Validating a Multidimensional Competency Model for AI Use in Arts Teaching: A Structural Equation Modeling Approach

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Manuscript received July 23, 2025; revised September 17, 2025; accepted November 12, 2025; published April 15, 2026

***Abstract*—In the context of accelerated digital transformation in education, Artificial Intelligence (AI) is increasingly recognized as a strategic enabler for personalized, efficient, and data-driven teaching practices. This study proposes and empirically validates a multidimensional competency model for AI integration in arts education. Grounded in the integration of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and Technological Pedagogical Content Knowledge (TPACK) frameworks, the model encompasses six latent constructs: foundational AI knowledge, AI-integrated pedagogical skills, ethical awareness, pedagogical efficacy, reflective thinking, and practical AI use behavior. A quantitative design was applied, with survey data collected from 202 arts teachers in Vietnamese K–12 schools. Structural Equation Modeling (SEM) was employed to assess the model's fit and predictive power. Findings confirm the structural coherence of the model and highlight the interplay between cognitive, ethical, and reflective dimensions in shaping AI adoption in artistic instruction. This research advances theoretical understanding of technology acceptance in creative domains and provides actionable insights for curriculum designers, policymakers, and teacher educators aiming to foster responsible and pedagogically meaningful AI usage in the digital age.**

***Keywords*—artificial intelligence, arts education, teacher competency, technology integration, Structural Equation Modeling (SEM)**

I. Introduction

The rapid evolution of Artificial Intelligence (AI) technologies is reshaping pedagogical frameworks across diverse educational sectors. In particular, AI offers educators scalable solutions for adaptive instruction, real-time feedback, and learner-centered content generation [1]. As education systems increasingly transition toward data-informed and digitally mediated models, integrating AI into classroom practices has become a critical focus of contemporary educational research. Compared to traditional teaching methods, AI integration provides advantages such as faster information retrieval, enhanced visualization, and personalized learning experiences. This is because AI can generate customized learning resources tailored to individual student needs throughtout the learning process [2–5]. As such, AI in education enables differentiated instruction and individualized learning.

However, AI integration in teaching is largely theoretical or experimental, typically limited to technologically advanced countries and pioneering researchers [6]. Teachers in developing nations are still lagging behind. To address this issue, scholars have examined the potentials, challenges, and implications of AI integration in education. This is evidenced by numerous review studies—for example, Tahiru [6] analyzed the opportunities and challenges of AI use in education; Chen *et al.* [7] evaluated AI's impact on education; and investigated opportunities and challenges [8, 9]. Recent studies [10, 11] have emphasized that AI should enrich and expand creative learning processes rather than replace human educators. Barriers such as lack of foundational AI knowledge, ethical concerns, insufficient institutional support, and fear of job displacement have been identified [12, 13]. From a theoretical standpoint, most prior studies on teacher readiness for AI adoption rely on frameworks like Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and Technological Pedagogical Content Knowledge (TPACK) [14, 15]. UTAUT2 focuses on socio-psychological factors such as performance expectancy, effort expectancy, social influence, and habit, while TPACK provides a foundation for integrating technology, pedagogy, and content knowledge—An essential basis for teaching in a rapidly evolving technological context [16, 17]. Recently, researchers have proposed extending the TPACK model to include AI elements, forming the AI-TPACK framework to better reflect the competencies required of digital-age teachers [18].

Although AI applications have been widely studied in general education, their role in arts education (including music, visual arts, and design) remains underexplored, despite increasing practical relevance [13, 19]. This comes as a surprise, particularly in the current educational landscape where art subjects are increasingly incorporating artificial intelligence tools such as DALL·E, ChatGPT, and Soundraw as effective assistants in facilitating creative expression and artistic design among teachers and students [10–12]. This is surprising, given the growing use of tools like DALL·E, ChatGPT, and Soundraw in creative teaching. These generative AI tools not only support ideation and multimodal expression but also facilitate personalized instruction in the arts. This trend highlights an urgent need to identify the competencies required for arts teachers to integrate AI effectively and responsibly into their teaching. Traditional arts education emphasizes creativity, emotional depth, and personal expression-areas often considered beyond the reach of algorithmic modeling [20, 21].

