Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Determinants of Preservice Music Teachers' Intention to Integrate AI-Based Accompaniment Tools into Classroom Teaching: An Extended Technology Acceptance Model

LIU CHANG

lc58585533@gmail.com

Handan College https://orcid.org/0000-0003-3162-2358

Research Article

Keywords: Generative AI, Music Pedagogy, Technology Acceptance Model, TPACK, Intelligent Accompaniment

Posted Date: March 3rd, 2026

DOI: https://doi.org/10.21203/rs.3.rs-8998993/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: The authors declare no competing interests.

Abstract

Generative artificial intelligence has revolutionized how musicians approach the enduring obstacle of obtaining real-time piano accompaniment during instruction. While numerous AI-powered solutions now exist for this purpose, scholarly understanding of what motivates prospective educators to embrace such innovations remains insufficient. The current research synthesizes two established theoretical perspectives—the Technology Acceptance Model alongside Technological Pedagogical Content Knowledge—to investigate variables affecting music education majors' willingness to incorporate intelligent accompaniment applications. Questionnaire responses were gathered from 150 undergraduates pursuing teacher certification in music at a Chinese provincial institution. Statistical procedures including descriptive analysis, internal consistency evaluation, structural validation, bivariate correlation assessment, and sequential multiple regression were performed through IBM SPSS 26.0 and AMOS 24.0 software packages. Findings indicate that TPACK ($\beta = .447$, $p < .001$), attitudinal orientation toward adoption ($\beta = .417$, $p < .001$), and usefulness beliefs ($\beta = .127$, $p < .05$) serve as meaningful predictors of implementation intentions. Ease of operation showed no direct influence but exhibited mediated pathways via usefulness perceptions and attitudinal dispositions. The combined framework captured 84.4% of variance in adoption intentions ($R^2 = .844$). Bias assessment confirmed that single-respondent methodology does not compromise result integrity. These discoveries suggest that preparing future music instructors demands attention beyond operational training toward cultivating pedagogical expertise for AI utilization, strengthening both applied value recognition and technology-pedagogy-content understanding. Ramifications for music educator preparation throughout Asia-Pacific territories receive consideration.

1. Introduction

Artificial intelligence applications within educational environments have attracted considerable scholarly and practitioner attention globally (Zawacki-Richter et al., 2019; Hwang et al., 2020; Crompton & Burke, 2023). Within the music education sphere, generative AI developments create remarkable possibilities for resolving persistent instructional difficulties, notably the practical challenge of delivering synchronized piano accompaniment supporting vocalists, instrumental performers, and choral practice sessions (Chu et al., 2022; Huang et al., 2023). Conventional music pedagogy depends substantially upon accomplished accompanists—professionals who remain scarce across educational institutions, particularly those situated in economically constrained areas and regional universities operating under budgetary restrictions (Creech & Papageorgi, 2014; Bauer & Mito, 2021).

Contemporary intelligent accompaniment platforms, exemplified by Metronaut, PianoMarvel, and comparable software, leverage sophisticated algorithmic approaches to produce responsive musical support capable of synchronizing with live performers instantaneously (Dannenberg & Raphael, 2006; Raphael, 2010). Such technological breakthroughs carry promise for equalizing access to professional-grade accompaniment services, facilitating flexible rehearsal scheduling, and delivering reliable assistance across diverse musical proficiency levels (Percival et al., 2007). Nevertheless, tool availability

alone fails to ensure meaningful classroom utilization. Elucidating elements influencing educator acceptance and implementation of AI accompaniment applications proves fundamental for advancing their substantive educational deployment (Ertmer & Ottenbreit-Leftwich, 2010).

Davis (1989) introduced the Technology Acceptance Model, subsequently deployed extensively for explaining how individuals adopt emerging technologies across numerous contexts including education (Scherer et al., 2019; Granić & Marangunić, 2019). This theoretical perspective suggests that beliefs regarding usefulness and operational simplicity constitute core determinants shaping user attitudes and utilization intentions. Although TAM offers sound theoretical grounding, researchers contend its explanatory scope may inadequately address technology adoption complexity within pedagogical environments where curriculum considerations assume central importance (Teo, 2011; Sánchez-Prieto et al., 2017).

Addressing this constraint, the present inquiry augments TAM through incorporation of Technological Pedagogical Content Knowledge, a conceptual structure articulated by Mishra and Koehler (2006) highlighting how technological, pedagogical, and disciplinary expertise interconnect within efficacious technology-mediated instruction. TPACK has achieved recognition as an indispensable capability for contemporary educators, shaping their capacity to identify, deploy, and assess instructional technologies appropriately within specific circumstances (Koehler & Mishra, 2009; Voogt et al., 2013). Embedding TPACK within TAM enables this investigation to furnish more thorough comprehension of variables influencing prospective music educators' disposition toward AI accompaniment tool adoption.

1.1 Research Gap and Contribution

Notwithstanding expanding curiosity regarding AI educational applications, multiple literature gaps persist. Initially, while TAM has received broad application examining technology acceptance, its deployment analyzing AI-specific instruments within specialized fields like music education remains constrained (Celik et al., 2022). Additionally, despite acknowledgment of TPACK significance for technology implementation, limited empirical work has scrutinized how TPACK shapes AI tool adoption concurrently with conventional TAM elements (Ng et al., 2023). Furthermore, scholarship addressing AI acceptance among education students throughout Asia-Pacific territories, especially mainland China, remains sparse despite substantial regional educational AI investments (Zhang et al., 2023).

This investigation addresses these deficiencies through: (1) expanding TAM via TPACK integration to construct a unified theoretical architecture for educational AI acceptance; (2) contributing empirical findings from the underinvestigated domain of music teacher preparation; and (3) delivering insights particular to Chinese educational circumstances potentially informing regional policy and practice. Centering attention on education students holds particular significance given that attitudes and intentions crystallizing during preparation programs typically influence subsequent classroom behaviors (Admiraal et al., 2017; Tondeur et al., 2019). Moreover, China represents a distinctive context having committed substantial resources toward educational technology and AI advancement as national

strategic priorities (Ministry of Education of the People's Republic of China, 2019), yet scholarship examining AI adoption within Chinese music education remains scarce.

This inquiry addresses three research questions:

1. What levels of usefulness perception, ease of use perception, attitudinal orientation, TPACK, and adoption intention characterize prospective music educators regarding AI accompaniment instruments?
2. What relationships exist among these theoretical constructs?
3. Which variables meaningfully forecast education students' intentions toward AI accompaniment tool utilization?

Through responding to these inquiries, this research endeavors to advance theoretical understanding within educational technology acceptance scholarship while informing practical approaches for music educator preparation across the Asia-Pacific.

2. Literature Review

2.1 AI in Music Education

Artificial intelligence deployment within music pedagogy has progressed markedly across recent decades. Early implementations concentrated upon computer-aided instruction alongside automated performance evaluation (Seddon & O'Neill, 2003; Webster, 2002). Through machine learning and neural network advances, present-day AI systems can compose music, generate real-time accompaniment, deliver customized feedback, and accommodate individual learner requirements (Briot et al., 2020; Huang & Huang, 2023).

Intelligent accompaniment platforms represent particularly promising application areas. These systems deploy score-tracking algorithms alongside machine learning methodologies to monitor performer location within musical compositions and generate corresponding accompaniment instantaneously (Dannenberg, 2019). Empirical work has established that such systems can approximate human accompanist benefits within particular circumstances, especially for practice and rehearsal functions (Raphael, 2010). However, institutional integration of these instruments has advanced slower than anticipated, emphasizing requirements for investigating determinants of educator acceptance (Deruty et al., 2022).

Within the Chinese setting, numerous studies have explored technology adoption in music instruction. Wang and associates (2021) determined that Chinese music educators generally maintain favorable technology perspectives yet encounter infrastructure, training, and curricular obstacles. Likewise, Liu and Chen (2022) documented that although Chinese music education students demonstrate receptiveness toward technology-enhanced learning, their practical deployment of sophisticated tools remains limited owing to insufficient familiarity and pedagogical direction. Comparable observations have emerged from

additional Asia-Pacific settings including Japan (Sasaki & Yamamoto, 2022), South Korea (Kim & Park, 2021), and Singapore (Chua & Ho, 2023), indicating the awareness-utilization gap in AI adoption constitutes a regional phenomenon warranting methodical examination.

2.2 Technology Acceptance Model (TAM)

Davis (1989) established the Technology Acceptance Model, furnishing a conceptual architecture for comprehending individual acceptance of information systems. TAM proposes that dual fundamental beliefs—Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)—shape user attitudes toward technology utilization, subsequently affecting adoption intentions. Usefulness perception denotes the extent an individual believes particular system usage would strengthen task performance, whereas ease of use perception signifies the degree one believes system operation would demand minimal exertion (Davis, 1989).

