the capacity to apply AI is a complex construct that requires a multidimensional approach—encompassing knowledge, skills, attitudes, ethical awareness, and reflective thinking (RE). Only a few recent studies have addressed the integration of these components into a single model to explain technology application behavior in education (Holmes et al., 2019; Zhang et al., 2021).
This study is grounded in foundational theoretical frameworks such as TPACK (technological pedagogical content knowledge) (Mishra & Koehler, 2006), TAM (technology acceptance model) (Davis, 1989), and TPB (theory of planned behavior) (Ajzen, 1993). This combination enables a comprehensive analysis of

how elements such as knowledge, skills, attitudes, and ethical awareness interact to form pedagogical competence and lead to AI application behavior. Based on the identified research gaps, the study aims to: (1) identify the factors influencing primary school teachers' capacity to apply AI in the mountainous areas of Northern Vietnam, and (2) explore how these factors interact in shaping AI application behavior.

Based on the objectives and research gaps outlined, this study sought to answer the following research questions (RQ):

- RQ1: What are the key factors that influence primary school teachers' competence in applying artificial intelligence (AI) in teaching in the northern mountainous regions of Vietnam?
- RQ2: How do knowledge, skills, attitudes, reflective thinking, ethical awareness, and pedagogical competence interact to shape teachers' AI application behavior in the classroom?

This study contributes theoretically by developing and validating a multi-component structural model, thereby expanding the applicability of TPACK, TAM, and TPB in the context of AI. Practically, the research findings provide a foundation for designing teacher training and professional development programs that emphasize the integration of foundational knowledge, practical skills, RE, and ethical awareness. More importantly, the study offers empirical evidence from an under-researched context—the mountainous provinces of Northern Vietnam—contributing to policy directions for teacher capacity development in the AI era, while also helping to bridge the digital divide between regions.

2. Literature Review

Artificial intelligence has been extensively studied in educational research for its transformative potential in teaching and learning. Existing studies can be categorized into four key themes: the roles and potential of AI, instructional strategies, impacts on learners, and challenges to implementation.

2.1 Roles and Potential of AI in Education

Educational processes can be enhanced by AI technologies through personalized learning pathways, adaptive content delivery, and automated administrative functions (Kong, 2020; Li, 2017; Popenici & Kerr, 2017; Wang & Zheng, 2020). By reducing teachers' routine workload, AI allows educators to focus on improving instructional quality and fostering student engagement (Ali, 2024). Early identification of students' learning needs are also supported by AI systems, enabling tailored pedagogical interventions that promote better academic and socio-emotional outcomes (Jia et al., 2024).

2.2 Instructional Strategies Leveraging AI

Researchers have proposed various AI-driven instructional approaches to support differentiated and personalized instruction (Luo, 2018; Niu et al., 2022; Rabelo et al., 2022; Yang et al., 2020). These include intelligent tutoring systems, chatbots for real-time learner support, and online platforms, such as MOOCs and

SPOCs, that provide flexible and adaptive learning environments, catering to diverse student needs and promoting effective learning outcomes.

2.3 Impacts on Students' Motivation and Attitudes

Many experimental studies have analyzed the impact of AI on learning motivation, attitudes, and behaviors. Huang pointed out that AI can enhance interest, improve learning attitudes, and develop self-directed learning skills (Huang, 2021; Huang, 2018). Schroeder et al. (2022) showed that integrating AI tools into teaching encourages more active student engagement and improves critical thinking skills. Additionally, AI brings benefits in creating a more equitable learning environment. AI-based learning support systems help identify differences in learning progress and outcomes, thereby allowing for appropriate adjustments in teaching methods and reducing the risk of students being left behind (Deveci Topal et al., 2021).

Several studies affirm that AI can contribute to the development of 21st-century skills in students, including digital literacy, critical thinking, and creativity (Jia et al., 2024). However, warnings have also been raised. Lin et al. (2022) emphasized that without proper management, the application of AI could lead to negative consequences, such as over-reliance on technology, reduced independent thinking, and potential misuse in learning activities. Moreover, AI poses challenges in ensuring that students do not misuse these tools for academic dishonesty or content copying without engaging in critical thinking.

2.4 Challenges and Barriers to AI Integration

Although AI offers significant potential, its implementation in education still faces many challenges. Unequal technological infrastructure across regions—especially in rural and mountainous areas—remains a major barrier to accessing and utilizing AI (Kannan & Munday, 2018). In addition, the lack of training and technological competence among teachers are two of the main reasons why the application of AI has not achieved the desired effectiveness (Li, 2017; Luo, 2018). Another notable barrier is the ethical and legal dimension.