However, recent research suggests that AI can enhance rather than diminish human creativity in learning experiences [13, 19]. Therefore, developing and validating a competency framework for AI integration in arts education is more crucial than ever. Existing frameworks like TPACK

doi: 10.18178/ijiet.2026.16.4.2576

and UTAUT2 provide valuable foundations but have not yet been sufficiently adapted or validated for the specific context of arts education [14, 15]. This study aims to address that gap by proposing and empirically testing a multidimensional competency model for AI use in arts teaching. The model integrates UTAUT2 and TPACK, and is refined through recent findings from educational technology and creative education research. It aims not only to evaluate pedagogical-technological competencies but also to support sustainable professional development in digital education.

Based on the aforementioned theoretical discussions and identified research gaps, this study focuses on addressing two core research questions:

1) What are the key factors that significantly influence arts teachers' competency in using artificial intelligence in teaching?
2) How do these factors interact and influence one another?

From these research questions, the overarching objective of this study is to develop and validate a multidimensional competency model for AI integration in arts education, with the aim of clarifying its constituent elements and their interrelations.

Specifically, the study pursues three objectives:

1) To identify the core components of AI competency in arts teachers, including foundational AI knowledge, AI-integrated pedagogical skills, digital ethics awareness, reflective thinking, professional attitudes, and practical usage behavior.
2) To analyze the structural relationships among these components by validating a theoretical model based on the integration of UTAUT2 and TPACK, clarifying how cognition, skills, attitudes, and reflection interact to form AI use behavior in arts teaching.
3) To propose practical implications for training and professional development of arts teachers, including guidelines for curriculum design, assessment tools, and policy recommendations to foster effective and responsible AI integration in creative education.

Grounded in the foundational theoretical frameworks of UTAUT2 and TPACK [14, 22], as well as a synthesis of recent studies on AI applications in arts education [10–12] this study proposes a conceptual model comprising six latent constructs:

1) Foundational Knowledge of AI (KN).
2) Pedagogical Skills for AI Integration (SK).
3) Ethical and Digital Responsibility Awareness (ET).
4) Pedagogical Efficacy (PE).
5) Reflective Thinking (RE).
6) Behavioral AI Use in Teaching Practice (BE)

In this study, Behavioral AI Use in Teaching Practice (BE) refers to the extent to which teachers actively apply AI tools in instructional settings. This includes frequency of use, the diversity of AI applications (e.g., content generation, lesson personalization, artistic enhancement), and the degree of intentionality and alignment with pedagogical goals. Rather than mere exposure to AI, this construct captures how deliberately and creatively teachers incorporate AI into their classroom practices in ways that support student learning and artistic expression.

Another key construct in the model is Attitude and Beliefs about AI (AT), which reflects teachers' perceptions, emotional responses, and openness toward the use of AI in teaching. This construct is grounded in the UTAUT2 framework, which emphasizes the role of affective and motivational factors in technology adoption. Positive attitudes are known to enhance teachers' willingness to explore and integrate new technologies [14, 23]. In the context of arts education, where creativity and personal expression are central, attitudes toward AI may significantly shape teachers' pedagogical decisions and willingness to experiment with AI-enhanced instructional tools. Based on this model, the following research hypotheses are formulated:

- H1: Foundational AI Knowledge (KN) positively influences Pedagogical Skills for AI Integration (SK).
- H2: Attitude and Beliefs about AI (AT) positively influence Pedagogical Skills (SK).
- H3: Foundational AI Knowledge (KN) positively influences Ethical and Digital Responsibility Awareness (ET).
- H4: Pedagogical Skills (SK) positively influence Behavioral AI Use in Teaching (BE).
- H5: Pedagogical Efficacy (PE) positively influences Behavioral AI Use (BE).
- H6: Reflective Thinking (RE) positively influences Behavioral AI Use (BE).

These hypotheses aim to validate the proposed structural model and explain the interplay among cognitive, skill-based, attitudinal, and behavioral elements in arts teachers' AI adoption. The validation will be conducted through Structural Equation Modeling (SEM), allowing for simultaneous assessment of multiple latent relationships within a multivariate model (Fig. 1).