TAM has undergone extensive validation spanning diverse technological settings and user groups. A meta-analytic synthesis by Scherer et al. (2019) amalgamated outcomes from 114 investigations examining educational technology acceptance, confirming substantial PU and PEOU impacts upon educator technology adoption. This synthesis additionally revealed PEOU exerts both direct adoption intention effects and indirect effects channeled through PU influence, corroborating theoretical associations TAM proposes.

Within pedagogical environments, scholars have expanded TAM through incorporating constructs germane to teaching circumstances. Teo (2011) embedded social influence and resource availability within TAM when examining Singaporean preservice teacher technology acceptance. Sánchez-Prieto et al. (2017) appended enjoyment perception and mobile efficacy to account for mobile learning acceptance among education students. Al-Emran et al. (2020) executed a comprehensive TAM applications review across Asia-Pacific educational settings, observing that cultural elements and organizational support mechanisms substantially moderate TAM linkages. These augmentations indicate TAM foundational constructs retain importance while context-specific variables may amplify explanatory capacity within particular domains.

2.3 Technological Pedagogical Content Knowledge (TPACK)

TPACK, articulated by Mishra and Koehler (2006), extends Shulman's (1986) pedagogical content knowledge conception through technological knowledge incorporation. This framework delineates seven knowledge dimensions: technological knowledge (TK), pedagogical knowledge (PK), content knowledge (CK), alongside their intersections—technological content knowledge (TCK), technological pedagogical knowledge (TPK), pedagogical content knowledge (PCK), and TPACK. The central element, TPACK, embodies integrated expertise essential for efficacious technology-enhanced instruction, incorporating understanding of how technologies can convey disciplinary concepts and bolster pedagogical approaches (Koehler & Mishra, 2009).

Scholarship has established TPACK maintains positive associations with educator technology implementation behaviors and technology utilization intentions (Voogt et al., 2013; Chai et al., 2013). Educators possessing elevated TPACK demonstrate superior capability identifying suitable technologies for particular learning goals, constructing technology-enhanced learning experiences, and resolving implementation obstacles (Harris & Hofer, 2011). Additionally, TPACK has been documented to mediate connections between educator technology-related convictions and actual technology deployment (Ertmer & Ottenbreit-Leftwich, 2010).

Within music education specifically, Bauer (2013) modified the TPACK framework to scrutinize music educator technology integration capabilities. That investigation revealed music teacher TPACK was shaped by technological self-assurance, professional learning experiences, and technology resource accessibility. Comparably, Dorfman (2016) documented that prospective music teacher TPACK advancement was facilitated through genuine technology integration encounters during preparation programs. Recent scholarship by Bauer and Mito (2021) extended these observations to Asia-Pacific circumstances, noting cultural perspectives toward technology and music education customs distinctively shape TPACK development across national contexts. These discoveries suggest TPACK constitutes a pertinent construct for understanding music educator preparedness to embrace intelligent accompaniment instruments.

2.4 Integrating TAM and TPACK

Although TAM and TPACK typically have undergone separate examination, numerous researchers have promoted their synthesis to deliver more thorough understanding of educational technology acceptance (Teo et al., 2019; Joo et al., 2018). The integration rationale holds that TAM captures general technology acceptance determinants applicable across settings, whereas TPACK addresses particular pedagogical aspects relevant to instruction. Combining these architectures permits researchers to investigate both psychological elements (beliefs and attitudes) and professional knowledge elements (pedagogical capabilities) shaping educator technology adoption choices.

The theoretical consolidation of TAM and TPACK rests upon recognition that educational technology acceptance fundamentally diverges from technology acceptance within alternative organizational contexts. Educators function not simply as technology consumers; they serve as pedagogical agents who must render intricate decisions regarding when, how, and why to embed technology within instructional practices (Ertmer, 2005). This decision-making necessitates not merely favorable technology attitudes but also professional expertise to harness technology effectively for student learning.

Multiple theoretical mechanisms may elucidate TPACK-adoption intention relationships. Initially, educators with elevated TPACK may encounter heightened self-assurance utilizing technology for instruction, previously demonstrated to affect technology adoption (Compeau & Higgins, 1995). Subsequently, TPACK may diminish perceived technology integration complexity by supplying educators with cognitive frameworks connecting technological capabilities with pedagogical objectives.

Additionally, educators possessing elevated TPACK may better anticipate technology utilization advantages, thereby strengthening their usefulness perceptions regarding specific instruments (Chai et al., 2020).

Empirical investigations supporting TAM-TPACK integration have generated encouraging outcomes. Joo et al. (2018) determined TPACK meaningfully forecasted education student technology utilization intentions even when TAM variables were statistically controlled. Comparably, Teo et al. (2019) exhibited TPACK contributed unique variance explaining practicing teacher technology acceptance beyond PU and PEOU influences. More contemporary inquiries by An et al. (2023) and Zhang et al. (2023) have verified these configurations specifically for AI-based educational instruments, indicating the integrated architecture proves especially suitable for scrutinizing nascent technologies.

Within AI-based educational tool contexts, TAM-TPACK integration may prove especially pertinent. AI technologies present distinctive pedagogical considerations that general technology acceptance elements may inadequately capture. Educators must not merely perceive AI instruments as useful and simple to operate but also comprehend how to embed these instruments meaningfully within instructional practice. Such understanding requires the specialized expertise TPACK represents—knowledge of how AI technologies can bolster particular pedagogical approaches and learning objectives within music education (Long & Magerko, 2020; Ng et al., 2021).

2.5 Research Hypotheses

Grounded in the theoretical bases discussed previously, this investigation advances the following hypotheses (refer to Fig. 1 for the conceptual framework):

H1: Ease of use perception (PEOU) exerts positive influence upon usefulness perception (PU).

H2: Usefulness perception (PU) exerts positive influence upon attitudinal orientation toward use (ATT).

H3: Ease of use perception (PEOU) exerts positive influence upon attitudinal orientation toward use (ATT).

H4: Usefulness perception (PU) exerts positive influence upon behavioral intention (BI).

H5: Ease of use perception (PEOU) exerts positive influence upon behavioral intention (BI).

H6: Attitudinal orientation toward use (ATT) exerts positive influence upon behavioral intention (BI).

H7: TPACK exerts positive influence upon behavioral intention (BI).

3. Method

3.1 Participants and Context

Study participants comprised 150 undergraduate students enrolled within a Musicology (Teacher Preparation) curriculum at a comprehensive university located in Hebei Province, China. Hebei Province occupies northern China, encircling Beijing and Tianjin metropolitan areas, and typifies provincial higher education settings nationally. The selected institution functions as a regional university primarily preparing music educators for employment within local elementary and secondary institutions.

Sample demographic attributes appear within Table 1. Female participants predominated (59.3%, n = 89), mirroring gender distributions characteristic of music education programs throughout China and broader Asia-Pacific nations (Chua & Ho, 2023). Concerning age distribution, most participants were aged 20 (52.0%, n = 78) or 21-plus (40.0%, n = 60), corresponding to undergraduate junior and senior cohorts. Regarding specialization within music education, vocal music majors constituted the largest segment (68.0%, n = 102), followed by piano (16.7%, n = 25) and alternative instruments (15.3%, n = 23).

Participant prior encounters with AI music generation or intelligent accompaniment applications varied considerably. Most reported awareness without utilization experience (63.3%, n = 95), while 18.0% (n = 27) had experimented occasionally. A smaller proportion lacked any awareness of intelligent accompaniment tools (16.0%, n = 24), with merely 2.7% (n = 4) qualifying as regular users. This distribution indicates that while AI accompaniment technology awareness proves relatively prevalent among prospective music educators, practical experience remains circumscribed—an observation consistent with findings from other Asia-Pacific settings (Kim & Park, 2021; Sasaki & Yamamoto, 2022).

Table 1
Sample Demographic Characteristics (N = 150)

Characteristic	Category	N	Percentage
Gender	Male	61	40.7%
	Female	89	59.3%
Age	18	2	1.3%
	19	10	6.7%
	20	78	52.0%
	21 and above	60	40.0%
Major	Piano	25	16.7%
	Vocal Music	102	68.0%
	Other Instruments	23	15.3%
Prior AI Experience	Never heard of	24	16.0%
	Heard but never used	95	63.3%
	Occasionally tried	27	18.0%
	Frequent user	4	2.7%

3.2 Instruments

The questionnaire instrument was constructed through adapting validated measurement tools from antecedent scholarship and contextualizing items for AI accompaniment applications within music pedagogy. The questionnaire encompassed dual components: demographic queries and measurement scales addressing five framework constructs.