The use of AI in classrooms raises important questions regarding data privacy, equitable access to technology, and the risk of replacing the traditional pedagogical role (Floridi et al., 2018; Zawacki-Richter et al., 2019). Without clear policies and support mechanisms, teachers may remain at the level of risk awareness rather than translating that awareness into actual action. This exemplifies the "knowing–doing gap" in education, in which teachers "know" about the risks but find it "difficult to act" without proper guidance and institutional frameworks.

2.5 Research Gaps

While prior research has explored AI's applications, benefits, and challenges, limited studies have investigated the determinants of teachers' competence in applying AI, particularly in under-resourced educational settings. Few multidimensional frameworks have been empirically tested to explain how teachers' knowledge, skills, attitudes, ethics, and RE shape AI adoption behaviors.

Addressing these gaps will contribute to both theoretical advancement and the development of practical strategies for teacher training in the era of Education 4.0.

3. Methodology

3.1 Research Design

This study employed a quantitative research design utilizing structural equation modeling (SEM) to examine the relationships among the components constituting primary school teachers' competence in applying AI in teaching. The proposed model was developed based on a synthesis of theoretical foundations, primarily drawing from the TPACK framework (Mishra & Koehler, 2006), TAM (Davis, 1989), and the TPB (Ajzen, 1993), with the aim of analyzing the influence of knowledge, skills, attitudes, ethical awareness, reflective habits, and pedagogical competence on teachers' behavior in using AI for instructional purposes.

To validate the proposed research model, the study employed the generalized structured component analysis (GSCA) technique. First, comparative studies have shown that GSCA-SEM outperforms PLS-SEM in terms of loading consistency, standard errors, and parameter estimation capability (Hwang et al., 2010; Hwang & Takane, 2004). Moreover, GSCA is a full-information method that optimizes a unified criterion for both measurement and structural models. It supports both reflective and formative constructs—unlike PLS-SEM, which only performs partial optimization and does not assess overall model fit indices (such as FIT, AFIT, and goodness-of-fit index) (Narimawati & Sarwono, 2024).

In addition, simulation-based experimental models indicate that GSCA (with reflective indicators) yields better parameter recovery and statistical power compared to PLSPM (Cho & Choi, 2020). Finally, GSCA does not require data to follow a normal distribution, which helps avoid the risk of invalid solutions, and it allows for the overall assessment of model fit—an aspect particularly well-suited to the research context.

3.2 Research Participants

The present study utilized primary school teachers in the northern mountainous region of Vietnam, with the survey encompassing educators currently teaching in the provinces of Bac Giang, Lang Son, Thai Nguyen, Lao Cai, and Cao Bang. The estimated number of potential participants was approximately 1,000. A purposive sampling method was employed to select participants from the accessible population.

Data was collected through an online survey administered via Google Forms. Participants were provided with comprehensive information regarding the research objectives, the nature of the data being collected, data storage and distribution procedures, as well as their right to withdraw from the survey at any time. The data collection was conducted over a one-month period, from April to May 2025.

3.3 Research Instruments

The questionnaire consisted of two sections: the first section gathered demographic information, while the second included 21 items measured using a five-point Likert scale, designed to assess the extent of various factors influencing teachers' competence in utilizing AI. The items used in this study were adapted from previous research on AI-related knowledge (KN) (Román-González et al., 2017; Miao & Shiohira, 2024); skills in using AI (SK) (El-Hamamsy et al., 2025; Mishra et al., 2011); and pedagogical competence in integrating AI (PE) (Mishra et al., 2011); RE (Schön, 2017); attitudes toward AI (AT) (Davis, 1989); behaviors related to AI usage (BE) (Venkatesh et al., 2016); and ethical awareness (ET) (Floridi et al., 2018). The items were also modified to suit the current research context.

Prior to distribution, the questionnaire items were reviewed by two experts in the field to ensure face validity and reliability. Listwise deletion was employed to eliminate incomplete or anomalous responses. Following data collection, the study excluded unsuitable responses, including questionnaires in which participants selected the same response for all items (n = 348) and those with missing data (n = 130). Consequently, the final sample size included in the analysis was 624, accounting for 56.62% of the total responses collected (n = 1102).