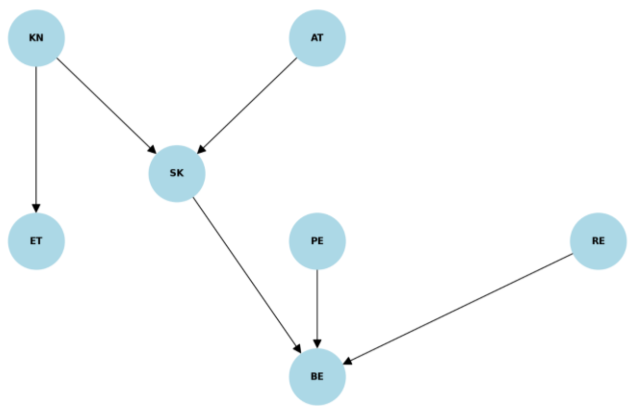

Fig. 1. Conceptual model exploring the predictors influencing arts teachers' AI usage behavior.

II. Theoretical Framework

A. Theoretical Foundations in Arts Pedagogy

Dewey [24] asserts that art is not merely the product of creation but an aesthetic process of experience that is inseparable from life. Learners engage in artistic activity through interaction, emotion, and reflection, thereby forming unified and meaningful experiences. Within contemporary educational contexts, the integration of Artificial Intelligence (AI) into art instruction can be viewed as an extension of aesthetic experience: rather than replacing the learner's role, AI generates new conditions that stimulate curiosity, nurture imagination, and deepen emotional engagement throughout the creative process. Building upon this view, Eisner [20] contends that the arts are fundamental to cultivating diverse forms of cognition. He emphasizes that art education fosters aesthetic sensitivity, flexible thinking, and personal expressiveness through processes of meaning-making and aesthetic judgment. In the current technological landscape, generative AI tools such as DALL·E or Soundraw can be regarded as supportive media that expand learners' aesthetic reasoning—encouraging exploration of alternative perspectives, expressive modes, and imaginative possibilities. This interpretation aligns with Eisner's view of art education as a pathway for intellectual and creative development grounded in aesthetic experience [20]. Extending this perspective, Greene [25] underscores the notion of "releasing the imagination" as a central principle of aesthetic education. She maintains that the arts possess the power to open new ways of perceiving both the world and the self, thereby fostering empathy, critical awareness, and the capacity to reimagine reality. In the context of increasing AI integration into art education, teachers are encouraged to guide learners to perceive AI not merely as a technical instrument but as a cultural-aesthetic agent. When applied creatively and reflectively, AI can serve as a medium through which students extend their imaginative horizons, enhance critical thinking, and interpret the world from multiple perspectives—consistent with Greene's emancipatory vision of education.

B. Aesthetic Foundations for AI Integration in Arts Education

In contemporary art classrooms, Artificial Intelligence (AI) functions not merely as a generative tool for producing images or sounds but as an aesthetic mediator that co-constructs perceptual situations with learners. It opens exploratory spaces for stylistic experimentation and stimulates a dynamic cycle of judgment, selection, and interpretation. Through this process, AI broadens and deepens learners' artistic experiences, creating opportunities to develop aesthetic judgment, conceptual thinking, and reflective capacity—qualities that transcend the mere acquisition of technical skills. Recent empirical evidence in educational and creative research supports this perspective [26].

AI facilitates ideation by rapidly generating multiple variations and enabling interdisciplinary blending across text, image, and sound. Such affordances offer learners a broader landscape for comparison, contrast, and the discovery of subtle distinctions. Experimental studies demonstrate that integrating generative models into creative processes significantly enhances both productivity and peer evaluation among art students. Although average novelty may slightly decrease, peak originality tends to increase, indicating that AI proves particularly effective during the stage of divergent ideation [26].

Within human-AI co-creation, learners alternate among the roles of director, interlocutor, and explorer in an iterative cycle of intention, generation, selection, and refinement. This process cultivates their capacity to exercise aesthetic judgment and interpret meaning rather than relying solely on technical manipulation. Survey evidence from young learners further indicates that most perceive AI as a collaborative partner that offers inspiration and expands creative boundaries, while simultaneously encouraging them to impose constraints, make informed trade-offs, and justify their aesthetic decisions [25].

III. Materials and Methods

A. Research Design

This study employed a quantitative research design using Structural Equation Modeling (SEM). SEM is a statistical method that allows the examination of complex relationships among variables and the validation of theoretical models. Specifically, the Partial Least Squares (PLS) approach was used in this study to conduct SEM analysis [27]. The proposed model was developed based on the integration of two foundational theoretical frameworks: UTAUT2 and TPACK [14, 15], along with insights from recent literature on technology-enhanced arts education.