Perceived Usefulness (PU) was assessed via four items modified from Davis (1989), centering upon participant beliefs that intelligent accompaniment instruments would strengthen instructional effectiveness and efficiency. Illustrative items include "Deploying AI accompaniment instruments would markedly enhance my instructional efficiency within future music courses" and "AI instruments can resolve technical challenges associated with executing sophisticated accompaniments instantaneously during instruction."

Perceived Ease of Use (PEOU) was evaluated through four items adapted from Davis (1989), gauging participant beliefs regarding operational effort demands for AI accompaniment instruments. Representative items include "Mastering AI accompaniment software operation proves straightforward for me" and "Generating desired accompaniment outcomes through AI requires minimal exertion."

Attitude Toward Using (ATT) was measured via four items modified from Taylor and Todd (1995), assessing participant overall evaluative judgments concerning intelligent accompaniment instrument utilization. Sample items include "Employing AI instruments within music instruction represents an excellent approach" and "I maintain favorable dispositions toward incorporating artificial intelligence within my prospective teaching career."

TPACK was assessed through four items adapted from Schmidt et al. (2009) and contextualized for AI instruments within music pedagogy. These items gauged participant perceived expertise integrating AI accompaniment instruments within particular music instructional activities. Exemplary items include "I understand how to embed AI accompaniment instruments within specific music instructional activities, including sight-reading or choral work" and "I can determine which instructional circumstances warrant AI accompaniment utilization and which do not."

Behavioral Intention (BI) was measured through four items modified from Venkatesh et al. (2003), addressing participant intentions to deploy intelligent accompaniment instruments within prospective teaching practice. Sample items include "I plan to experiment with AI accompaniment instruments supporting instruction during future educational practicums or professional work" and "Whenever feasible, I will endeavor to incorporate AI technology throughout every music lesson prospectively."

All items employed 5-point Likert scaling from 1 (strongly disagree) through 5 (strongly agree). The questionnaire underwent original English development, Chinese translation by a bilingual researcher, and reverse translation by an independent bilingual specialist ensuring precision. Minor inconsistencies were reconciled through deliberation. Preceding primary data collection, the questionnaire underwent pilot assessment with 20 students excluded from final sampling, with modifications implemented following their responses to enhance clarity and cultural suitability. Complete questionnaire details appear in the Appendix.

3.3 Procedure

Data gathering transpired during autumn 2024. Researchers liaised with Musicology (Teacher Preparation) program course instructors, securing authorization to distribute questionnaires during instructional sessions. Prior to questionnaire administration, researchers furnished concise AI accompaniment tool overviews, incorporating demonstrations of representative applications including Metronaut and PianoMarvel. This orientation ensured all participants possessed foundational technology understanding regardless of prior exposure.

Participants received information concerning study objectives, confidentiality assurances regarding responses, and reminders that involvement was elective with no academic standing implications. Consenting participants completed paper questionnaires requiring roughly 15–20 minutes. From 155 distributed questionnaires, 150 valid responses emerged following incomplete submission exclusion (response rate = 96.8%). Institutional review board approval was secured for study procedures.

3.4 Data Analysis

Analyses employed IBM SPSS Statistics 26.0 alongside AMOS 24.0, proceeding through multiple phases:

Descriptive statistics (means, standard deviations, skewness, kurtosis) were computed for all measurement items and constructs to scrutinize response distributions.

Internal consistency assessment via Cronbach's alpha and composite reliability (CR) gauged construct measurement reliability.

Validity examination including confirmatory factor analysis (CFA) evaluated construct validity. Convergent validity was appraised through average variance extracted (AVE) and factor loadings. Discriminant validity was assessed by juxtaposing AVE square roots with inter-construct correlations.

Common method variance assessment employed Harman's single-factor procedure and common latent factor methodology to verify single-source bias did not compromise finding validity.

Correlation analysis via Pearson's r scrutinized bivariate construct associations.

Sequential multiple regression examined hypothesized associations and identified meaningful adoption intention predictors. Multicollinearity was evaluated through variance inflation factors (VIF), with values beneath 10 deemed satisfactory (Hair et al., 2019).

4. Results

4.1 Reliability Analysis

Construct reliability underwent evaluation through both Cronbach's alpha coefficient and composite reliability (CR). Table 2 displays all constructs demonstrating excellent internal consistency. Alpha values spanned .919 to .962, substantially surpassing the conventional .70 threshold (Nunnally & Bernstein, 1994). CR values ranged from .923 to .964, uniformly exceeding the recommended .70 benchmark (Hair et al., 2019). These outcomes confirm measurement scales possess robust internal consistency and suit subsequent analyses.

Table 2
Reliability and Convergent Validity Metrics

Construct	Items	Cronbach's α	CR	AVE
Perceived Usefulness (PU)	4	.962	.964	.869
Perceived Ease of Use (PEOU)	4	.919	.923	.751
Attitude Toward Using (ATT)	4	.957	.959	.854
TPACK	4	.952	.955	.841
Behavioral Intention (BI)	4	.953	.956	.844

Note. CR = composite reliability; AVE = average variance extracted. All factor loadings ranged from .82 to .94, exceeding the .70 threshold.*

4.2 Validity Analysis

4.2.1 Convergent Validity

Convergent validity underwent assessment through factor loadings and average variance extracted (AVE). Table 2 indicates all AVE values spanned .751 to .869, exceeding the recommended .50 threshold (Fornell & Larcker, 1981). Additionally, all standardized CFA factor loadings ranged from .82 to .94, substantially above the .70 criterion. These findings furnish strong convergent validity evidence.

4.2.2 Discriminant Validity

Discriminant validity was examined via the Fornell-Larcker criterion, requiring each construct's AVE square root to surpass its correlations with remaining constructs. Table 3 indicates all diagonal entries (AVE square roots) exceeded corresponding off-diagonal entries (inter-construct correlations), confirming satisfactory discriminant validity.

Table 3
Discriminant Validity Evaluation

Construct	PU	PEOU	ATT	TPACK	BI
PU	.932				
PEOU	.632	.867			
ATT	.771	.672	.924		
TPACK	.722	.733	.788	.917	
BI	.770	.685	.866	.865	.919

Note. Diagonal values (in bold) represent the square root of AVE; off-diagonal values represent inter-construct correlations. All correlations significant at p < .001.*

4.2.3 Confirmatory Factor Analysis

Measurement model evaluation proceeded through AMOS 24.0 CFA. The five-factor structure exhibited acceptable data fit: $\chi^2(160) = 287.42$, $p < .001$; $\chi^2/df = 1.80$; CFI = .967; TLI = .961; RMSEA = .073 [90% CI: .059, .087]; SRMR = .042. All indices satisfied recommended benchmarks (CFI and TLI > .95; RMSEA < .08; SRMR < .08), signifying the measurement structure adequately represents data patterns (Hu & Bentler, 1999).

4.3 Common Method Variance Assessment

Given single-source self-report data collection, common method variance (CMV) was examined via dual approaches.

Harman's single-factor procedure was executed loading all 20 items within exploratory factor analysis. The unrotated solution revealed the initial factor captured 43.7% of total variance, beneath the 50% threshold signifying problematic CMV (Podsakoff et al., 2003).

The common latent factor (CLF) approach served as more stringent assessment. A common latent factor was appended to the CFA structure, permitting all items to load simultaneously upon this factor alongside their theoretical constructs. Standardized regression weight comparisons between structures with and without CLF revealed all differences fell beneath .20, suggesting CMV does not meaningfully threaten finding validity (Podsakoff et al., 2012).

4.4 Descriptive Statistics

Table 4 displays descriptive statistics for five framework constructs. Generally, participants reported moderately favorable perceptions spanning constructs, with means ranging from 3.45 to 3.91 on the 5-point continuum. Perceived Usefulness exhibited the highest mean (M = 3.91, SD = 0.83), suggesting participants broadly believed intelligent accompaniment instruments could strengthen instructional effectiveness. Attitude Toward Using followed (M = 3.82, SD = 0.80), then Behavioral Intention (M = 3.78, SD = 0.80) and TPACK (M = 3.61, SD = 0.88). Perceived Ease of Use showed the lowest mean (M = 3.45, SD = 0.87), intimating participants perceived some operational challenges despite acknowledging usefulness.