The determination of an appropriate sample size for a study remains a subject of ongoing debate in the academic literature, with various recommendations put forward by different researchers. For example, Kline (2023) recommended a minimum sample size of 200 for SEM (Kline, 2023), while Anderson and Gerbing (1984) suggested that 100 participants are sufficient to achieve convergence, and a sample of 150 ensured both convergence and adequate estimation accuracy when dealing with latent constructs with three or more indicators (Anderson & Gerbing, 1984). In the present study, sample size determination followed the recommendations by Wolf (2013), who noted that while simple models may require only 80 to 150 cases, more complex models may necessitate a sample size exceeding 400 to 500 (Wolf et al., 2013).

The descriptive statistics in Table 1 present the characteristics of the 624 primary school teachers who participated in the survey.

Table 1: Descriptive statistics of respondents (n = 624)

<table>
<tr><th>Variables</th><th>Item</th><th>Frequency</th><th>Percentage (%)</th></tr>
<tr><td rowspan="2">Gender</td><td>Male</td><td>101</td><td>16,2</td></tr>
<tr><td>Female</td><td>523</td><td>83,8</td></tr>
<tr><td rowspan="4">Age group</td><td>25–30</td><td>81</td><td>13,0</td></tr>
<tr><td>31–40</td><td>92</td><td>14,7</td></tr>
<tr><td>41–50</td><td>198</td><td>31,8</td></tr>
<tr><td>Over 50</td><td>253</td><td>40,5</td></tr>
<tr><td rowspan="2">Educational qualification</td><td>Bachelor's degree</td><td>499</td><td>80,0</td></tr>
<tr><td>Postgraduate</td><td>125</td><td>20,0</td></tr>
<tr><td rowspan="3">Years of teaching experience</td><td>Less than 5 years</td><td>83</td><td>13,3</td></tr>
<tr><td>5–10 years</td><td>87</td><td>13,9</td></tr>
<tr><td>10–20 years</td><td>191</td><td>30,6</td></tr>
</table>

	Over 20 years	263	42,2
Place of residence	Mountainous or remote area	392	62,8
	Rural areas	150	24,0
	Major urban centers	82	13,2
	Total	624	100

Regarding gender, the majority of respondents were female (83.8%), while male participants accounted for only 16.2%, reflecting the commonly observed gender distribution among primary school teachers in Vietnam. Most participants were middle-aged or senior teachers, with 31.8% aged 41–50 years old and 40.5% over 50 years old, indicating an aging teaching workforce in the surveyed regions. Younger teachers (25–30 years old: 13.0%; 31–40 years old: 14.7%) represented smaller proportions.

In terms of qualifications, 80.0% held a bachelor's degree, while 20.0% had postgraduate education, suggesting that most teachers met professional standards but with scope for higher academic advancement. Teaching experience was predominantly high, with 72.8% having more than 10 years in service, including 42.2% over 20 years. Regarding residence, 62.8% lived in mountainous or disadvantaged areas, 24.0% in rural regions, and 13.2% in urban centers, aligning with the study's focus on Vietnam's northern mountainous provinces. Data were collected using a structured questionnaire (Table 2), which comprised of seven latent variables and 21 indicators (items).

Table 2: Survey items

Items	Survey Items
kn1	I clearly understand the basic definition and nature of AI.
kn2	I can list and explain at least three practical applications of AI in primary education.
kn3	I can distinguish between traditional AI and generative AI and provide concrete examples of each.
sk1	I can write clear prompts for ChatGPT to generate digital learning materials or lesson content appropriate for primary students.
sk2	I know how to refine AI-generated outputs to align with learning objectives and student levels.
sk3	I can use at least two AI tools (e.g., ChatGPT, Canva AI, Quizizz AI) to support teaching and education in primary schools.
pe1	I can integrate AI tools into lessons while ensuring alignment with the objectives and pedagogy of the primary education curriculum
pe2	I know how to use AI to differentiate instruction based on students' varying levels (e.g., support struggling students, extend for advanced learners).
pe3	I clearly understand the differences in applying AI by student age and proficiency, and I can adjust content accordingly.
et1	I am aware of potential ethical risks when students independently use AI tools (e.g., plagiarism, overreliance, access to inappropriate content).
et2	I know how to guide students in verifying, editing, and responsibly using AI-generated content in their learning process.
et3	I am committed to protecting data privacy when using AI tools in teaching (e.g., not sharing students' personal data on AI platforms).
re1	I regularly self-assess the relevance and effectiveness of AI-generated content before using it in teaching.

re2	I have a habit of taking notes on what needs improvement when applying AI to enhance lesson quality.
re3	I often discuss experiences with colleagues or peers to refine my use of AI in education.
at1	I proactively explore and experiment with new AI tools for teaching, education, and research purposes.
at2	I feel positive when seeing AI effectively support educational and scientific work.
at3	I believe AI is a valuable tool to enhance teachers' capabilities, but it cannot replace the role of educators.
be1	I have used AI tools to create digital materials for at least one specific lesson.
be2	I have applied AI in guiding students with individual or group tasks.
be3	I regularly use AI platforms (e.g., LuyenAI.vn, ChatGPT, Copilot) to improve my professional knowledge and teaching effectiveness.