B. Participants and Sample Size

The participants were arts teachers (in music and visual arts) currently teaching in primary and lower secondary schools across Vietnam. A stratified random sampling method was used to ensure regional representation (North, Central, South; urban–rural). A total of 202 valid responses were collected and used in the analysis, meeting the minimum sample size requirement for SEM studies [28, 29].

The demographic characteristics of the participants are presented in Table 1.

Table 1. Demographic characteristics of participants

Category	Subcategory	Number	Percentage (%)
Gender	Male	57	28.2
	Female	145	71.8
Year of experience	Under 5 years	3	1.5
	5–10	13	6.4
	10–20	124	61.4
	Over 20 years	62	30.7
Workplace	Rural	55	27.2
	Mountainous	129	63.9
	Urban center	18	8.9

In terms of gender, the majority of survey participants were female (71.8%), while males accounted for 28.2%. This distribution reflects the prevalent gender characteristics of Vietnam's primary education workforce, where women hold a dominant presence in the teaching profession.

Regarding years of teaching experience, most respondents were seasoned educators: 61.4% had between 10 and under 20 years of teaching experience, and 30.7% had more than 20 years. Only 6.4% had between 5 and under 10 years of experience, while just 1.5% had less than 5 years. These figures suggest that the participating teachers possess a strong professional foundation and extensive experience, highlighting the stability and long-term commitment within the teaching profession.

In terms of workplace location, the majority of teachers worked in mountainous or remote areas (63.9%), followed by those in rural areas (27.2%), with only 8.9% based in major urban centers. This composition indicates that the study primarily focused on challenging regions, where teaching conditions and infrastructure remain limited, thereby providing a realistic portrayal of the primary teaching workforce in these specific contexts. These demographic features suggest that the sample adequately represents the teaching population targeted by this study, providing a sound basis for further analysis using SEM.

C. Instruments and Measurements

Data were collected via a self-administered questionnaire developed by the research team, consisting of 21 items measuring six latent variables: Foundational AI Knowledge (KN); Attitudes and Beliefs about AI (AT); Pedagogical Skills for AI Integration (SK); Ethical and Digital Responsibility Awareness (ET); Pedagogical Efficacy (PE); Reflective Thinking (RE); and Behavioral AI Use (BE). All items were rated on a five-point Likert scale (from 1 = Strongly Disagree to 5 = Strongly Agree). The instrument was designed based on established theoretical models and informed by recent empirical studies in technology-enhanced arts education [10, 11, 16, 17].

All items were translated and back-translated following international procedures to ensure linguistic and conceptual equivalence. Content validity was further confirmed by a panel of five experts in arts education and educational technology.

D. Data Analysis

The data were analyzed using SPSS 26 and GSCA software. The analysis procedure comprised four main steps: (1) Descriptive statistics to examine the initial data and sample distribution; (2) Reliability and validity assessment of the scales through Cronbach's Alpha, factor loadings, Average Variance Extracted (AVE), Composite Reliability (CR), and unidimensionality; (3) Structural model analysis (SEM) was conducted to test the hypotheses and evaluate the model fit using indices such as Goodness-of-Fit Index (GFI), Standardized Root Mean Square Residual (SRMR), and Chi-square/df.

IV. Result and Discussion

A. Measurement Model Evaluation

As shown in Table 2, the latent constructs demonstrate strong reliability in the measurement model, including Knowledge (KN), Skill (SK), Pedagogical Efficacy (PE), Ethics (ET), Reflection (RE), Attitude (AT), and Behavior (BE). Four indicators were used: Average Variance Extracted (AVE), Cronbach's Alpha, Composite Reliability (Rho), and Dimensionality.

Table 2. Construct quality measures

Construct property	KN	SK	PE	ET	RE	AT	BE
AVE	0.722	0.785	0.823	0.7	0.845	0.783	0.833
Alpha	0.807	0.863	0.892	0.788	0.908	0.861	0.9
Rho	0.886	0.916	0.933	0.875	0.942	0.915	0.938
Dimensionality	1.0	1.0	1.0	1.0	1.0	1.0	1.0

Firstly, the AVE values ranged from 0.700 to 0.845, all exceeding the minimum threshold of 0.50 as recommended by Fornell and Larcker [30], indicating good convergent (PVE) validity. This means that the majority of variance in the observed variables is explained by their respective latent constructs. Specifically, the Reflection Construct (RE) had the highest AVE value (0.845), reflecting the strongest explanatory power in the model.