Skewness ranged from − 0.99 to -0.24, with kurtosis spanning 0.43 to 2.19, confirming all constructs fell within acceptable normality ranges (skewness < |2|, kurtosis < |7|; Curran et al., 1996). Mild negative skewness suggests favorable response tendencies, commonly observed within technology acceptance scholarship (Scherer et al., 2019).

Table 4
Construct Descriptive Statistics

Construct	N	M	SD	Min	Max	Skewness	Kurtosis
PU	150	3.91	0.83	1.00	5.00	-0.99	2.19
PEOU	150	3.45	0.87	1.00	5.00	-0.24	0.43
ATT	150	3.82	0.80	1.00	5.00	-0.65	1.47
TPACK	150	3.61	0.88	1.00	5.00	-0.44	0.51
BI	150	3.78	0.80	1.00	5.00	-0.72	1.48

Note. PU = Perceived Usefulness; PEOU = Perceived Ease of Use; ATT = Attitude Toward Using; TPACK = Technological Pedagogical Content Knowledge; BI = Behavioral Intention.*

4.5 Correlation Analysis

Table 5 presents Pearson correlation coefficients spanning five constructs. All bivariate correlations proved positive and statistically meaningful at $p < .001$, confirming constructs are meaningfully interrelated. Coefficients ranged from .63 to .87, representing moderate through substantial effect magnitudes per Cohen's (1988) conventions.

Adoption intention exhibited strongest correlations with Attitude Toward Using ($r = .87$) and TPACK ($r = .87$), followed by Perceived Usefulness ($r = .77$) and Perceived Ease of Use ($r = .69$). These findings furnish preliminary hypothesized relationship support, indicating both attitudinal elements (from TAM) and pedagogical knowledge elements (from TPACK) maintain close associations with prospective music educator willingness to employ AI accompaniment instruments.

Among predictor variables, TPACK exhibited robust correlations with all TAM constructs: Attitude Toward Using ($r = .79$), Perceived Ease of Use ($r = .73$), and Perceived Usefulness ($r = .72$). This configuration suggests TPACK relates not solely to adoption intention but additionally to general technology acceptance elements, underscoring the interconnected character of pedagogical expertise and technology convictions.

Table 5
Correlation Matrix

Variable	PU	PEOU	ATT	TPACK	BI
PU	1				
PEOU	.63*	1			
ATT	.77*	.67*	1		
TPACK	.72*	.73*	.79*	1	
BI	.77*	.69*	.87*	.87*	1
Note. N = 150. ***p < .001.*					

4.6 Sequential Multiple Regression Analysis

Sequential multiple regression was executed to examine hypothesized associations and identify meaningful adoption intention predictors. Analysis proceeded through three phases to scrutinize incremental contribution from each predictor set. Preceding regression execution, multicollinearity was evaluated via variance inflation factors (VIF). Table 6 indicates all VIF values spanned 2.31 to 3.47, substantially beneath the 10 threshold, confirming multicollinearity posed no analytical concern (Hair et al., 2019).

Phase 1 incorporated solely demographic variables (gender, age, specialization, prior AI exposure) as controls, accounting for 8.2% of adoption intention variance.

Phase 2 appended TAM constructs (PU, PEOU, ATT), meaningfully elevating explained variance to 78.9% ($\Delta R^2 = .707$, $p < .001$).

Phase 3 incorporated TPACK, further elevating explained variance to 84.4% ($\Delta R^2 = .055$, $p < .001$).

The complete regression model incorporating Perceived Usefulness, Perceived Ease of Use, Attitude Toward Using, and TPACK as predictors proved statistically meaningful, $F(4, 145) = 196.13$, $p < .001$, accounting for 84.4% of adoption intention variance ($R^2 = .844$, Adjusted $R^2 = .840$). This constitutes substantial explained variance, suggesting the augmented TAM framework furnishes comprehensive explanation of prospective music educator inclinations toward AI accompaniment instrument utilization.

Scrutinizing individual predictors within the complete model, TPACK emerged as the most powerful adoption intention predictor ($\beta = .447$, $p < .001$), followed by Attitude Toward Using ($\beta = .417$, $p < .001$). Perceived Usefulness additionally exhibited meaningful positive influence ($\beta = .127$, $p = .020$), albeit smaller in magnitude. Notably, Perceived Ease of Use did not exhibit meaningful direct influence upon adoption intention ($\beta = -.004$, $p = .941$) when remaining predictors were incorporated.

Table 6
Sequential Multiple Regression Outcomes

Variable	B	SE	β	t	p	VIF
(Constant)	0.266	0.136	—	1.96	.052	—
PU	0.123	0.052	.127	2.35	.020	2.74
PEOU	-0.003	0.046	− .004	-0.07	.941	2.31
ATT	0.415	0.061	.417	6.83	< .001*	3.47
TPACK	0.403	0.055	.447	7.35	< .001*	3.44
Note. R^2 = .844, Adjusted R^2 = .840, F(4, 145) = 196.13, p < .001.*						

4.7 Path Analysis

To further scrutinize TAM construct associations and assess hypothesized Attitude mediation, supplementary regression analyses were executed. Table 7 presents path analysis outcomes.

Initially, Perceived Ease of Use influence upon Perceived Usefulness was examined. Outcomes revealed a meaningful positive association (β = .632, p < .001, R^2 = .400), supporting H1. This discovery suggests prospective music educators perceiving intelligent accompaniment instruments as operationally simple more probably view them as pedagogically valuable.

Subsequently, Perceived Usefulness and Perceived Ease of Use influences upon Attitude Toward Using were assessed. Both predictors exhibited meaningful positive effects (PU: β = .576, p < .001; PEOU: β = .307, p < .001), with the model accounting for 65.1% of Attitude variance (R^2 = .651). These findings support H2 and H3, suggesting both usefulness perceptions and ease of use perceptions contribute toward favorable AI accompaniment instrument attitudes, though usefulness exerts stronger influence.

To assess Attitude mediation, Perceived Usefulness direct influence upon adoption intention was examined both including and excluding Attitude. When Perceived Usefulness served as sole predictor, it exhibited substantial adoption intention influence (β = .770, p < .001, R^2 = .593). However, when Attitude was incorporated, Perceived Usefulness influence decreased markedly (β = .253, p < .001), while Attitude exhibited substantial influence (β = .671, p < .001). This configuration suggests Attitude partially mediates Perceived Usefulness-adoption intention associations.

Table 7
Path Analysis Outcomes

Path	β	t	p	R^2
PEOU → PU	.632	9.93	< .001***	.400
PU → ATT	.576	9.16	< .001***	.651
PEOU → ATT	.307	4.89	< .001***	
PU → BI	.127	2.35	.020*	.844
PEOU → BI	− .004	-0.07	.941	
ATT → BI	.417	6.83	< .001***	
TPACK → BI	.447	7.35	< .001***	
Note. *p < .05. ***p < .001.*				

4.8 Hypothesis Testing Synopsis

Table 8 encapsulates hypothesis testing outcomes. Among seven hypotheses advanced, six received empirical support. H1, H2, H3, H4, H6, and H7 gained corroboration, revealing: (a) Perceived Ease of Use positively influences Perceived Usefulness; (b) both Perceived Usefulness and Perceived Ease of Use positively influence Attitude Toward Using; (c) Perceived Usefulness, Attitude Toward Using, and TPACK positively influence adoption intention. H5, proposing direct Perceived Ease of Use influence upon adoption intention, lacked support.

Table 8
Hypothesis Testing Synopsis

Hypothesis	Path	β	Result
H1	PEOU → PU	.632*	Supported
H2	PU → ATT	.576*	Supported
H3	PEOU → ATT	.307*	Supported
H4	PU → BI	.127	Supported
H5	PEOU → BI	− .004	Not Supported
H6	ATT → BI	.417*	Supported
H7	TPACK → BI	.447*	Supported
Note. *p < .05. ***p < .001.*			

5. Discussion

This inquiry scrutinized determinants shaping prospective music educator inclinations to incorporate AI-driven accompaniment systems within classroom instruction through augmenting the Technology Acceptance Model with TPACK. Discoveries furnish valuable insights regarding elements influencing AI technology adoption within music pedagogy and bear implications for both theory and practice throughout the Asia-Pacific.

5.1 Theoretical Implications

This study's outcomes advance ongoing theoretical dialogue concerning educational technology acceptance through illustrating the merit of integrating TAM with domain-specific architectures such as TPACK. The augmented framework captured 84.4% of adoption intention variance, representing substantial improvement over conventional TAM investigations typically explaining 40–60% of variance (Scherer et al., 2019; Granić & Marangunić, 2019). This elevated explanatory capacity aligns with recent appeals for more comprehensive theoretical architectures within educational AI scholarship (Holmes et al., 2022; Zawacki-Richter et al., 2019; Crompton & Burke, 2023).