All items were measured using a five-point Likert scale (1 = Strongly disagree, to 5 = Strongly agree). The measurement scales were developed based on previously validated instruments and were adapted to align with the context of primary education in Vietnam, specifically, KN (Román-González et al., 2017; Miao & Shiohira, 2024); SK (El-Hamamsy et al., 2025; Mishra et al., 2011); PE (Mishra et al., 2011); RE (Schön, 2017); AT(Davis, 1989); BE (Venkatesh et al., 2016); and ET (Floridi et al., 2018).

3.4 Data Analysis

Data were processed and analyzed using GSCA Pro software, following several steps: assessment of internal consistency through Cronbach's alpha and composite reliability; evaluation of convergent validity based on factor loadings and average variance extracted; and structural model testing via estimation of path coefficients and 95% confidence intervals (CI) (95% CI). Statistical significance was determined by assessing whether the CI included zero. Indicators with factor loadings greater than 0.7, CI excluding zero, and composite reliability values above 0.7 were considered acceptable (Hair, 2009).

4. Results

4.1 RQ1: What Are the Key Factors That Influence Primary School Teachers' Competence in Applying AI in Teaching in the Northern Mountainous Regions of Vietnam?

To address RQ1, the study examined the reliability, convergent validity, and measurement quality of the seven latent constructs: KN, SK, PE, ET, RE, AT, and BE.

4.1.1 Measurement Model Evaluation

Convergent validity: Average variance extracted values ranged from 0.67 (KN) to 0.788 (PE), all exceeding the recommended threshold of 0.50 (Hair, 2009). This indicates that each construct explains a substantial proportion of variance in its indicators. Internal consistency: Cronbach's alpha values varied from 0.754 to 0.866, with the highest reliability observed for PE (0.866).

Composite reliability: All constructs exceeded the 0.70 threshold (range 0.858–0.918).

Unidimensionality: All constructs reported a value of 1.0, confirming that each latent factor was well-defined by a single dimension.

Table 3: Reliability and convergent validity of the measurement scales

	Construction	PVE	Cronbach's Alpha	Composite Reliability	Unidimensionality
1	KN	0.67	0.754	0.858	1.0
2	SK	0.758	0.84	0.904	1.0
3	PE	0.788	0.866	0.918	1.0
4	ET	0.705	0.79	0.877	1.0
5	RE	0.769	0.85	0.909	1.0
6	AT	0.737	0.822	0.894	1.0
7	BE	0.756	0.839	0.903	1.0

4.1.2 Indicator Reliability

All factor loadings exceeded 0.70, and 95% CI excluded zero, confirming statistical significance. Examples include KN (0.743–0.909), SK (0.868–0.873), PE (0.881–0.891), indicating robust alignment of items with their constructs.

Table 4: Factor loadings and confidence intervals for latent variables

	Estimate	SE	95%CI	
			KN	
kn1	0.794	0.022	0.759	0.845
kn2	0.909	0.008	0.895	0.925
kn3	0.743	0.026	0.693	0.797
			SK	
sk1	0.868	0.018	0.827	0.897
sk2	0.873	0.017	0.842	0.908
sk3	0.87	0.013	0.84	0.892
			PE	
pe1	0.881	0.015	0.857	0.909
pe2	0.89	0.013	0.866	0.918
pe3	0.891	0.015	0.86	0.916
			ET	
et1	0.85	0.016	0.817	0.879
et2	0.872	0.015	0.846	0.902
et3	0.794	0.027	0.74	0.838
			RE	
re1	0.873	0.017	0.839	0.905
re2	0.891	0.011	0.864	0.909
re3	0.868	0.021	0.829	0.904
			AT	
at1	0.858	0.017	0.829	0.892
at2	0.889	0.014	0.858	0.909
at3	0.827	0.023	0.782	0.866
			BE	
be1	0.884	0.015	0.852	0.91
be2	0.877	0.013	0.848	0.902
be3	0.848	0.02	0.803	0.875

The analysis shows that skills (β=0.399), ethical awareness (β=0.289), and RE (β=0.210) significantly influence PE, while AT does not have a meaningful direct effect. Hence, SK, ethics, and reflection are the key motivators of competence in AI integration.