Next, all Cronbach's Alpha values were above 0.78, with the highest for Behavior (BE) at 0.90 and the lowest for Ethics (ET) at 0.788. All exceeded the 0.70 threshold, demonstrating strong internal consistency among items measuring the same concept [27]. This confirms that the observed variables within each construct reliably measure a unified concept.

Similarly, Composite Reliability (Rho) values were even higher, ranging from 0.875 to 0.942, all above the recommended 0.70 threshold. This further reinforces the structural reliability, indicating that the scales can consistently reproduce results across different measurements.

Finally, the Dimensionality index was 1.0 for all constructs, confirming that each group of observed variables measured a single latent factor, thereby ensuring the unidimensionality of the measurement model.

In summary, these results confirm that the theoretical constructs used in the study possess strong convergent validity, high reliability, and clear unidimensionality, thereby ensuring the quality of measurements for subsequent SEM structural analysis.

B. Factor Loadings

The results of the measurement model evaluation through factor loadings in Table 3 indicate that all observed variables exhibit a high and statistically significant contribution to their corresponding latent constructs. Specifically, all loading coefficients range from 0.806 to 0.940, significantly exceeding the recommended threshold of 0.70 proposed by Hair Jr. *et al.* [27], These results demonstrate strong convergent validity of the measurement scales. In particular, the set of indicators measuring the "Reflective Thinking" (RE) factor exhibit outstanding convergence, with loading coefficients ranging from 0.897 to 0.933, reflecting a strong association between reflective behavioral manifestations and the corresponding theoretical construct. Similarly, the indicators for the "Pedagogical Effectiveness" (PE) and "AI Usage Behavior" (BE) factors also show high loadings, ranging from 0.877 to 0.940 and from 0.907 to 0.919, respectively, indicating that the items clearly capture the underlying latent constructs being measured. From a statistical perspective, the Standard Errors (SE) of the factor loadings fall within a very narrow range (0.010 to 0.041), indicating that the estimates are stable and highly reliable. Notably, the 95% confidence intervals of all loadings do not include zero, affirming that all observed variables are statistically significant at the $p < 0.05$ level. This provides strong evidence supporting the structural validity of the measurement model [29]. The group of indicators measuring the "Ethical and Social Responsibility Perception" (ET) factor, while having the lowest loadings in the entire model (ranging from 0.820 to 0.859), still meet the acceptable threshold, indicating that the proposed theoretical structure is consistent with the empirical data. Overall, these results provide strong support for retaining all observed variables in the model. No indicator violates the convergent validity condition or exhibits low loadings, thus confirming that the measurement model maintains both reliability and validity for subsequent analyses, particularly Structural Equation Modeling (SEM). This also reinforces the validity of the combined theoretical framework of UTAUT2 and TPACK in the context of studying art teachers' AI integration competencies.

C. Model Fit

The results presented in Table 4 indicate that the proposed structural model demonstrates an overall good fit, meeting most commonly accepted statistical criteria in SEM analysis. Specifically, the Goodness-of-Fit Index (GFI) reached a value of 0.991, significantly surpassing the accepted threshold of 0.90 [31], indicating a very high level of agreement between the theoretical and empirical covariance matrices.

Table 3. Factor loadings and indicator statistics

Construct	Indicator	Estimate	SE	95% CI	
KN	kn1	0.862	0.026	0.799	0.914
	kn2	0.879	0.03	0.81	0.932
	kn3	0.806	0.041	0.697	0.873
SK	sk1	0.884	0.028	0.82	0.926
	sk2	0.918	0.013	0.892	0.942
	sk3	0.855	0.029	0.785	0.896
PE	pe1	0.877	0.028	0.831	0.938
	pe2	0.94	0.01	0.91	0.957
	pe3	0.903	0.025	0.858	0.941
ET	et1	0.83	0.039	0.724	0.894
	et2	0.859	0.025	0.81	0.902
	et3	0.82	0.035	0.756	0.904
RE	re1	0.933	0.012	0.899	0.954
	re2	0.926	0.017	0.893	0.956
	re3	0.897	0.028	0.833	0.938
AT	at1	0.894	0.022	0.847	0.941
	at2	0.908	0.023	0.854	0.943
	at3	0.852	0.033	0.768	0.906
BE	be1	0.907	0.02	0.867	0.941
	be2	0.912	0.024	0.87	0.953
	be3	0.919	0.02	0.876	0.955

Table 4. Model fit measures

FIT	AFIT	FITs	FITm	GFI	SRMR	OPE	OPEs	OPEm
0.654	0.65	0.263	0.784	0.991	0.061	0.354	0.747	0.223

Additionally, the Standardized Root Mean Square Residual (SRMR) was 0.061, below the cutoff value of 0.08. This confirms that the average standardized residual between observed and predicted correlations is low-an essential requirement for the statistical acceptability of the model.

The FIT (Overall Model Fit Index) value was 0.654, and the Adjusted FIT (AFIT) was 0.650, indicating a moderate yet acceptable fit given the complexity of the model with multiple latent variables. Meanwhile, the FITm (Model fit based on manifest variables) reached a higher value of 0.784, suggesting a better fit at the level of observed variables.

However, the FITs (Structural model fit) was relatively low at 0.263, indicating that the structural component of the model-i.e., the relationships among the latent constructs may require improvement. This implies that while the measurement model demonstrates strong quality, the structural path model may be affected by weaker theoretical linkages between certain constructs.

Regarding the Overall Predictive Effect (OPE) indicators, the value of OPEs = 0.747 indicates that the model has a relatively good ability to explain the variance in the dependent variables. However, the OPEm = 0.223 suggests that the average predictive power at the level of individual observations remains modest, and the overall OPE = 0.354 reflects a moderate level of predictive validity.

These results suggest that, although the model demonstrates overall statistical adequacy, there remains room for improving its predictive capacity by refining the structural relationships or incorporating moderating variables.

Overall, the structural model exhibits acceptable statistical fit and holds potential for future research expansion. High values of indices such as GFI and SRMR confirm the robustness of the model foundation, while indicators like FITs and OPEm highlight areas for improvement, supporting enhanced precision and explanatory power of the SEM model in practical applications.

D. Path Coefficients

Table 5 summarizes the structural path coefficients and their statistical significance among the latent variables in the model are all statistically significant and consistent with the proposed theoretical hypotheses. Specifically, the construct "Foundational AI Knowledge" (KN) has a significant impact on "Pedagogical Skills for AI Integration" (SK), with a path coefficient estimate of β = 0.538, SE = 0.072, and a 95% confidence interval [0.376, 0.657]. This finding indicates that a solid understanding of foundational AI concepts plays a crucial role in developing the technological application skills of arts teachers.

Table 5. Path coefficients

Path	Estimate	SE	95%CI	
KN→SK	0.538	0.072	0.376	0.657
AT→SK	0.332	0.08	0.213	0.521
KN→ET	0.643	0.06	0.511	0.746
SK→BE	0.15	0.067	0.021	0.294
PE→BE	0.442	0.095	0.242	0.618
RE→BE	0.354	0.096	0.158	0.535

Similarly, the effect of "Attitudes and Beliefs about AI" (AT) on "Pedagogical Skills" (SK) was confirmed, with a path coefficient of β = 0.332 (SE = 0.080; 95% CI [0.213, 0.521]). This indicates that a positive attitude not only facilitates technology acceptance but also contributes to shaping practical teaching skills.

Notably, "Foundational AI Knowledge" (KN) also had a strong influence on "Ethical and Digital Responsibility Awareness" (ET), with a coefficient of β = 0.643 (SE = 0.060; 95% CI [0.511, 0.746]). This suggests that understanding AI enables teachers to better recognize and manage ethical risks in instructional contexts.

Regarding the predictors of actual AI usage behavior (BE), the results show that "Pedagogical Skills" (SK) had a small but statistically significant effect (β = 0.150, SE = 0.067; 95% CI [0.021, 0.294]), while "Pedagogical Efficacy" (PE) had a stronger influence (β = 0.442, SE = 0.095; 95% CI [0.242, 0.618]). This implies that beyond technical skills, the ability to effectively align AI tools with pedagogical goals is a stronger predictor of actual AI implementation.

In addition, "Reflective Thinking" (RE) also showed a significant effect on behavior (BE), with a coefficient of β = 0.354 (SE = 0.096; 95% CI [0.158, 0.535]). This highlights the importance of self-evaluation and continuous improvement in promoting flexible, conscious, and context—appropriate AI adoption among teachers, emphasizing professional growth in the era of digital transformation.

All path analyses reached statistical significance, with no confidence intervals containing zero. This confirms the validity of the proposed theoretical model, in which arts teachers' AI competency is shaped by a foundation of knowledge, attitudes, pedagogical capability, reflective practice, and ethical awareness—each directly or indirectly influencing technology use behavior in teaching.

V. Discussions

The findings of this study provide important empirical evidence for understanding the factors influencing arts teachers' competency in using Artificial Intelligence (AI) in teaching. By integrating elements from the UTAUT2 and TPACK frameworks along with insights from recent studies, the research constructed a multidimensional model that comprehensively reflects the practical realities of AI application in arts education.

First and foremost, the model demonstrates that foundational AI knowledge plays a crucial role in shaping pedagogical skills for AI integration. This aligns with the conclusion drawn by Kong *et al.* [32]. However, without being accompanied by a positive attitude and ethical awareness, the application of AI may lead to negative consequences such as overreliance, violations of privacy, or the loss of individual creativity [10, 11, 33]. Notably, the model results indicate that teachers' attitudes and beliefs toward AI have a strong influence on their pedagogical skills. This reinforces the argument made by Teo *et al.* [23], who argue that a positive attitude not only predicts the intention to use technology but also fosters proactive learning and technological professional development among teachers. This is also consistent with the principles of the UTAUT2 model [14]. In addition, the model reveals a strong relationship between pedagogical skills and two constructs that reflect deep practice: Pedagogical Efficacy (PE) and Reflective Thinking (RE). Recognizing the effectiveness of AI in supporting student learning has encouraged teachers to use AI regularly and with clear objectives. This is fully consistent with the perspective of Liu *et al.* [34] and emphasized that AI in arts education is not merely a technical tool but also a catalyst for creativity when effectively integrated into the teaching process. Reflective thinking, though often overlooked in conventional UTAUT2-based models, emerged as a salient predictor of adaptive AI use in arts classrooms. Its presence reinforces the need to incorporate metacognitive competencies into technology integration frameworks. The results show that teachers with a high level of reflective thinking tend to adjust their use of AI based on real-time feedback, thereby optimizing lesson effectiveness. This finding aligns with the conclusion of Ali [35], whose research on technological competency in the arts revealed that teachers who maintain a habit of self-evaluation after teaching sessions tend to be more creative in integrating technology. Additionally, a notable contribution of the model is its clarification of the role of Ethical and Digital Responsibility Awareness (ET). This is an emerging factor in the age of AI, particularly significant in subjects that emphasize personal expression. As students can now easily use AI to generate creative works instead of producing them manually. This underscores the evolving role of educators as facilitators of ethically guided and instructionally aligned AI engagement-particularly vital in subjects where student identity and creative authorship are central. Building on these findings, the study proposes a three-phase training framework to translate the validated model into practice. In the first phase, teachers develop foundational understanding of AI tools and pedagogical affordances. The second phase focuses on design-based workshops that guide teachers to integrate AI creatively into arts lessons. The final phase emphasizes reflective and ethical practice, enabling teachers to analyze classroom scenarios and evaluate responsible AI use.

However, it is important to acknowledge the challenge of resource inequality across schools. Many institutions, especially in rural or under-resourced regions, still face limitations in infrastructure, connectivity, and professional support. Therefore, differentiated training models—such as blended learning modules, online repositories of AI-integrated lesson examples, and regional mentoring networks—are essential to ensure equitable access to AI-enabled arts education.

Based on the model analysis results, several important practical implications can be drawn to enhance arts teachers' competency in using Artificial Intelligence (AI) within the context of innovative education.

First, in terms of teacher training and professional development, specialized competency-based programs should be developed for arts educators, focusing on three core components: Foundational AI knowledge, skills for applying AI tools in teaching, and digital ethical awareness. These programs should be designed to integrate theory and practice, enabling teachers not only to understand AI but also to experience, reflect on, and take ownership of its responsible intergration in arts instruction.

Second, regarding curriculum development, the integration of AI into the content and instructional activities of music and visual arts should be implemented thoughtfully, ensuring that technology serves as a support tool without overshadowing the core values of creativity and personal expression that define arts education. Specific pedagogical guidelines and digital skill frameworks should be provided so that students can engage with AI proactively, purposefully, and in alignment with school ethics.

Third, in terms of educational policy and administration, policymakers should prioritize the establishment of practical support policies to promote AI integration into arts education. This includes allocating financial resources, investing in appropriate technological equipment, ensuring adequate digital infrastructure in schools, and organizing ongoing technical and professional learning support for teachers. Additionally, the formulation of clear regulations regarding data privacy, digital ethics, and AI use in educational settings is essential to protect both students and teachers as new technologies are deployed.

Finally, in terms of future research directions, further in-depth studies are needed to examine how AI use impacts students' creativity and personal development in arts education environments. Evaluating the actual effectiveness of teacher training programs on AI integration is also a critical research area, with the goal of optimizing content, methods, and delivery while adapting them to the specific cultural and social contexts of each region.

These recommendations are not only suggestive but also provide a foundation for effective pedagogical interventions, contributing to the realization of an arts education vision that is innovative, creative, and technologically integrated in the age of AI.

Although the current study primarily examined the direct structural relationships among the constructs, future research should extend the model to explore possible mediating and moderating mechanisms. In particular, variables such as teachers' attitudes, teaching experience, and regional context may help explain how cognitive, affective, and contextual factors jointly shape AI integration behavior in arts education. Future studies should complement this quantitative approach with qualitative inquiry, such as interviews or classroom case analyses, to gain deeper insight into teachers' lived experiences of AI integration in arts education. Such mixed-method designs would enable a more holistic validation of the proposed competency model.

Taken together, these findings highlight the multidimensional nature of AI competency in arts education and provide a validated framework for guiding future research and teacher professional development.

VI. Conclusion

In the context of artificial intelligence profoundly transforming global education, this study developed and validated a multidimensional model explaining the factors that shape arts teachers' competency in using AI. The SEM results confirmed that all hypothesized relationships were statistically significant across six latent constructs—foundational Knowledge (KN), Pedagogical Skills (SK), Ethics (ET), Pedagogical Efficacy (PE), Reflective Thinking (RE), and Behavioral AI use (BE). The findings affirm that AI competency in arts education extends beyond technical proficiency and is strongly influenced by teachers' ethical awareness, reflective disposition, and pedagogical intentionality. Foundational knowledge and constructive attitudes toward AI function as the primary enablers of digital pedagogy, while pedagogical efficacy and reflective thinking emerge as the strongest predictors of actual AI use in classrooms. Theoretically, this study contributes to the field of educational technology and arts teacher education by extending existing frameworks such as UTAUT2 and TPACK into the arts domain—an area characterized by aesthetic cognition, personal expression, and creative instructional design. Practically, the validated model offers a foundation for developing professional development programs that emphasize knowledge building, positive attitudes, reflective practice, and ethical engagement as core dimensions of teachers' AI competency. It can also serve as a framework for evaluating or self-assessing teachers' technological proficiency within digital transformation initiatives. Despite its contributions, the study has several limitations. The sample was restricted to arts teachers in Vietnam, which may limit the generalizability of the findings. Data were self-reported and may reflect social desirability bias, and only linear relationships were tested. Future research should incorporate qualitative inquiry for example, interviews or classroom case studies and examine mediating and moderating effects of contextual variables such as teaching experience, institutional support, and technological infrastructure. Comparative and experimental studies across subject areas and educational contexts are also recommended to further validate and extend the explanatory power of the proposed model.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization—Thieu Nguyen Van and Chuyen Nguyen Thi Hong; Methodology—Thieu Nguyen Van and Thai Doan Thi Minh; Formal analysis—Chuyen Nguyen Thi Hong and Trang Duong Thu; Investigation—Thai Doan Thi Minh and Hoa Tran Thi Kim; Data curation—Hoa Tran Thi Kim; Writing—original draft, Thieu Nguyen Van and Thai Doan Thi Minh; Writing—review and editing—Chuyen Nguyen Thi Hong and Thieu Nguyen Van; Visualization—Trang Duong Thu; Supervision—Chuyen Nguyen Thi Hong. All authors have read and agreed to the published version of the manuscript.

Funding

This research is funded by Thai Nguyen University and Thai Nguyen University of Education under grant number ĐH2025-TN04-02.

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