TPACK's emergence as the most potent adoption intention predictor challenges particular entrenched presumptions within technology acceptance scholarship. Conventional TAM scholarship has accentuated perceived usefulness primacy as the principal adoption decision driver (Davis, 1989). Nevertheless, recent educational AI investigations have intimated that educator professional expertise and AI competency assume progressively critical roles shaping adoption behaviors (Ng et al., 2023; Celik et al., 2022). Our discoveries corroborate this emergent viewpoint, suggesting future educational AI acceptance scholarship should routinely incorporate pedagogical knowledge constructs alongside conventional TAM elements.

The TAM-TPACK theoretical synthesis demonstrated herein responds to recent critiques that educational technology acceptance scholarship has excessively relied upon generic models failing to capture teaching context distinctiveness (Teo et al., 2019; Joo et al., 2018). Through TPACK incorporation, this inquiry acknowledges educators function not as passive technology consumers but as active pedagogical decision-makers who must evaluate technology alignment with instructional objectives and learner requirements (Ertmer & Ottenbreit-Leftwich, 2010; Mishra & Koehler, 2006). This integrated approach proves especially pertinent for AI technologies, demanding educators cultivate novel capabilities understanding algorithmic systems, appraising AI-generated outputs, and constructing learning experiences appropriately harnessing AI capabilities (Long & Magerko, 2020; Ng et al., 2021).

5.2 The Role of TPACK in Technology Acceptance

A pivotal finding concerns the meaningful and substantial TPACK influence upon adoption intention ($\beta = .447$, $p < .001$). Among complete model predictors, TPACK exhibited the largest standardized coefficient, signifying prospective music educator technological pedagogical content knowledge constitutes the paramount factor forecasting their willingness to employ AI accompaniment instruments. This discovery supports arguments that TPACK integration within TAM amplifies model

explanatory capacity within educational contexts (Joo et al., 2018; Teo et al., 2019) and extends this association to the nascent domain of AI within music pedagogy.

TPACK prominence aligns with contemporary scholarship emphasizing AI competency and AI pedagogical expertise importance for educators. Ng et al. (2023) advanced a K-12 AI literacy framework accentuating educator requirements to comprehend both technical capabilities and pedagogical applications of AI instruments. Correspondingly, Celik et al. (2022) determined educator perceived competence deploying AI for instructional purposes meaningfully forecasted their AI tool integration intentions. Our discoveries extend these insights to music education contexts specifically, suggesting prospective music educator confidence integrating AI instruments within activities including sight-reading, choral rehearsals, and instrumental practice proves critical for adoption decisions.

The observation that TPACK exhibited stronger influence than Perceived Usefulness within the complete model warrants particular attention given contemporary discussions regarding pedagogical transformation requisite for meaningful educational AI integration (Luckin et al., 2022; Holmes & Tuomi, 2022). While prospective educators may acknowledge intelligent accompaniment instrument general utility, their intention to actually deploy these instruments appears more powerfully shaped by confidence in pedagogical application knowledge. This intimates educator preparation programs should transcend AI tool feature and benefit demonstration toward actively cultivating competencies integrating these instruments within instructional practice, a recommendation aligned with contemporary AI education policy frameworks (UNESCO, 2021; OECD, 2021).

5.3 The Mediating Role of Attitude

Consistent with TAM theory, Attitude Toward Using emerged as meaningful adoption intention predictor ($\beta = .417$, $p < .001$). Path analysis additionally revealed Attitude partially mediates associations between perception-based constructs (PU and PEOU) and adoption intention. This mediating configuration aligns with contemporary meta-analytic discoveries regarding educator technology acceptance (Scherer et al., 2019) and extends to AI-based educational instruments specifically.

Contemporary scholarship has accentuated educator AI attitudes importance in shaping adoption behaviors. Chounta et al. (2022) determined educator AI attitudes were shaped by their understanding of AI capabilities and constraints, their ethical implication concerns, and their convictions regarding appropriate AI educational roles. Correspondingly, Chiu et al. (2023) documented educator AI anxiety and AI enthusiasm meaningfully forecasted willingness to deploy AI instructional tools. Our discoveries contribute to this scholarship by establishing that within music education contexts, attitudes are primarily shaped by usefulness perceptions ($\beta = .576$) rather than ease of use perceptions ($\beta = .307$), intimating prospective music educators prioritize AI tool instrumental value over usability considerations.

Findings additionally resonate with scholarship addressing affective dimensions of educational human-AI interaction. Kim et al. (2022) determined user emotional responses to AI systems shaped continued

utilization intentions beyond cognitive usefulness and ease evaluations. Within music education contexts, where aesthetic and affective dimensions prove especially salient, intelligent accompaniment instrument attitudes may be shaped not solely by practical considerations but additionally by convictions regarding AI-generated musical accompaniment authenticity and expressiveness (Huang & Huang, 2023; Deruty et al., 2022).

5.4 The Non-Meaningful Direct Influence of Perceived Ease of Use

Contrary to H5, Perceived Ease of Use failed to exhibit meaningful direct adoption intention influence within the complete model (β = − .004, p = .941). This discovery appears to contradict original TAM, proposing both direct PEOU-adoption intention pathways and indirect pathways via attitude. Nevertheless, this outcome aligns with contemporary meta-analytic evidence intimating PEOU direct influence upon adoption intention frequently proves weaker than PU influence and occasionally becomes non-meaningful when additional variables are incorporated (Scherer et al., 2019; King & He, 2006; Granić & Marangunić, 2019).

Multiple contemporary literature-grounded explanations may account for this finding. Initially, as "digital natives" maturing alongside technology, study participants may possess elevated baseline technology self-assurance levels, diminishing ease of use concern salience within adoption decisions (Wang et al., 2021). Contemporary scholarship has determined younger educators tend to report elevated digital capability and demonstrate reduced concern regarding new technology usability (Seufert et al., 2021; Lucas et al., 2021). This configuration has been consistently observed throughout Asia-Pacific contexts including China, Japan, and South Korea (Kim & Park, 2021).

Subsequently, the non-meaningful PEOU direct influence may reflect evolving AI-based educational tool characteristics, increasingly designed featuring user-friendly interfaces and intuitive interactions (Hwang et al., 2020; Chen et al., 2022). As AI instruments become increasingly accessible and user-oriented, ease of use may transform into a "hygiene factor" preventing adoption when absent yet failing to actively encourage adoption when present (Venkatesh & Bala, 2008).

Additionally, within AI accompaniment tool contexts for music education specifically, path analysis confirmed PEOU exerts meaningful indirect adoption intention influences via PU (β = .632) and Attitude (β = .307). This indirect pathway may prove especially pertinent for domain-specific instruments where users must initially comprehend how technology can serve professional purposes before developing utilization intentions (Teo et al., 2019).

5.5 Implications for Educator Preparation

This inquiry's discoveries bear multiple practical implications for music educator preparation programs, resonating with contemporary recommendations for equipping educators to engage with AI (Luckin et al., 2022; Holmes et al., 2022; UNESCO, 2021).

Initially, considering TPACK's prominent role forecasting adoption intention, educator preparation curricula should incorporate explicit instruction and practical encounters integrating intelligent accompaniment instruments within particular music instructional activities. This recommendation aligns with the "learning through design" TPACK development approach advocated by Koehler and Mishra (2009) and recently adapted for AI contexts by Ng et al. (2023). Coursework might encompass selecting appropriate AI instruments for varying instructional objectives, constructing lesson plans harnessing AI accompaniment, and troubleshooting implementation obstacles within authentic classroom environments.

Subsequently, the meaningful Perceived Usefulness influence suggests educator preparation faculty should accentuate AI accompaniment tool practical advantages for addressing genuine instructional obstacles. Contemporary AI educational adoption scholarship has underscored demonstrating clear applications and concrete benefits importance rather than concentrating upon technological novelty (Celik et al., 2022; An et al., 2023). Demonstrations and case analyses illustrating how AI instruments can resolve difficulties prospective educators will probably encounter—including accompanist scarcity, restricted practice duration, or heterogeneous learner proficiency levels—may prove more efficacious promoting adoption than general AI capability discussions.

Additionally, the attitude mediating role signals cultivating favorable AI dispositions within music education matters. Contemporary scholarship has emphasized addressing AI apprehension and establishing AI self-assurance as adoption prerequisites (Chiu et al., 2023; Wang et al., 2023). This might be accomplished through creating positive initial AI tool encounters, addressing misconceptions regarding AI replacing human musicians, and highlighting successful AI integration exemplars within music pedagogy. Constructing supportive communities where prospective educators can exchange experiences and learn from peers may additionally foster more favorable attitudes (Trust et al., 2020; Jiang et al., 2022).

Furthermore, although ease of use failed to exhibit direct adoption intention influence, it shaped both usefulness perceptions and attitudes. Consequently, educator preparation faculty should not disregard AI accompaniment tool technical operation training. Ensuring prospective educators feel comfortable with fundamental tool operations can strengthen usefulness perceptions and foster more favorable attitudes. This recommendation aligns with scholarship addressing technology adoption scaffolding among novice educators (Admiraal et al., 2017; Tondeur et al., 2020).

5.6 Contextual Implications for Chinese Music Education and the Asia-Pacific

This inquiry's discoveries bear particular implications for music educator preparation within China, currently experiencing substantial transformation within national AI development strategy contexts (Ministry of Education of the People's Republic of China, 2019; State Council of China, 2017). Additionally, these discoveries furnish insights pertinent to the broader Asia-Pacific, where comparable policy initiatives drive educational technology adoption.

Initially, TPACK prominence forecasting adoption intentions suggests Chinese educator preparation programs should integrate AI-centered pedagogical training within curricula. Presently, numerous programs concentrate upon conventional musicianship skills and traditional instructional approaches, with technology training frequently relegated to separate elective courses (Liu & Chen, 2022; Wang et al., 2021). A more integrated approach embedding AI instrument training within methods courses and practicum encounters may prove more efficacious cultivating pedagogical expertise requisite for meaningful technology integration, as recommended by contemporary TPACK development scholarship within Chinese contexts (Chai et al., 2020). Comparable configurations have been observed within Japan and South Korea, where conventional pedagogical approaches frequently exist in tension with technology integration imperatives (Sasaki & Yamamoto, 2022; Kim & Park, 2021).

Subsequently, the finding that most participants had encountered AI accompaniment instruments without utilizing them (63.3%) signals an awareness-experience gap educator preparation programs should address. This "awareness-experience disparity" has been identified as a meaningful barrier to AI educational adoption more broadly throughout the Asia-Pacific (Zhang et al., 2023; An et al., 2023). Furnishing hands-on opportunities to experiment with AI instruments within low-stakes settings, including peer teaching sessions or simulated classrooms, may help bridge this gap and establish confidence requisite for prospective adoption. Singapore's technology integration approach within educator preparation, emphasizing extensive practicum encounters with nascent technologies, furnishes a potential model (Chua & Ho, 2023).

Additionally, comparatively lower Perceived Ease of Use scores versus alternative constructs suggest contemporary AI accompaniment instruments may not be optimally designed for Chinese music education contexts. Cross-cultural technology adoption scholarship has emphasized culturally responsive educational technology design importance (Young, 2020). AI music instrument developers might consider partnering with Chinese music educators to craft interfaces and features better aligning with local instructional practices, musical traditions, and cultural preferences within music pedagogy. This recommendation extends to additional Asia-Pacific contexts, where heterogeneous musical traditions and pedagogical approaches necessitate localized technology design (Bauer & Mito, 2021).

Furthermore, regional universities within China, comparable to the institution in this inquiry, confront distinctive technology integration obstacles including limited infrastructure, fewer professional development resources, and faculty who may themselves lack familiarity with nascent technologies (Huang et al., 2022). Targeted support programs furnishing both technical resources and pedagogical guidance may prove indispensable promoting AI adoption within these contexts, aligned with recommendations from contemporary scholarship addressing educational equity in AI deployment (Holmes et al., 2022; UNESCO, 2021). Australian experience supporting regional and remote school technology adoption furnishes valuable lessons addressing comparable obstacles throughout the Asia-Pacific (Thompson & Whitfield, 2022).

5.7 Policy Implications

This inquiry's discoveries inform multiple policy recommendations for educational authorities throughout the Asia-Pacific:

Curriculum transformation: National and regional educational policies should mandate AI literacy and TPACK development integration within educator preparation programs, progressing beyond optional technology courses toward embedded, discipline-specific training.

Professional development: Ongoing professional development opportunities should be furnished for both prospective and practicing educators, concentrating upon practical AI integration competencies rather than general technology awareness.

Infrastructure investment: Equitable AI tool and supporting infrastructure access should be ensured across institutions, with particular attention toward regional and under-resourced universities.

Research support: Funding should be allocated for continued scholarship examining AI adoption within specialized educational domains including music pedagogy to inform evidence-grounded policy development.

Cross-regional collaboration: Asia-Pacific nations should establish collaborative frameworks sharing best practices regarding AI educational integration, leveraging diverse regional experiences.

5.8 Limitations and Future Directions

Multiple limitations warrant acknowledgment. Initially, the sample derived from a single Hebei Province university, potentially constraining finding generalizability to alternative contexts. Future scholarship should replicate this inquiry with samples from varying regions, institution types, and cultural backgrounds throughout the Asia-Pacific to evaluate finding robustness and boundary conditions, as recommended by contemporary AI education scholarship reviews (Zawacki-Richter et al., 2019; Chen et al., 2022; Crompton & Burke, 2023).

This inquiry deployed cross-sectional design, precluding causal inference regarding variable associations. While the theoretical framework presumes particular causal directions, data cannot exclude alternative explanations including reciprocal causation. Longitudinal investigations tracking prospective educator beliefs and behaviors across time would furnish stronger proposed causal relationship evidence and could scrutinize how these elements evolve as educators gain AI tool experience (Tondeur et al., 2020; Ertmer et al., 2012).

The inquiry depended upon self-reported measures, potentially susceptible to social desirability bias and may incompletely capture participant actual technology acceptance and utilization. Although common method variance assessment signaled single-source bias does not pose meaningful threat, future scholarship could supplement self-report measures with behavioral data including actual usage logs, observational data from practice teaching encounters, or experimental investigations examining AI tool adoption within controlled conditions (Celik et al., 2022; Chiu et al., 2023).

While this inquiry extended TAM via TPACK, additional elements potentially shaping AI adoption within music education remained unexamined. Contemporary scholarship has identified supplementary constructs potentially especially pertinent for AI technology acceptance including AI apprehension (Chiu et al., 2023), AI ethics concerns (Chounta et al., 2022), AI system trust (Glikson & Woolley, 2020), and organizational AI integration support (An et al., 2023). Future scholarship could investigate these variables furnishing more comprehensive AI educational adoption understanding.

This inquiry concentrated upon adoption intention rather than actual utilization. While intention strongly forecasts behavior, the intention-behavior gap remains well-documented within technology acceptance scholarship (Venkatesh et al., 2003; Sheeran & Webb, 2016). Future scholarship could scrutinize elements facilitating or impeding intention translation into actual AI instrument deployment within music classrooms, potentially employing experimental or intervention designs assessing adoption promotion strategies (Lucas et al., 2021; Trust et al., 2020).

Future inquiries should explore cross-cultural comparisons within the Asia-Pacific to discern how cultural elements moderate associations identified herein. Comparative investigations encompassing China, Japan, South Korea, Singapore, and Australia would furnish valuable insights regarding integrated TAM-TPACK model cultural specificity versus universality.

Ultimately, rapid AI technology evolution presents both opportunities and obstacles for scholarship within this domain. Intelligent accompaniment tool capabilities improve rapidly, with novel applications continuously emerging (Deruty et al., 2022; Huang & Huang, 2023). Future scholarship should continue scrutinizing how educator perceptions and adoption intentions evolve as AI technologies mature and achieve wider availability, and how educator preparation programs can equip teachers for ongoing technological transformation (Luckin et al., 2022; Holmes & Tuomi, 2022).

6. Conclusion

This inquiry scrutinized determinants shaping prospective music educator intentions to incorporate AI-driven accompaniment systems within classroom instruction through augmenting the Technology Acceptance Model with Technological Pedagogical Content Knowledge. Outcomes established that TPACK ($\beta = .447$, $p < .001$), Attitude Toward Using ($\beta = .417$, $p < .001$), and Perceived Usefulness ($\beta = .127$, $p < .05$) meaningfully forecast adoption intention, whereas Perceived Ease of Use shapes adoption intention indirectly via usefulness perceptions and attitudinal influences. The augmented framework captured 84.4% of adoption intention variance, signifying excellent explanatory capacity surpassing conventional TAM investigations within educational contexts (Scherer et al., 2019; Granić & Marangunić, 2019).

Discoveries advance multiple scholarly contributions regarding AI educational adoption. Initially, this inquiry illustrates domain-specific pedagogical framework integration value with general technology acceptance models when scrutinizing AI adoption within educational environments. TPACK prominence as the most potent adoption intention predictor suggests educator professional expertise regarding AI

tool pedagogical integration matters more than general technology usefulness perceptions, a discovery bearing substantial implications for both theoretical advancement and practical intervention (Ng et al., 2023; Celik et al., 2022).

Subsequently, this inquiry contributes to expanding AI music education scholarship through furnishing empirical evidence regarding elements shaping prospective music educator intentions to deploy intelligent accompaniment instruments. As AI technologies become progressively capable of supporting musical activities including accompaniment, composition, and performance assessment, comprehending educator preparedness to embrace these instruments proves essential for realizing their educational promise (Huang & Huang, 2023; Deruty et al., 2022).

Additionally, this inquiry furnishes insights particular to Chinese circumstances and the broader Asia-Pacific, where substantial national AI and educational technology investments drive rapid educational landscape transformations (Ministry of Education of the People's Republic of China, 2019; State Council of China, 2017). Discoveries suggest policy initiatives advancing AI educational adoption should be accompanied by educator preparation programs cultivating both favorable attitudes and pedagogical capabilities for AI integration (Chai et al., 2020; Zhang et al., 2023).

This inquiry's practical implications prove evident: educator preparation programs should transcend technical training to concentrate upon AI pedagogical integration within music curricula. This encompasses cultivating prospective educator TPACK through genuine AI tool encounters within instructional contexts, accentuating AI practical utility resolving authentic pedagogical obstacles, and nurturing favorable attitudes via supportive learning communities (Luckin et al., 2022; Holmes et al., 2022; UNESCO, 2021). Through addressing these elements, music educator preparation faculty can more effectively equip future educators to harness AI technologies strengthening music instruction.

As AI technologies continue advancing rapidly, capacity to efficaciously integrate AI instruments within instructional practice is becoming indispensable competency for music educators throughout the Asia-Pacific and beyond (Ng et al., 2021; Long & Magerko, 2020). This inquiry furnishes foundation for comprehending elements shaping this integration and offers guidance preparing prospective educators to meet AI-enhanced music education challenges and opportunities. Future scholarship should continue scrutinizing how these elements evolve as AI technologies mature and achieve greater prevalence within educational environments, ensuring educator preparation maintains pace with technological transformation (Holmes & Tuomi, 2022; Luckin et al., 2022).

References

1. Admiraal W, van Vugt F, Kranenburg F, Koster B, Smit B, Weijers S, Lockhorst D (2017) Preparing pre-service teachers to integrate technology into K-12 instruction: Evaluation of a technology-infused approach. Technol Pedagogy Educ 26(1):105–120. https://doi.org/10.1080/1475939X.2016.1163283

2. Al-Emran M, Mezhuyev V, Kamaludin A (2020) Towards a conceptual model for examining the impact of knowledge management factors on mobile learning acceptance. Technol Soc 61:101247. https://doi.org/10.1016/j.techsoc.2020.101247
3. An X, Chai CS, Li Y, Zhou Y, Shen X, Zheng C, Chen M (2023) Modeling English teachers' behavioral intention to use artificial intelligence in middle schools. Educ Inform Technol 28(5):5187–5208. https://doi.org/10.1007/s10639-022-11286-z
4. Bauer WI (2013) The acquisition of musical technological pedagogical and content knowledge. J Music Teacher Educ 22(2):51–64. https://doi.org/10.1177/1057083712457881
5. Bauer WI, Mito H (2021) ICT in music education. In: Ruthmann SA, Mantie R (eds) The Oxford handbook of technology and music education. Oxford University Press, pp 91–107. https://doi.org/10.1093/oxfordhb/9780199372133.013.8
6. Briot JP, Hadjeres G, Pachet FD (2020) Deep learning techniques for music generation. Springer. https://doi.org/10.1007/978-3-319-70163-9
7. Celik I, Dindar M, Muukkonen H, Järvelä S (2022) The promises and challenges of artificial intelligence for teachers: A systematic review of research. TechTrends 66(4):616–630. https://doi.org/10.1007/s11528-022-00715-y
8. Chai CS, Koh JHL, Tsai CC (2013) A review of technological pedagogical content knowledge. Educational Technol Soc 16(2):31–51
9. Chai CS, Rahmawati Y, Jong MSY (2020) Indonesian science, mathematics, and engineering preservice teachers' experiences in STEM-TPACK design-based learning. Sustainability 12(21):9050. https://doi.org/10.3390/su12219050
10. Chen X, Zou D, Xie H, Cheng G, Liu C (2022) Two decades of artificial intelligence in education: Contributors, collaborations, research topics, challenges, and future directions. Educational Technol Soc 25(1):28–47
11. Chiu TKF, Moorhouse BL, Chai CS, Ismailov M (2023) Teacher support and student motivation to learn with artificial intelligence (AI) based chatbot. Interact Learn Environ 31(8):4982–4998. https://doi.org/10.1080/10494820.2023.2172044
12. Chounta IA, Bardone E, Raudsep A, Pedaste M (2022) Exploring teachers' perceptions of artificial intelligence as a tool to support their practice in Estonian K-12 education. Int J Artif Intell Educ 32(3):725–755. https://doi.org/10.1007/s40593-021-00243-5
13. Chu HC, Hwang GJ, Tu YF, Yang KH (2022) Roles and research trends of artificial intelligence in higher education: A systematic review of the top 50 most-cited articles. Australasian J Educational Technol 38(3):22–42. https://doi.org/10.14742/ajet.7526
14. Chua SL, Ho HP (2023) Technology integration in music teacher education in Singapore: Current practices and future directions. Asia-Pacific J Teacher Educ 51(2):178–195. https://doi.org/10.1080/1359866X.2023.2180123
15. Cohen J (1988) Statistical power analysis for the behavioral sciences, 2nd edn. Lawrence Erlbaum Associates

16. Compeau DR, Higgins CA (1995) Computer self-efficacy: Development of a measure and initial test. MIS Q 19(2):189–211. https://doi.org/10.2307/249688
17. Creech A, Papageorgi I (2014) Concepts of ideal musicians and teachers: Ideal selves and possible selves. In: Papageorgi I, Welch G (eds) Advanced musical performance: Investigations in higher education learning. Ashgate, pp 99–113
18. Crompton H, Burke D (2023) Artificial intelligence in higher education: The state of the field. Int J Educational Technol High Educ 20(1):22. https://doi.org/10.1186/s41239-023-00392-8
19. Curran PJ, West SG, Finch JF (1996) The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis. Psychol Methods 1(1):16–29. https://doi.org/10.1037/1082-989X.1.1.16
20. Dannenberg RB (2019) Computer accompaniment: Music listening and score following. In R. Bader (Ed.), Springer handbook of systematic musicology (pp. 529–545). Springer. https://doi.org/10.1007/978-3-662-55004-526
21. Dannenberg RB, Raphael C (2006) Music score alignment and computer accompaniment. Commun ACM 49(8):38–43. https://doi.org/10.1145/1145287.1145311
22. Davis FD (1989) Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q 13(3):319–340. https://doi.org/10.2307/249008
23. Deruty E, Grachten M, Lattner S, Nistal J, Aouameur C (2022) On the development and practice of AI technology for contemporary popular music production. Trans Int Soc Music Inform Retr 5(1):35–49. https://doi.org/10.5334/tismir.100
24. Dorfman J (2016) Theory and practice of technology-based music instruction, 2nd edn. Oxford University Press
25. Ertmer PA (2005) Teacher pedagogical beliefs: The final frontier in our quest for technology integration? Education Tech Research Dev 53(4):25–39. https://doi.org/10.1007/BF02504683
26. Ertmer PA, Ottenbreit-Leftwich AT (2010) Teacher technology change: How knowledge, confidence, beliefs, and culture intersect. J Res Technol Educ 42(3):255–284. https://doi.org/10.1080/15391523.2010.10782551
27. Ertmer PA, Ottenbreit-Leftwich AT, Sadik O, Sendurur E, Sendurur P (2012) Teacher beliefs and technology integration practices: A critical relationship. Comput Educ 59(2):423–435. https://doi.org/10.1016/j.compedu.2012.02.001
28. Fornell C, Larcker DF (1981) Evaluating structural equation models with unobservable variables and measurement error. J Mark Res 18(1):39–50. https://doi.org/10.1177/002224378101800104
29. Glikson E, Woolley AW (2020) Human trust in artificial intelligence: Review of empirical research. Acad Manag Ann 14(2):627–660. https://doi.org/10.5465/annals.2018.0057
30. Granić A, Marangunić N (2019) Technology acceptance model in educational context: A systematic literature review. Br J Edu Technol 50(5):2572–2593. https://doi.org/10.1111/bjet.12864

31. Hair JF, Black WC, Babin BJ, Anderson RE (2019) Multivariate data analysis, 8th edn. Cengage Learning
32. Harris JB, Hofer MJ (2011) Technological pedagogical content knowledge (TPACK) in action: A descriptive study of secondary teachers' curriculum-based, technology-related instructional planning. J Res Technol Educ 43(3):211–229. https://doi.org/10.1080/15391523.2011.10782570
33. Holmes W, Tuomi I (2022) State of the art and practice in AI in education. Eur J Educ 57(4):542–570. https://doi.org/10.1111/ejed.12533
34. Holmes W, Porayska-Pomsta K, Holstein K, Sutherland E, Baker T, Shum SB, Santos OC, Rodrigo MT, Cukurova M, Bittencourt II, Koedinger KR (2022) Ethics of AI in education: Towards a community-wide framework. Int J Artif Intell Educ 32(3):504–526. https://doi.org/10.1007/s40593-021-00239-1
35. Hu L, Bentler PM (1999) Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Struct Equ Model 6(1):1–55. https://doi.org/10.1080/10705519909540118
36. Huang AYQ, Lu OHT, Yang SJH (2023) Effects of artificial intelligence–enabled personalized recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom. Comput Educ 194:104684. https://doi.org/10.1016/j.compedu.2022.104684
37. Huang CJ, Huang MC (2023) Application of artificial intelligence in music education: A systematic review. Int J Inform Educ Technol 13(3):530–537. https://doi.org/10.18178/ijiet.2023.13.3.1841
38. Huang X, Zou D, Cheng G, Chen X, Xie H (2022) Trends, research issues and applications of artificial intelligence in language education. Educational Technol Soc 25(1):1–27
39. Hwang GJ, Xie H, Wah BW, Gašević D (2020) Vision, challenges, roles and research issues of artificial intelligence in education. Computers Education: Artif Intell 1:100001. https://doi.org/10.1016/j.caeai.2020.100001
40. Jiang H, Islam AA, Gu X, Spector JM (2022) Online learning satisfaction in higher education during the COVID-19 pandemic: A regional comparison between Eastern and Western Chinese universities. Educ Inform Technol 27(2):2083–2115. https://doi.org/10.1007/s10639-021-10640-8
41. Joo YJ, Park S, Lim E (2018) Factors influencing preservice teachers' intention to use technology: TPACK, teacher self-efficacy, and technology acceptance model. Educational Technol Soc 21(3):48–59
42. Kim J, Merrill K, Xu K, Sellnow DD (2022) My teacher is a machine: Understanding students' perceptions of AI teaching assistants in online education. Int J Human–Computer Interact 38(7):609–621. https://doi.org/10.1080/10447318.2021.1978828
43. Kim S, Park M (2021) AI technology adoption in music education: A study of Korean preservice teachers. J Music Educ Res 49(3):312–328
44. King WR, He J (2006) A meta-analysis of the technology acceptance model. Inf Manag 43(6):740–755. https://doi.org/10.1016/j.im.2006.05.003
45. Koehler MJ, Mishra P (2009) What is technological pedagogical content knowledge? Contemp Issues Technol Teacher Educ 9(1):60–70

46. Liu Y, Chen X (2022) Technology integration in music education in China: Current status, challenges, and future directions. Int J Music Educ 40(3):423–439. https://doi.org/10.1177/02557614221089156
47. 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). ACM. https://doi.org/10.1145/3313831.3376727
48. Lucas M, Bem-Haja P, Siddiq F, Moreira A, Redecker C (2021) The relation between in-service teachers' digital competence and personal and contextual factors: What matters most? Comput Educ 160:104052. https://doi.org/10.1016/j.compedu.2020.104052
49. Luckin R, Cukurova M, Kent C, du Boulay B (2022) Empowering educators to be AI-ready. Computers Education: Artif Intell 3:100076. https://doi.org/10.1016/j.caeai.2022.100076
50. Ministry of Education of the People's Republic of China (2019) China's educational modernization 2035. http://www.moe.gov.cn/jybxwfb/s6052/moe838/201902/t20190223370857.html
51. Mishra P, Koehler MJ (2006) Technological pedagogical content knowledge: A framework for teacher knowledge. Teachers Coll Record 108(6):1017–1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x
52. Ng DTK, Leung JKL, Chu SKW, Qiao MS (2021) Conceptualizing AI literacy: An exploratory review. Computers Education: Artif Intell 100041. 2https://doi.org/10.1016/j.caeai.2021.100041
53. Ng DTK, Leung JKL, Su J, Ng RCW, Chu SKW (2023) Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world. Education Tech Research Dev 71(1):33–59. https://doi.org/10.1007/s11423-023-10203-6
54. Nunnally JC, Bernstein IH (1994) Psychometric theory, 3rd edn. McGraw-Hill
55. OECD (2021) OECD Digital Education Outlook 2021: Pushing the frontiers with artificial intelligence, blockchain and robots. OECD Publishing. https://doi.org/10.1787/589b283f-en
56. Percival G, Wang Y, Tzanetakis G (2007) Effective use of multimedia for computer-assisted musical instrument tutoring. In Proceedings of the International Workshop on Educational Multimedia and Multimedia Education (pp. 67–76). ACM. https://doi.org/10.1145/1290144.1290156
57. Podsakoff PM, MacKenzie SB, Lee JY, Podsakoff NP (2003) Common method biases in behavioral research: A critical review of the literature and recommended remedies. J Appl Psychol 88(5):879–903. https://doi.org/10.1037/0021-9010.88.5.879
58. Podsakoff PM, MacKenzie SB, Podsakoff NP (2012) Sources of method bias in social science research and recommendations on how to control it. Ann Rev Psychol 63:539–569. https://doi.org/10.1146/annurev-psych-120710-100452
59. Raphael C (2010) Music plus one and machine learning. In Proceedings of the 27th International Conference on Machine Learning (pp. 21–28). Omnipress
60. Sánchez-Prieto JC, Olmos-Migueláñez S, García-Peñalvo FJ (2017) MLearning and pre-service teachers: An assessment of the behavioral intention using an expanded TAM model. Comput Hum Behav 72:644–654. https://doi.org/10.1016/j.chb.2016.09.015

61. Sasaki T, Yamamoto K (2022) Technology acceptance in Japanese music education: Cultural factors and pedagogical traditions. Music Educ Res 24(4):456–471
62. Scherer R, Siddiq F, Tondeur J (2019) The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. Comput Educ 128:13–35. https://doi.org/10.1016/j.compedu.2018.09.009
63. Schmidt DA, Baran E, Thompson AD, Mishra P, Koehler MJ, Shin TS (2009) Technological pedagogical content knowledge (TPACK): The development and validation of an assessment instrument for preservice teachers. J Res Technol Educ 42(2):123–149. https://doi.org/10.1080/15391523.2009.10782544
64. Seddon FA, O'Neill SA (2003) Creative thinking processes in adolescent computer-based composition: An analysis of strategies adopted and the influence of instrumental music training. Music Educ Res 5(2):125–137. https://doi.org/10.1080/1461380032000085513
65. Seufert S, Guggemos J, Sailer M (2021) Technology-related knowledge, skills, and attitudes of pre- and in-service teachers: The current situation and emerging trends. Comput Hum Behav 115:106552. https://doi.org/10.1016/j.chb.2020.106552
66. Sheeran P, Webb TL (2016) The intention–behavior gap. Soc Pers Psychol Compass 10(9):503–518. https://doi.org/10.1111/spc3.12265
67. Shulman LS (1986) Those who understand: Knowledge growth in teaching. Educational Researcher 15(2):4–14. https://doi.org/10.3102/0013189X015002004
68. State Council of China (2017) New generation artificial intelligence development plan. http://www.gov.cn/zhengce/content/2017-07/20/content5211996.htm
69. Taylor S, Todd PA (1995) Understanding information technology usage: A test of competing models. Inform Syst Res 6(2):144–176. https://doi.org/10.1287/isre.6.2.144
70. Teo T (2011) Factors influencing teachers' intention to use technology: Model development and test. Comput Educ 57(4):2432–2440. https://doi.org/10.1016/j.compedu.2011.06.008
71. Teo T, Huang F, Hoi CKW (2019) Explicating the influences that explain intention to use technology among English teachers in China. Interact Learn Environ 27(3):302–319. https://doi.org/10.1080/10494820.2018.1489291
72. Thompson P, Whitfield J (2022) Supporting technology integration in regional Australian schools: Lessons for the Asia-Pacific. