Exploring the Relationship between Human–AI Interaction Experiences and Teacher' Intention to Use AI in Teaching: Evidence from Stem and Non-Stem Teachers in Vietnam

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Abstract

This study explores how human–AI interaction experiences developed through AI professional development (PD) relate to teachers' intention to use AI in teaching, with particular attention to differences between STEM and non-STEM teachers in Vietnam. Grounded in Expectancy–Value Theory, the study proposes a structural model in which Human–AI interaction

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experiences are linked to AI self-efficacy, professional value, and trust, which in turn are associated with teachers' intention to use AI in teaching. Data were collected from 97 secondary school teachers who completed a two-day AI-focused PD program and were analyzed using PLS-SEM with multi-group analysis. Results indicate that human–AI interaction experiences were significantly and positively associated with AI self-efficacy, professional value, and trust. Among the proximal predictors, AI self-efficacy showed the strongest association with intention, followed by professional value, while trust did not show a significant direct association in the full sample. Multi-group findings suggest disciplinary differences: AI self-efficacy was a stronger predictor among STEM teachers, whereas professional value and trust played comparatively stronger roles among non-STEM teachers. Based on a cross-sectional post-intervention design, the study provides preliminary evidence on the role of experiential AI training and suggests the potential value of differentiated PD strategies to support AI integration across subject areas.

Keywords: Human–AI interaction experiences; AI professional development; intention to use AI in teaching; STEM and non-STEM teachers; PLS-SEM.

1. Introduction

Generative Artificial Intelligence (GenAI) has rapidly become a major force in education worldwide, reshaping how teachers design learning activities, generate instructional materials, provide feedback, and support differentiated learning (Yu & Guo, 2023). Emerging evidence suggests that meaningful AI integration depends not only on technological infrastructure but also on developing teachers’ pedagogical, ethical, and professional capacities to use AI in human-centered ways (UNESCO, 2023). UNESCO’s recent AI competency framework further conceptualizes teacher readiness as a multidimensional construct encompassing AI pedagogy, ethical awareness, and sustained professional learning pathways. However, such capacities are unlikely to emerge through tool exposure alone; rather, they require structured professional development (PD) and guided experiential practice (Ding et al., 2024).

In the Vietnamese context, national digital transformation and AI strategies, including the National Digital Transformation Program and the National Strategy for Research, Development, and Application of Artificial Intelligence to 2030, have accelerated the introduction of AI-related initiatives in education (Government of Vietnam, 2020, 2021). This agenda has been further supported by education-sector policies promoting the application of ICT, digital learning platforms, digital learning resources, and data-based school management (Government of Vietnam, 2022). Recent policy directions also emphasize AI literacy, digital competencies, and the piloting of AI-related content in general education (Ministry of Education and Training, 2025). Despite this policy momentum and increasing AI PD activities, empirical evidence remains limited regarding how short-term experiential training is associated with teachers’ psychological readiness and intention to use AI in classroom practice (Nguyen et al., 2025).

Grounded in Expectancy–Value Theory (EVT), this study examines whether Human–AI interaction experiences developed through AI PD are associated with teachers’ intention to use AI in teaching, mediated by AI self-efficacy and perceived professional value. Teachers who believe they can effectively use AI tools and perceive AI as instructionally meaningful are more likely to report stronger intentions to integrate AI into teaching (Eccles & Wigfield, 2002; Rajapakse et al., 2024). In addition, given concerns regarding algorithmic reliability, transparency, and ethical implications, teacher trust in AI is incorporated as an AI-specific cognitive predictor (Choi et al., 2023). Furthermore, disciplinary background may shape teachers’ epistemological orientations and confidence patterns toward emerging technologies. Prior research suggests that subject area is related to beliefs about the relevance and alignment of technology with disciplinary practices (Han & Guo, 2025; Nguyen et al., 2025; Paredes-Aguirre et al., 2026). However, empirical evidence examining such differences specifically in AI adoption among teachers remains scarce. Therefore, this study examines subject area as a grouping variable in the structural model to explore whether the direct relationships among Human–AI interaction experiences, AI self-efficacy, professional value, trust, and intention to use AI in teaching differ between STEM and non-STEM teachers.

2. THEORETICAL FRAMEWORK

This study is grounded in EVT, a leading framework in motivational psychology that explains how individuals' achievement-related choices are shaped by their expectancies for success and the values they attach to tasks (Eccles & Wigfield, 2002). In its full formulation, EVT includes multiple value components (e.g., intrinsic, utility, and attainment value) as well as perceived cost (Eccles & Wigfield, 2020). However, in applied research contexts, these components are often selectively operationalized depending on the research focus. In studies of technology and AI adoption, expectancy is commonly represented as self-efficacy, while value is frequently captured as perceived usefulness or professional relevance (Wang et al., 2023; Yin & Goh, 2024; Yurt, 2024). Consistent with this approach, the present study focuses on AI self-efficacy and professional value as the two core motivational constructs most directly aligned with teachers' instructional decision-making. The cost dimension and finer distinctions among value components were not included in the current model, which should be acknowledged as a theoretical boundary of the study.

Expectancy refers to an individual's belief in their likelihood of successfully performing a task (Eccles & Wigfield, 2002). In AI-related contexts, recent studies have conceptualized expectancy beliefs as self-efficacy when examining individuals' intentions to learn or use AI (Wang et al., 2023; Yin & Goh, 2024). Consistent with this approach, expectancy in the present study is operationalized as AI self-efficacy, reflecting teachers' confidence in their capability to successfully use AI tools in instructional practice. Prior research on teachers' AI readiness also suggests that self-efficacy-based competence beliefs are central to teachers' willingness to engage with AI-related teaching practices (Rajapakse et al., 2024). Moreover, comparative evidence indicates that STEM and non-STEM teachers may differ in AI-related attitudes and behavioral intention, suggesting that the role of motivational beliefs in AI adoption may vary across disciplinary groups (Ayanwale & Sanusi, 2023; Aktulun et al., 2024).