Before testing the structural model hypotheses, the study conducted a reliability and validity assessment of the measurement model by examining the factor loadings of each observed variable on its corresponding latent construct. The results, presented in Table 4, indicate that all observed variables exhibited factor loadings greater than 0.70, satisfying the criterion for individual indicator reliability as recommended by Hair (2009).

Additionally, the 95% CI for all factor loadings did not include zero, confirming that these coefficients are statistically significant and that no indicators were excluded from the model. Specifically, the three indicators measuring KN showed loadings ranging from 0.743 to 0.909 (kn1 = 0.794; kn2 = 0.909; kn3 = 0.743), indicating a strong conceptual alignment between the items and the latent construct. Similarly, SK demonstrated high internal consistency, with uniformly high loadings (sk1 = 0.868; sk2 = 0.873; sk3 = 0.870).
For the latent variable PE, all three indicators demonstrated near-perfect factor loadings (pe1 = 0.881; pe2 = 0.890; pe3 = 0.891), reflecting excellent representativeness of the measured construct. Meanwhile, the ET construct also maintained strong reliability, with loadings of et1 = 0.850; et2 = 0.872; and et3 = 0.794. Although et3 had the lowest loading within the group, it still exceeded the 0.70 threshold and was statistically significant. The RE construct exhibited high reliability, with factor loadings of re1 = 0.873; re2 = 0.891; and re3 = 0.868.

The AT construct also demonstrated consistency and strength, with loadings of at1 = 0.858; at2 = 0.889; and at3 = 0.827. Although at 3 it had the lowest loading within the group, it remained within the acceptable range and was statistically significant, thus retained in the model. Finally, BE showed very strong reliability, with be1 = 0.884; be2 = 0.877; and be3 = 0.848. These results indicate that the measurement scale effectively captures the extent to which teachers are implementing AI in their instructional practices.

A synthesis of the factor loading results confirms that all indicators met the key criteria: individual indicator reliability (loadings > 0.70), statistical significance (95% CI excluding zero), and no indicators were removed due to weak statistical or conceptual performance. Thus, the measurement model demonstrated excellent quality and was considered suitable for subsequent structural model analysis, which aimed to test the causal relationships among the theoretical constructs proposed in the research model.

After establishing the reliability and validity of the measurement model, the study proceeded to assess the overall fit of the structural model using several model fit indices. As shown in Table 2, the structural model demonstrated a good fit, satisfying widely accepted criteria in SEM. Specifically, the FIT index was 0.63, and the adjusted FIT (AFIT) was 0.629, indicating that the model accounted for approximately 63% of the shared variance among the dependent variables—a satisfactory level of explanatory power in the context of educational research. The FIT value of 0.74 suggests a substantial improvement over the baseline model. However, the FITs value of 0.30 implies that there remains room for improvement in certain model components.

The goodness-of-fit index (GFI) was 0.992, approaching the ideal value of 1.0, indicating a strong alignment between the theoretical model and the empirical data. Additionally, the standardized root mean square residual (SRMR) was 0.047, well below the recommended threshold of 0.08, reflecting low prediction error and model adequacy (Hair, 2009). In terms of predictive power and error indices, the overall prediction error (OPE) was 0.373 and the standardized OPEs was 0.709, suggesting a relatively acceptable predictive performance. However, the marginal prediction index was only 0.262, indicating that the model's predictive accuracy at the individual level remains limited and warrants further investigation in future studies.

4.2 RQ2: How Do Knowledge, Skills, Attitudes, Reflective Thinking, Ethical Awareness, and Pedagogical Competence Interact to Shape Teachers' AI Application Behavior in the Classroom?

Considering RQ2, SEM was used to analyze interrelationships among the constructs and their effects on BE.

Table 5: Model fit indices

	Index	Value	Description
1	FIT	0.630	Total variance explained by the model
2	AFIT	0.629	Adjusted FIT index
3	GFI	0.992	Overall goodness-of-fit index
4	SRMR	0.047	Standardized root mean square residual

The model fit indices presented in Table 5 demonstrate that the structural model showed a good level of fit with the survey data. Specifically, the FIT index (0.63) and adjusted FIT (AFIT = 0.629) indicated that the model explains over 63% of the total variance among the dependent variables. Overall model fit was further confirmed by a GFI of 0.992, nearly reaching the ideal value of 1.0—and an SRMR of 0.047, which was well below the commonly accepted threshold of 0.08, indicating low standardized residual error.

Table 6 presents the standardized path coefficients, standard errors, and 95% CI for each hypothesized relationship between latent variables.

Table 6: Path coefficients

	Estimate	Standard Errors	95%CI	
KN→SK	0.697	0.026	0.649	0.748
SK→PE	0.399	0.047	0.31	0.488
ET→PE	0.289	0.058	0.182	0.396
RE→PE	0.21	0.058	0.084	0.328
AT→PE	0.037	0.048	-0.043	0.131

KN→AT	0.549	0.032	0.495	0.627
PE→BE	0.199	0.056	0.1	0.308
ET→BE	0.024	0.065	-0.109	0.139
RE→BE	0.248	0.07	0.124	0.405
AT→BE	0.42	0.064	0.297	0.538

The results indicate that KN exerts a strong and positive influence on SK, with a path coefficient of β = 0.697, $p < 0.001$, and a 95% CI that does not include zero (CI: [0.649; 0.748]). This was the strongest relationship in the model, confirming that teachers' understanding of AI serves as a fundamental basis and plays a crucial role in developing their ability to apply this technology in primary education practice. Additionally, SK was found to have a significant positive effect on PE, with a path coefficient of β = 0.399 and a 95% CI of 0.310: 0.488.

This suggests that teachers with stronger technological SK are more likely to effectively integrate AI into their teaching practices. Additionally, ET and RE had significant positive impacts on PE, with β = 0.289 and β = 0.210, respectively, both statistically significant as indicated by CI, that did not contain zero. In contrast, the influence of AT on PE was not statistically significant (β = 0.037; CI included zero), suggesting that a positive AT alone is insufficient to enhance pedagogical integration of AI in the absence of technical skills or institutional support.

Furthermore, KN had a strong and statistically significant effect on AT (β = 0.549; CI: [0.495; 0.627]), indicating that deeper understanding of AI contributes to the formation of more positive attitudes toward its application in education. With regard to BE, three variables exerted significant effects: PE with β = 0.199, RE with β = 0.248, and AT with β = 0.420. Among these, the effect of AT on BE was the strongest, highlighting that belief in and positive attitudes toward AI are critical motivators for its adoption in classroom practice.

Conversely, the effect of ET on BE was not statistically significant (β = 0.024; CI included zero), suggesting that although ethics is an important consideration, it may not directly influence teachers' behavioral implementation of AI in the short term. In summary, the structural model analysis confirmed that knowledge, SK, RE, and AT are significant predictors of AI adoption in teaching among primary school teachers in the northern mountainous regions of Vietnam. In contrast, factors such as ethical awareness and attitude do not exert strong indirect effects via pedagogical competence, implying a need for targeted training policies that can translate awareness and beliefs into practical skills and action.

5. Discussions

5.1 RQ1: Key Factors Influencing Primary School Teachers' Competence in Applying AI

This study contributes to understanding the core determinants of teachers' competence in applying AI, highlighting the crucial roles of knowledge, skills, ethical awareness, and RE in shaping PE.

The results show that KN exerts a strong positive influence on both skills (β = 0.697) and AT (β = 0.549) toward AI. This finding aligns with the TPB (Ajzen, 1993), which posits that cognition and understanding shape behavioral intentions. However, the findings raise the important question of what type of knowledge truly matters for enhancing competence. If knowledge remains at a purely conceptual level, its potential to be transformed into practical action may be limited (Holmes et al., 2019; Zhang et al., 2021).

Therefore, a deeper discussion suggests that professional development programs should emphasize applied, classroom-oriented knowledge—such as integrating AI, such as ChatGPT, to design differentiated learning activities or using AI for formative assessment—rather than merely offering general conceptual overviews. This also reflects the view of Holmes et al. (2019) and Zhang et al. (2021), who argued that technological knowledge only holds value when situated within specific pedagogical contexts.

Second, SK continued to demonstrate its importance in developing pedagogical competence (β = 0.399). However, a clearer distinction needs to be made between tool-specific skills and digital pedagogical skills. Recent education and technology studies indicate that if teachers are only proficient in technical operations but lack a pedagogical framework, their use of technology tends to remain at an experimental level and struggles to achieve sustainability (Teo, 2011; Holmes et al., 2019; Zhang et al., 2021).

Conversely, when technological skills are combined with lesson design competence, classroom management, and student assessment capabilities, AI can be truly and effectively integrated. This reinforces the argument of the TPACK model, which posits that the intersection of technological knowledge, pedagogical knowledge, and content knowledge is the key to instructional innovation (Mishra & Koehler, 2006)

Likewise, ET (β = 0.289) also contributed to competence, suggesting that understanding responsible AI use—such as ensuring fairness, privacy, and transparency—helps teachers apply AI more effectively. Similarly, RE (β = 0.210) played a role in enhancing competence, reinforcing Schön's (2017) concept of the "reflective practitioner," who adapts continuously to improve instructional practices in complex educational environments.

Third, the results also highlight the role of ET in shaping competence (β = 0.289). This finding aligns with recent AI competency frameworks (Floridi et al., 2018; UNESCO, 2024) which place ethics, transparency, and data privacy as foundational pillars. However, it is essential to recognize an "implementation gap": although teachers may be fully aware of ethical risks, such as data privacy or overreliance on AI, this awareness does not automatically translate into safe and sustainable application practices. Therefore, to transform awareness into action, institutional mechanisms are required—for example, regulations on student data protection, clear guidelines for AI use in the classroom, and support systems provided by schools. Introducing such policies can help bridge the gap between individual awareness and actual practice.

Fourth, RE emerges as a particularly noteworthy factor (β = 0.210), contributing to the enrichment of pedagogical competence. The value of RE goes beyond the improvement of personal skills—it is also closely tied to the concept of teacher agency, which refers to teachers' autonomy and adaptability within the context of educational innovation. As Schön (2017) described, teachers are "reflective practitioners," constantly engaged in a process of trial, error, and adjustment.

More recently, Zhai (2024) also emphasized that the emergence of next-generation AI demands that teachers not only be tool users but also active innovators and collaborators—capable of RE to restructure their roles in teaching. Therefore, instead of focusing solely on technical skill training, professional development programs should encourage collective reflective practice, where teachers collaboratively discuss, analyze, and adjust their use of AI based on real-world experiences

Finally, a notable finding is that AT does not have a significant impact on competence (β = 0.037), which contrasts with many previous studies on technological innovation (Teo, 2011). This may be explained by the research context: most of the surveyed teachers were female, over 40 years old, and living in mountainous areas where opportunities to engage with AI remain limited. They may exhibit a form of "theoretical optimism" about AI yet lack the practical resources to translate that into real competence.

This finding suggests that a positive attitude alone is not sufficient; it only becomes effective when accompanied by resources, infrastructure, and managerial support. In other words, in contexts with limited facilities and training opportunities, even positive attitudes are unlikely to serve as a strong driver for capacity development.

5.2 RQ2: Interactions Among Factors Shaping Teachers' AI Application Behavior

The research findings indicate that primary school teachers' AI application behavior in teaching is not the result of a single factor, but rather the outcome of a complex network of interacting elements—including knowledge, skills, attitudes, RE, ethical awareness, and pedagogical competence. The use of SEM helps clarify how these factors influence not only directly but also indirectly, forming a multi-step pathway that leads to AI application behavior.

First, KN serves as a foundational trigger, exerting a strong influence on both SK (β = 0.697) and AT (β = 0.549). This underscores the pivotal role of knowledge in the process of technology acceptance and application, aligning with the TPB (Ajzen, 1993) and previous studies on educational technology (Holmes et al., 2019; Zhang et al., 2021). However, this knowledge should not be limited to conceptual knowledge—it must also include procedural knowledge. If teachers only possess theoretical understanding, it is difficult to translate it into action; conversely, context-embedded knowledge linked to teaching practice provides a foundation for meaningful skills and positive, practical attitudes.

Second, SK act as a "bridge" between technology and pedagogy. The results show that technological skills not only have a direct impact on PE (β = 0.399), but also indirectly influence behavior through BE (β = 0.199). This finding reinforces the perspective of the TPACK model. Accordingly, technological skills only become truly meaningful when they are transformed into pedagogical competence—that is, the ability to integrate AI into lesson design, manage learning activities, and assess student progress. This also implies that training programs should go beyond merely instructing teachers on how to use AI tools; instead, they should connect skill development with real teaching practices to ensure long-term sustainability (Mishra & Koehler, 2006),

Third, RE plays a particularly important role, as it influences both pedagogical competence (β = 0.210) and directly impacts application behavior (β = 0.248). This finding reflects the nature of teachers as "reflective practitioners" constantly engaged in a process of experimentation, evaluation, and adjustment (Schön, 2017). More importantly, RE is closely linked to the concept of teacher agency—the ability of teachers to act autonomously and innovate in the face of rapidly evolving technology. Zhai (2024) emphasized that next-generation AI is compelling teachers to restructure their roles—from mere tool users to co-creators and innovators. Thus, RE not only enhances the quality of AI integration but also ensures the long-term sustainability of behavior, avoiding superficial or trend-driven adoption

Fourth, AT emerges as the strongest direct predictor of application behavior (β = 0.420), consistent with the TAM (Davis, 1989) and other studies by Teo (2011). However, AT does not have a significant impact on pedagogical competence (β = 0.037). This suggests an interesting paradox: a positive attitude may motivate initial behavior, but it is not sufficient to build sustainable competence. This phenomenon can be explained by the concept of the "intention–action gap" in educational technology—the disconnect between intention and practical capability (Venkatesh et al., 2016). In other words, AT needs to be reinforced by practical skills, reflective experience, and a supportive environment in order to translate motivation into competence.

Fifth, ET has a positive impact on competence (β = 0.289) but does not directly influence behavior (β = 0.024). This serves as a clear example of the "knowing–doing gap": although teachers are fully aware of the risks associated with AI use—such as violating student data privacy, plagiarism, or overreliance on tools—this understanding is difficult to translate into actual action without supportive mechanisms (Floridi et al., 2018).

In the current Vietnamese context, official guidelines from the Ministry of Education and Training remain at a general advisory level, while many schools have yet to issue clear regulations or codes of conduct regarding the use of AI in teaching and learning (Socialist Republic of Vietnam, 2024). Therefore, in addition to training, it is essential to establish operational policy frameworks at the institutional level—such as data privacy procedures, safe AI usage guidelines in the classroom, and transparent rules for AI use in assessment. Only when ethical awareness is institutionalized at the school/classroom level can it be transformed into responsible and sustainable teaching practices.

Overall, these results depict a multi-step interaction pathway in which knowledge facilitates skills and positive attitudes, skills strengthen competence, and competence, together with AT and RE, drives behavioral adoption of AI. Ethical awareness underpins responsible practice indirectly but requires contextual reinforcement. These insights suggest that teacher professional development programs should adopt a holistic approach that combines knowledge-building, technical training, reflective practice, attitudinal support, and practical ethics to foster sustainable and effective AI integration in under-resourced educational settings.

6. Conclusion

In a rapidly evolving general education system influenced by digital transformation and the rapid advancement of AI, it is essential to understand the factors affecting teachers' competence in AI application. This research established and validated a comprehensive structural model that integrates knowledge, skills, attitudes, reflective thinking, ethical awareness, pedagogical competence, and the behavioral application of AI. The GSCA analysis indicated robust reliability and an acceptable overall fit, clarifying both direct and indirect pathways to AI adoption in classroom practice. The findings indicated that AI knowledge serves as a fundamental component, significantly enhancing both skills and attitudes. Skills and reflective thinking emerged as essential mediators, enhancing pedagogical competence and enabling practical behavioral implementation.

Attitude toward AI emerged as the most significant predictor of behavioral application, underscoring the critical influence of motivation and perception in the adoption of technology. To enhance AI knowledge and skills, measures include encouraging teachers' self-directed learning, offering training opportunities, fostering professional learning communities, and strengthening AI awareness and competencies among administrators. Conversely, although ethical awareness had a positive impact on pedagogical competence, it did not directly manifest in classroom behavior, indicating that ethical understanding necessitates conducive conditions for implementation.

7. Implications

The research presents multiple practical implications for teacher professional development and educational policy. Training programs must prioritize foundational AI knowledge to ensure that educators have the conceptual understanding required for confident implementation. Practical skill development must be integrated into lesson planning and classroom practices, facilitated by opportunities for experimentation and ongoing enhancement. Third, the cultivation of RE is essential for improving adaptive and context-responsive applications of AI. Technology ethics education should be effectively incorporated into professional development frameworks, underpinned by explicit guidelines and practical strategies for the responsible application of AI in various educational contexts.

8. Limitations and Future Research

The study only included primary school instructors in northern mountainous Vietnam, which may limit its applicability. The model also fails to account for institutional and infrastructural constraints to behavioral AI adoption. Future study should evaluate how these characteristics change over time and across educational contexts using longitudinal and cross-regional studies. Further research should examine school-level support systems, leadership practices, and regulatory frameworks that affect AI integration to understand the ecosystem needed for sustained AI adoption in education better.

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