Subjective task value refers to individuals' perceptions of the usefulness, importance, and relevance of engaging in a task (Eccles & Wigfield, 2002). In this study, this construct is operationalized as professional value toward AI integration, capturing teachers' perceptions that AI use is instructionally meaningful and professionally worthwhile within their teaching context. This operationalization is consistent with AI and technology adoption studies showing that perceived usefulness, relevance, and value are important predictors of teachers' intention to adopt educational technologies (Choi et al., 2023; Yurt, 2024). In the context of AI, professional value is particularly important because teachers are more likely to intend to use AI when they perceive it as supporting lesson preparation, assessment design, feedback, and pedagogical decision-making. Accordingly, the following hypotheses are proposed:

H1: AI self-efficacy is positively associated with teachers' intention to use AI in teaching.

H2: Professional value toward AI integration is positively associated with teachers' intention to use AI in teaching.

Beyond expectancy and value beliefs, AI integration involves an additional AI-specific construct: trust in AI. Trust is commonly defined as the willingness to accept vulnerability to another entity (Hosmer, 1995), and in AI contexts, it is regarded as a necessary condition for cooperative behavior and adoption (Choi et al, 2023; Zhang et al, 2025). Unlike traditional instructional tools, AI systems operate with a degree of autonomy, opacity, and algorithmic decision-making, which may generate uncertainty in educational contexts (Viberg et al, 2025). So teachers who perceive AI tools as trustworthy are more likely to rely on their outputs and integrate them into instructional practice (Choi et al, 2023; Zhang et al, 2025). Therefore, we propose:

H3: Trust in AI is positively associated with teachers' intention to use AI in teaching.

In addition, recent developments in EVT emphasize the situated nature of motivational beliefs, suggesting that expectancy and value are shaped not only by internal beliefs but also by concrete experiences in specific learning environments (Eccles & Wigfield, 2020). In the context of AI PD, Human–AI interaction should therefore be understood not as simple exposure to AI tools, but as a situated pedagogical process in which teachers articulate instructional intentions, interpret and evaluate AI outputs, and iteratively refine prompts and responses for teaching purposes (Ding et al., 2024; Long & Magerko, 2020). Such interaction is theoretically important because it moves AI use beyond passive tool consumption toward an experiential process of sense-making and professional control, through which teachers can examine AI's capabilities and limitations in relation to authentic instructional tasks (Ding et al., 2024; Nazaretsky et al., 2022). When these interactional experiences are repeated and guided in PD settings, they may be associated with teachers' confidence in using

AI, perceived professional value of AI integration, and trust in AI's instructional potential. Accordingly, we propose that Human–AI interaction experiences developed during AI PD are positively associated with teachers' AI self-efficacy, understood here as self-efficacy for using AI to support teaching practice, as well as with professional value toward AI integration and trust in AI.

H4: Human-AI interaction experiences are positively associated with teachers' AI self-efficacy.

H5: Human-AI interaction experiences are positively associated with teachers' professional value toward AI integration.

H6: Human-AI interaction experiences are positively associated with teachers' trust in AI.

Beyond the direct paths specified above, the proposed model further assumes that Human–AI interaction experiences may be indirectly associated with teachers' intention to use AI in teaching through AI self-efficacy, professional value, and trust. This mediation logic is grounded in self-efficacy theory and EVT. Bandura (1977) argued that mastery-like experiences are a central source of self-efficacy because individuals develop capability beliefs through task-relevant performance and feedback. Similarly, EVT suggests that intention is shaped by both perceived capability and the value attached to the task (Eccles & Wigfield, 2020; Wigfield & Eccles, 2000). Therefore, guided Human–AI interaction experiences in PD may be associated with stronger AI use intention by strengthening teachers' AI self-efficacy and helping them recognize the professional value of AI for instructional work.

Trust may also serve as a mediating mechanism because AI use in education involves uncertainty, opacity, and professional judgment. Nazaretsky et al. (2022) suggest that trust can be shaped through interaction with a system and is consequential for users' willingness to rely on automated technologies. Accordingly, Human–AI interaction experiences may be linked to AI use intention, at least in part, through the extent to which these experiences foster trust in AI as a reliable and pedagogically appropriate support tool. Therefore, the following mediation hypotheses are proposed:

H7a: AI self-efficacy mediates the relationship between Human–AI interaction experiences and teachers' intention to use AI in teaching.

H7b: Professional value mediates the relationship between Human–AI interaction experiences and teachers' intention to use AI in teaching.

H7c: Trust mediates the relationship between Human–AI interaction experiences and teachers' intention to use AI in teaching.

Prior research also suggests that disciplinary background may shape teachers' AI-related beliefs and intentions. Ayanwale and Sanusi (2023) found significant differences between STEM and non-STEM teachers in AI anxiety, attitudes, and behavioral intention to teach AI, although readiness did not differ significantly. Studies with preservice teachers similarly showed that STEM participants tended to report more positive attitudes or greater enthusiasm toward AI integration than non-STEM participants (Aktulun et al., 2024; Colen, 2025). However, such differences appear to be construct-specific rather than universal; for example, Bohari et al. (2025) found no significant STEM/non-STEM differences in affective or behavioral AI literacy, but reported a small STEM advantage in cognitive AI literacy. Related technology research also suggests that teachers' technology-related self-efficacy and motivation may vary by subject area (Morrison et al., 2025). These findings support treating the subject area as a plausible grouping variable for examining whether the direct structural paths in the proposed model differ between STEM and non-STEM teachers.

Based on the theoretical arguments and empirical evidence reviewed above, this study proposes a structural model in which Human–AI interaction experiences developed through AI PD are treated as the primary experiential antecedent associated with teachers' motivational beliefs and trust in AI (Figure 1). Specifically, Human–AI interaction experiences are expected to be positively associated with teachers' AI self-efficacy, professional value perceptions toward AI integration, and trust in AI systems. In turn, these three proximal constructs are expected to be directly associated with teachers' intention to use AI in teaching. The model also includes indirect pathways from Human–AI interaction experiences to AI use intention through AI self-efficacy, professional value, and trust. Furthermore, recognizing disciplinary differences in epistemological orientations and technology-related confidence patterns, subject area (STEM vs. non-STEM) is examined as a grouping variable in the multi-group analysis to explore whether the direct structural paths differ across teacher groups. This model provides a theoretically grounded, context-sensitive framework for examining how AI training experiences are associated with teachers' AI-related beliefs and their intention to use AI in teaching.

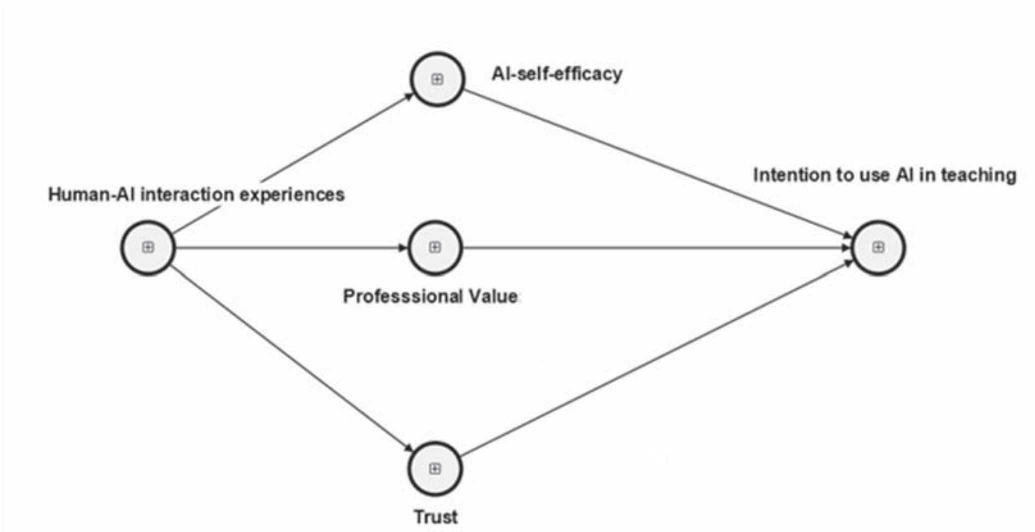

Figure 1 Research model

3. METHOD

3.1. Research Context and Participants

Participants were teachers who voluntarily enrolled in a two-day PD program on AI use in teaching in Vietnam. The program attracted approximately 200 teachers from lower- and upper-secondary schools, among whom 97 completed the post-training survey and were included in the present analysis. Because participation in both the PD program and the survey was voluntary, the sample was treated as a non-probability convenience sample, and potential self-selection bias should be acknowledged.

The 97 participants were classified into STEM and non-STEM groups based on their self-reported main teaching subjects. Teachers of mathematics, natural sciences, physics, chemistry, biology, technology, and information technology were classified as STEM teachers, whereas teachers of languages, literature, history, geography, civic education, arts, national defense and security education, primary education, and other social science or humanities-related subjects were classified as non-STEM teachers. Based on this criterion, 56 teachers were categorized as STEM teachers (57.7%) and 41 as non-STEM teachers (42.3%).

The PD program emphasized practical, classroom-oriented applications of AI rather than technical theory. It was organized around guided, hands-on pedagogical tasks and moved from trainer modeling to supported practice and then to more independent application. During the sessions, teachers worked with instructional scenarios related to lesson preparation, assessment design, and learner feedback. They practiced formulating instructional prompts, refining AI responses through iterative dialogue, evaluating the accuracy and pedagogical appropriateness of AI-generated outputs, detecting errors or limitations, and adapting AI-generated materials for classroom use. The "evaluate" and ethical-judgment dimensions of AI literacy were scaffolded by asking teachers to assess the reliability, relevance, bias, and potential risks of AI outputs before using them in teaching. This design aligns with contemporary AI competency and AI literacy frameworks, which emphasize context-sensitive, reflective, and judgment-based pedagogical use of AI (Miao & Cukurova, 2024; UNESCO, 2023; Ng et al., 2021; Sperling et al., 2024).

3.2 Measurement Instruments

The measurement instrument was a structured questionnaire designed to capture five constructs in the proposed model: Human–AI Interaction experiences, AI self-efficacy, trust in AI, professional value, and intention to use AI in teaching. The scales were constructed through a theory-informed adaptation process rather than direct transplantation of a single existing instrument, because the study targets a specific context: teachers who had just completed short-term AI-focused PD and whose experiences were strongly tied to hands-on Human–AI interaction in pedagogical tasks. In line with established scale development practice, items were first conceptualized, then formulated to reflect the language and practical experiences of teachers in the PD setting (Bandura, 1977, 2001; Boateng et al., 2018).

To strengthen content validity, the initial item pool was reviewed by two experts in educational technology and educational measurement. They assessed the conceptual relevance, clarity, and contextual appropriateness of the items for teachers who had completed the AI PD program. Based on their feedback, minor revisions were made to improve wording clarity and alignment with classroom-oriented AI use. All items were measured using a 5-point Likert scale ranging from strongly disagree to strongly agree.

Human-AI Interaction Experiences was operationalized as a practice-based interaction reflecting teachers' experiences to engage productively and reflectively with AI systems during instructional work. HAIS is defined here as a process-oriented construct capturing what teachers actually do during interaction with AI systems. It reflects situated, enacted behaviors and experiences during instructional tasks, rather than teachers' perceived capability to perform those actions. This distinction is important because, in line with social cognitive theory, such interaction experiences function as mastery experiences that contribute to, but are conceptually distinct from, self-efficacy beliefs. In other words, HAIS captures observable interaction processes as they unfold in practice, rather than teachers' judgments about their capability.

Conceptually, these items were grounded in AI literacy (especially the "use/apply," "evaluate," and ethical-judgment dimensions) and in the study's SCT-based interpretation of AI training as a source of mastery experience (Bandura, 1977; Long & Magerko, 2020; Ng et al., 2021; Sperling et al., 2024). The HAIS indicators in this study focus on *interaction processes and iterative actions* rather than technical knowledge or perceived competence. As shown in the questionnaire items, HAIS includes five items: (a) formulating requests clearly and coherently before asking AI, (b) evaluating and revising prompt quality based on AI responses, (c) iteratively refining wording and questioning strategies across a dialogue, (d) identifying hidden gaps or blind spots revealed through AI interaction, and (e) developing metacognitive awareness about one's reasoning through engagement with AI. These indicators collectively capture how teachers interact with, respond to, and learn from AI during instructional tasks.

Unlike HAIS, which reflects situated interaction processes during AI-supported tasks, **AI self-efficacy** represents a generalized belief about one's capability to perform such tasks effectively in teaching contexts. The item pool comprised five items informed by Bandura's self-efficacy theory and the teacher self-efficacy literature, and contextualized for AI-supported instructional work (Bandura, 1977, 2001; Tschannen-Moran & McMaster, 2009; Rajapakse et al., 2024). These items emphasize confidence in initiating AI use, recognizing and handling domain-specific inaccuracies, guiding AI with appropriate disciplinary terminology and context, maintaining control over the interaction process, and evaluating the quality of AI-assisted outputs after iterative refinement. This construct was included as a central mediator because the study assumes that short-term PD influences later AI usage intention primarily when teachers leave the training with a strengthened belief that they can actually manage AI in real teaching situations. Thus, the self-efficacy scale was intentionally framed around capability-in-action rather than general confidence in technology.

Trust in AI had six items, which were measured as teachers' belief that AI can provide sufficiently reliable, stable, and pedagogically useful support for teaching-related tasks. The trust items were conceptually aligned with prior educational AI acceptance research, especially work emphasizing perceived trust as a key antecedent of AI acceptance among teachers (Choi et al., 2023; Cabero-Almenara et al., 2024). In this study, the trust indicators capture multiple facets relevant to classroom use: perceived accuracy of AI-generated academic information, perceived reliability/consistency of AI as a support tool, confidence in AI's ability to generate novel and useful instructional ideas, and trust in AI's ability to handle more complex requests beyond simple commands. Importantly, trust was not treated as a purely technical belief (e.g., whether AI is "correct" in general), but as a situated professional judgment about whether AI can be depended on in pedagogically meaningful tasks. This distinction is important in teacher research because classroom adoption requires not only technical acceptance but also professional confidence in the consequences of using AI with real learners.

Professional value included five items, which were measured as teachers' judgment that AI use contributes meaningful benefits to their professional thinking and instructional practice. This construct draws conceptually on EVT (task value) while being adapted to the PD and teaching context of this study (Eccles & Wigfield, 2002). Rather than operationalizing value only as usefulness in a narrow efficiency sense, the items in this study emphasize deeper professional benefits, including cognitive support, idea generation, reflective thinking, and instructional creativity. Specifically, the value items reflect whether AI helps teachers reduce cognitive load in routine work, functions as a "thinking partner" for pedagogical analysis, supports the generation of lesson or project ideas, creates time for deeper reflection on teaching strategy and learner support, and is experienced as more than a tool, as a professional cognitive aid. This broader conceptualization is consistent with the study's focus on Human–AI interaction in PD, where the meaningfulness of AI use may emerge not only from speed or convenience but from its contribution to teachers' pedagogical reasoning.

The intention to use AI in teaching comprised five items that measured teachers' self-reported intention or tendency to use AI in concrete teaching-related activities after the PD program. The items were informed by technology acceptance and AI-in-education adoption studies that treat behavioral intention as an important outcome of capability, trust, and value judgments (Venkatesh et al., 2003; Choi et al., 2023; Cabero-Almenara et al., 2024). The indicators captured teachers' intention to use AI for clearly defined professional tasks, such as drafting, summarizing, brainstorming instructional ideas, engaging in iterative dialogue with AI, automating repetitive tasks, and exploring new pedagogical possibilities. Because participants were still in the early stage of AI adoption, this construct was framed as AI use intention rather than sustained instructional behavior.

3.3. Data Collection and Analysis

Data were collected immediately after the completion of the 2-day PD program so that the measured constructs would reflect participants' actual training experiences rather than prior expectations or hypothetical views of AI. The post-intervention timing was methodologically important because the study sought to capture both the Human–AI interaction experiences developed through guided hands-on practice and the related attitudinal outcomes, including AI self-efficacy, trust, professional value, and intention to use AI in teaching. Accordingly, the questionnaire was administered only after participants had completed practical AI-supported teaching tasks such as prompt construction, iterative refinement, output evaluation, and pedagogical adaptation. This sequencing ensured that responses were grounded in direct instructional experience, which is consistent with the study's conceptualization of HAIS as a practice-based construct emerging through guided Human–AI interaction rather than as a pre-existing technical skill (Bandura, 1977, 2001; Ng et al., 2021; Sperling et al., 2024; Tschannen-Moran & McMaster, 2009).

The data were subsequently analyzed using partial least squares structural equation modeling (PLS-SEM), followed by multi-group analysis to compare STEM and non-STEM teachers. PLS-SEM was considered appropriate given the relatively small sample size and the study's predictive orientation rather than strict theory confirmation. Unlike covariance-based SEM, PLS-SEM is particularly suitable for exploratory and prediction-focused research, especially when the primary objective is to maximize explained variance (R^2) and to examine complex relationships among constructs under sample-size constraints (Hair et al., 2019). Therefore, PLS-SEM provided a robust analytical approach for estimating the structural relationships and comparing group differences within the proposed model.

To ensure the validity of the group comparisons, the Measurement Invariance of Composite Models (MICOM) procedure was performed. The results established invariance for most constructs; however, the Trust construct did not fully meet the criteria for compositional invariance (Step 2). Consequently, while the multi-group analysis proceeded for the overall model, the comparative results for 'Trust' are interpreted with caution, acknowledging that observed differences may partially reflect measurement nuances between STEM and non-STEM groups rather than purely behavioral variations.

4. RESULTS

4.1. Measurement model and PLS-SEM results

The measurement model was assessed for internal consistency reliability, convergent validity, and discriminant validity, following Hair et al.'s (2019) guidelines. First, as shown in Table 1, Cronbach's alpha values ranged from 0.91 to 0.94, exceeding the recommended threshold of 0.70. Composite reliability values ranged from 0.91 to 0.94, further confirming strong internal consistency across all constructs. Next, convergent validity was evaluated using Average Variance Extracted (AVE). All AVE values ranged from 0.73 to 0.80, surpassing the recommended threshold of 0.50. These results indicate that each construct explains a substantial proportion of variance in its indicators. Discriminant validity was assessed using the Fornell–Larcker criterion (Table 2). The square roots of AVE (ranging from 0.85 to 0.90) were greater than the inter-construct correlations, demonstrating adequate discriminant validity among the five constructs. Overall, the measurement model demonstrated satisfactory reliability and validity, supporting its suitability for subsequent structural model analysis.

Table 1
Reliability and Convergent Validity of the Measurement Model

	Cronbach's alpha	Composite reliability (rho_a)	Average variance extracted (AVE)
AI self-efficacy	0.91	0.92	0.74
Human–AI interaction experiences	0.93	0.94	0.75
Intention to use AI in teaching	0.91	0.92	0.73
Professional Value	0.94	0.94	0.80
Trust	0.92	0.94	0.73

Table 2
Fornell–Larcker discriminant validity matrix

	AI self-efficacy	Human-AI interaction experiences	Intention to use AI in teaching	Professional Value	Trust
AI self-efficacy	0.86				
Human-AI interaction experiences	0.55	0.87			
Intention to use AI in teaching	0.82	0.70	0.85		
Professional Value	0.66	0.77	0.70	0.90	
Trust	0.70	0.45	0.65	0.59	0.85

4.2 Structural Model Results

The structural model was evaluated using the partial least squares structural equation modeling (PLS-SEM) approach. To assess the significance of the hypothesized relationships, a bootstrapping procedure with 5,000 resamples was conducted, following recommended guidelines for stable standard error estimation and hypothesis testing. This nonparametric resampling technique allows robust estimation of path coefficients and their statistical significance without assuming normality.

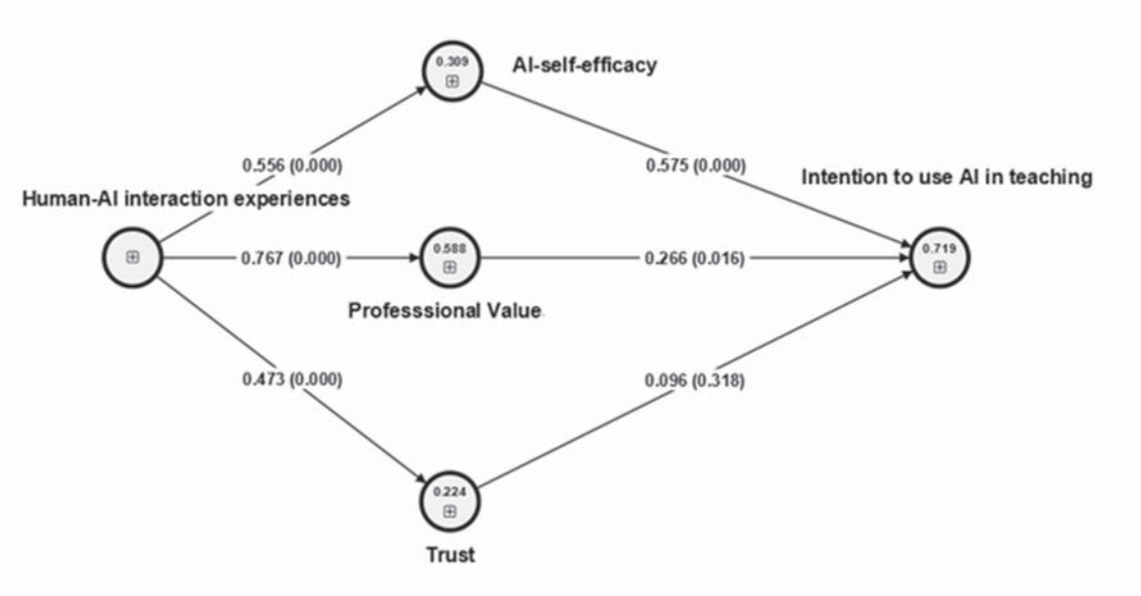

Figure 2 SEM results

The structural model results (Figure 2) indicated that most of the hypothesized relationships were supported. Among the three proximal predictors of teachers' intention to use AI in teaching, AI self-efficacy showed a strong and statistically significant positive association with intention (β = 0.56, p < .001), supporting H1. Professional value toward AI integration was also positively and significantly associated with intention (β = 0.27, p = .016), supporting H2. In contrast, trust in AI did not demonstrate a statistically significant direct effect on intention (β = 0.10, p = .31), and therefore H3 was not supported. Comparing the relative strengths of these predictors, AI self-efficacy exerted the strongest influence on intention, followed by professional value, whereas trust showed a weak and non-significant association in the overall sample.

With respect to the antecedent relationships, Human–AI interaction experiences were positively and significantly associated with AI self-efficacy (β = 0.55, p < .001), professional value (β = 0.77, p < .001), and trust (β = 0.45, p < .001), thus supporting H4, H5, and H6. Finally, the specific indirect effects were examined. The results showed that Human–AI interaction experiences had a significant indirect association with teachers' intention to use AI in teaching through AI self-efficacy ($\beta = 0.32$, $p = .002$), supporting H7a. The indirect association through professional value was also statistically significant ($\beta = 0.20$, $p = .01$), supporting H7b. However, the indirect association through trust was not statistically significant ($\beta = 0.045$, $p = .378$), indicating that H7c was not supported. These findings suggest that Human–AI interaction experiences were indirectly linked to AI use intention mainly through teachers' AI self-efficacy and perceived professional value, rather than through trust.

In terms of explained variance, the model accounted for 71.9% of the variance in teachers' intention to use AI in teaching ($R^2 = .719$). Additionally, Human–AI interaction experiences explained 30.9% of the variance in AI self-efficacy ($R^2 = .309$), 58.8% of the variance in professional value ($R^2 = .588$), and 22.4% of the variance in trust ($R^2 = .224$), indicating moderate to substantial explanatory power across the endogenous constructs.

4.3. Multi-group Analysis of STEM and Non-STEM Teachers

A multi-group analysis was conducted to examine whether the structural relationships differed between STEM and non-STEM teachers. The results revealed several significant group differences. The path from AI self-efficacy to intention to use AI in teaching was significantly stronger among STEM teachers than among non-STEM teachers ($\Delta\beta = 0.27$, $p < .001$). In contrast, the path from trust to intention was stronger among non-STEM teachers than among STEM teachers ($\Delta\beta = -0.26$, $p < .001$). However, this difference should be interpreted with caution because compositional invariance was not fully established in the MICOM procedure.

Similarly, the relationship between human–AI interaction experiences and trust differed significantly between the two groups ($\Delta\beta = -0.44$, $p < .001$), with a stronger effect observed among non-STEM teachers. The path from professional value to intention also showed a significant group difference ($\Delta\beta = -0.17$, p < .001), again indicating a stronger relationship among non-STEM teachers. No significant group differences were found for the paths from human–AI interaction experiences to AI self-efficacy ($\Delta\beta = -0.30$, p = .19) or to professional value ($\Delta\beta = -0.15$, p = .19). Overall, the findings suggest that AI self-efficacy is a more salient predictor of intention among STEM teachers, whereas professional value and trust play comparatively stronger roles among non-STEM teachers.

Table 3
Comparison of STEM and non-STEM teachers' results

	Difference (Group_STEM - Group_non-STEM)	2-tailed (Group_STEM vs Group_non-STEM) p value
Human-AI interaction experiences-> AI self-efficacy	-0.30	0.19
Human-AI interaction experiences-> Professional Value	-0.15	0.19
Human-AI interaction experiences-> Trust	-0.44	< .001
AI self-efficacy -> Intention to use AI in teaching	0.27	< .001
Professional Value -> Intention to use AI in teaching	-0.17	< .001
Trust -> Intention to use AI in teaching	-0.26	< .001

5. DISCUSSION AND CONCLUSION

This study examined how human–AI interaction experiences developed through AI PD were associated with teachers' motivational beliefs, trust, and intention to use AI in teaching, while also comparing differences between STEM and non-STEM teachers. First, human–AI interaction experiences were positively associated with AI self-efficacy, professional value, and trust. These findings suggest that guided hands-on engagement may be linked to stronger AI-related capability beliefs, perceived professional value, and trust. From a PD perspective, the results point to the potential value of guided human–AI interaction and iterative practice, rather than merely introducing technical concepts. However, given the post-intervention cross-sectional design, these findings should be interpreted as associations between teachers' PD-based interaction experiences and their AI-related beliefs, rather than as evidence that the PD program directly produced these changes.

Second, among the three proximal predictors of intention, AI self-efficacy, professional value, and trust, AI self-efficacy demonstrated the strongest effect on teachers' intention to use AI. This finding aligns with prior expectancy–value–based AI research, which consistently identifies confidence in one's capability as a central determinant of AI-related behavioral intention (Wang et al., 2023; Yin & Goh, 2024). Professional value also significantly predicted intention, whereas trust did not show a significant direct effect in the full sample. The indirect-effect results further showed that Human–AI interaction experiences were linked to intention primarily through AI self-efficacy and professional value, reinforcing the central role of capability beliefs and perceived professional relevance in teachers' AI adoption. The non-significant effect of trust may be explained by the "adoption–trust paradox," whereby teachers adopt AI for its functional benefits while remaining cautious about its epistemic reliability (Panagopoulos et al., 2026). In this sense, trust may not operate as a direct motivational driver but rather as a background condition that enables use without necessarily increasing intention. Moreover, in institutionalized educational contexts, trust may serve as a baseline, providing only limited additional explanatory power once a minimum level is established. This interpretation is consistent with evidence from Vietnam, where the role of trust varies across teacher characteristics (Nguyen et al., 2025), and is further supported by the observed differences between STEM and non-STEM teachers in this study.

Third, the comparison between STEM and non-STEM teachers revealed different motivational patterns. AI self-efficacy was more strongly associated with intention among STEM teachers, whereas professional value and trust were more salient among non-STEM teachers. This aligns with prior evidence that STEM and non-STEM teachers may differ in AI-related attitudes, anxiety, literacy, and behavioral intention (Ayanwale & Sanusi, 2023; Aktulun et al., 2024; Bohari et al., 2025). Regarding trust, the group differences should be interpreted cautiously because the Trust construct did not fully establish compositional invariance in the MICOM procedure. This suggests that STEM and non-STEM teachers may have responded to trust-related items somewhat differently. Nevertheless, the observed pattern remains theoretically meaningful. STEM teachers' intention to use AI appeared to be more strongly linked to AI self-efficacy, suggesting the importance of perceived capability and technical control. In contrast, non-STEM teachers' intention was more closely associated with professional value and trust, indicating that they may place greater emphasis on whether AI is pedagogically meaningful, appropriate, and reliable. These findings suggest that AI PD should be differentiated by subject area: STEM teachers may benefit more from activities that strengthen task-specific efficacy, whereas non-STEM teachers may need discipline-relevant examples that clarify pedagogical value and support informed trust in AI.

Given the small sample size and post-intervention cross-sectional design, the findings suggest a set of preliminary theoretical and practical implications. Theoretically, the study extends expectancy–value–based explanations of teachers' AI adoption by showing that Human–AI interaction experiences are associated with intention mainly through AI self-efficacy and professional value, while trust appears to play a more context-dependent role. This suggests that, in short-term AI PD, teachers' intention to use AI is shaped more strongly by perceived capability and professional relevance than by trust alone. The STEM/non-STEM comparison further indicates that disciplinary background may condition how these motivational mechanisms operate, with self-efficacy being more salient for STEM teachers and professional value and trust being more relevant for non-STEM teachers. Practically, these results suggest the potential value of AI PD that moves beyond general tool demonstrations and provides guided, task-specific interaction activities to help teachers evaluate AI outputs, adapt them to teaching tasks, and recognize their instructional value. In line with Vietnam's ongoing digital transformation and AI-related education policies, such training may also benefit from subject-area differentiation: STEM teachers may need activities that strengthen technical control and task-specific efficacy, whereas non-STEM teachers may benefit from discipline-relevant examples that clarify pedagogical value and support informed trust in AI-supported teaching.

6. LIMITATIONS AND FUTURE RESEARCH

Several limitations should be acknowledged. First, the study employed a non-probability convenience sample of teachers who voluntarily enrolled in an AI PD program. This may limit the generalizability of the findings to the broader Vietnamese teacher population. Second, data were collected immediately after the PD intervention using self-reported measures. Given the post-intervention, self-report, and cross-sectional design, the findings should be interpreted as theoretically informed associations rather than causal effects. Accordingly, the results are more likely to capture teachers' short-term perceptions and AI use intentions than sustained changes in actual instructional behavior.

Future research should incorporate longitudinal designs to examine whether the effects of human–AI interaction experiences on self-efficacy, professional value, trust, and AI use persist over time. Pre–, post-, and follow-up measurements would allow stronger conclusions about developmental change. Additionally, qualitative methods such as interviews or classroom observations could provide deeper insight into how teachers translate AI-related beliefs into actual instructional practice. Expanding the sample size and including teachers from diverse educational contexts would further enhance the robustness and external validity of the findings.

References

Ayanwale, M. A., & Sanusi, I. T. (2023). Perceptions of STEM vs. non-STEM teachers toward teaching artificial intelligence. In *2023 IEEE AFRICON* (pp. 1-5). IEEE. https://doi.org/10.1109/AFRICON55910.2023.10293455

Aktulun, O. U., Kasapoğlu, K., & Aydoğdu, B. (2024). Comparing Turkish pre-service STEM and non-STEM teachers' attitudes and anxiety toward artificial intelligence. *Journal of Baltic Science Education*, *23*(5), 950-963. https://doi.org/10.33225/jbse/24.23.950

Aravantinos, S., Lavidas, K., Komis, V., Karalis, T., & Papadakis, S. (2026). Artificial intelligence in K-12 education: A systematic review of teachers' professional development needs for AI integration. *Computers*, *15*(1), 49. https://doi.org/10.3390/computers15010049

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191-215. https://doi.org/10.1037/0033-295X.84.2.191

Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology*, *52*, 1-26. https://doi.org/10.1146/annurev.psych.52.1.1

Boateng, G. O., Neilands, T. B., Frongillo, E. A., Melgar-Quiñonez, H. R., & Young, S. L. (2018). Best practices for developing and validating scales for health, social, and behavioral research: A primer. *Frontiers in Public Health*, *6*, 149. https://doi.org/10.3389/fpubh.2018.00149

Bohari, A., Kaliappan, A., & Loh, S. L. (2025). AI literacy beyond STEM: Rethinking teacher education for the AI era. *International Journal of Humanities Technology and Civilization*, *10*(2), 126-133. https://doi.org/10.15282/ijhtc.v10i2.13274

Cabero-Almenara, J., Palacios-Rodríguez, A., Loaiza-Aguirre, M. I., & Rivas-Manzano, M. d. R. (2024). Acceptance of educational artificial intelligence by teachers and its relationship with some variables and pedagogical beliefs. *Education Sciences*, *14*(7), 740. https://doi.org/10.3390/educsci14070740

Choi, S., Jang, Y., & Kim, H. (2023). Influence of pedagogical beliefs and perceived trust on teachers' acceptance of educational artificial intelligence tools. *International Journal of Human-Computer Interaction*, *39*(4), 910-922. https://doi.org/10.1080/10447318.2022.2049145

Colen, J. (2025). Teacher candidates' perceptions of AI integration in secondary education: A comparative study of STEM and non-STEM majors. *International Journal of Education in Mathematics, Science and Technology*, *13*(5), 1097-1112. https://doi.org/10.46328/ijemst.5701

Diamante, R. E. J., Martin, A. B., & Berry, E. B. (2025). Developing trust and confidence in the delivery of AI-oriented teaching strategies among non-ICT expert teachers. *Environment and Social Psychology*, *10*(8), 3851.

Ding, A. C. E., Shi, L., Yang, H., & Choi, I. (2024). Enhancing teacher AI literacy and integration through different types of cases in teacher professional development. *Computers and Education Open*, *6*, 100178.

Eccles, J. S., & Wigfield, A. (2002). Motivational beliefs, values, and goals. *Annual Review of Psychology*, *53*, 109-132. https://doi.org/10.1146/annurev.psych.53.100901.135153

Eccles, J. S., & Wigfield, A. (2020). From expectancy–value theory to situated expectancy–value theory: A developmental, social cognitive, and sociocultural perspective on motivation. *Contemporary Educational Psychology*, *61*, 101859. https://doi.org/10.1016/j.cedpsych.2020.101859

Government of Vietnam. (2020). *Decision No. 749/QĐ-TTg approving the National Digital Transformation Program to 2025, with orientation to 2030*.

Government of Vietnam. (2021). *Decision No. 127/QĐ-TTg promulgating the National Strategy for Research, Development and Application of Artificial Intelligence to 2030*.

Government of Vietnam. (2022). *Decision No. 131/QĐ-TTg approving the scheme on strengthening ICT application and digital transformation in education and training for 2022-2025, with orientation to 2030*.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2-24.

Han, F., & Guo, J. (2025). How does university students' academic major (STEM vs. non-STEM) affect their acceptance of e-learning: A multi-group analysis. *International Journal of Educational Technology in Higher Education*, *22*, Article 41. https://doi.org/10.1186/s41239-025-00543-z

Hosmer, L. T. (1995). Trust: The connecting link between organizational theory and philosophical ethics. *Academy of Management Review*, *20*(2), 379-403.

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1-16). Association for Computing Machinery. https://doi.org/10.1145/3313831.3376727

Miao, F., & Cukurova, M. (2024). *AI competency framework for teachers*. UNESCO. https://doi.org/10.54675/ZJTE2084

Ministry of Education and Training. (2025). *Guidance on piloting artificial intelligence education content in general education*.

Morrison, A., Smart, J., Wiles, D., & Bennett, L. (2025). Examining differences among K–12 teachers' motivation for online teaching. *Online Learning*, *29*(4), 162-173. https://doi.org/10.24059/ Zolj.v29i4.5218

Nazaretsky, T., Ariely, M., Cukurova, M., & Alexandron, G. (2022). Teachers' trust in AI-powered educational technology and a professional development program to improve it. *British Journal of Educational Technology*, *53*(4), 914-931.

Ng, D. T. K., Leung, J. K. L., Chu, S. K. W., & Qiao, M. S. (2021). Conceptualizing AI literacy: An exploratory review. *Computers and Education: Artificial Intelligence*, *2*, 100041. https://doi.org/10.1016/j.caeai.2021.100041

Nguyen, H., Thanh, V. D. T., & Dinh, V. P. (2025). Bringing AI into teaching: Understanding Vietnamese teachers' perspectives and pedagogical challenges. *International Journal of Educational Methodology*, *11*(3), 335-347. https://doi.org/10.12973/ijem.11.3.335

Panagopoulos, E., Liapis, C. M., Adamopoulou, A., Kamarianos, I., & Kotsiantis, S. (2026). Trust, education, and artificial intelligence: Adoption, explainability, and epistemic authority among teacher-education undergraduates in Greece. *Algorithms*, *19*(5), 350. https://doi.org/10.3390/a19050350

Paredes-Aguirre, M., Bolanos-Mendoza, C., Ortiz-Rojas, M., Martinez-Tovar, J., Sanchez-Mendoza, M., & Moreno-Abramowicz, M. (2026). Understanding perceived learning and the role of digital self-efficacy in generative AI adoption among STEM and non-STEM students. *Cogent Education, 13*(1), 2614093.

Rajapakse, C., Ariyarathna, W., & Selvakan, S. (2024). A self-efficacy theory-based study on the teachers' readiness to teach artificial intelligence in public schools in Sri Lanka. *ACM Transactions on Computing Education*, *24*(4), 1-25. https://doi.org/10.1145/3691354

Sperling, K., Stenberg, C.-J., McGrath, C., Åkerfeldt, A., Heintz, F., & Stenliden, L. (2024). In search of artificial intelligence literacy in teacher education: A scoping review. *Computers and Education Open*, *6*, 100169. https://doi.org/10.1016/j.caeo.2024.100169

Tan, X., Cheng, G., & Ling, M. H. (2025). Artificial intelligence in teaching and teacher professional development: A systematic review. *Computers and Education: Artificial Intelligence*, *8*, 100355. https://doi.org/10.1016/j.caeai.2024.100355

Tschannen-Moran, M., & McMaster, P. (2009). Sources of self-efficacy: Four professional development formats and their relationship to self-efficacy and implementation of a new teaching strategy. *The Elementary School Journal*, *110*(2), 228-245. https://doi.org/10.1086/605771

UNESCO. (2023). *Guidance for generative AI in education and research*. UNESCO. https://doi.org/10.54675/EWZM9535

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425-478. https://doi.org/10.2307/30036540

Viberg, O., Cukurova, M., Feldman-Maggor, Y., et al. (2025). What explains teachers' trust in AI in education across six countries? *International Journal of Artificial Intelligence in Education*, *35*, 1288-1316. https://doi.org/10.1007/s40593-024-00433-x

Wang, F., King, R. B., Chai, C. S., & Zhou, Y. (2023). University students' intentions to learn artificial intelligence: The roles of supportive environments and expectancy–value beliefs. *International Journal of Educational Technology in Higher Education*, *20*(1), 51.

Wigfield, A., & Eccles, J. S. (2000). Expectancy–value theory of achievement motivation. *Contemporary Educational Psychology*, *25*(1), 68-81.

Yin, S. X., & Goh, D. H.-L. (2024). Expectancy-value beliefs as predictors of student intentions in AI learning and application. In *International Conference on Asian Digital Libraries*.

Yu, H., & Guo, Y. (2023). Generative artificial intelligence empowers educational reform: Current status, issues, and prospects. *Frontiers in Education*, *8*, 1183162.

Yurt, E. (2024). Theoretical examination of teachers' motivations for using artificial intelligence applications in education: Expectancy-value theory perspective. *International Society for Technology, Education, and Science*.

Zhang, C., Hu, M., Wu, W., Kamran, F., & Wang, X. (2025). Unpacking perceived risks and AI trust influences pre-service teachers' AI acceptance: A structural equation modeling-based multi-group analysis. *Education and Information Technologies*, *30*(2), 2645-2672.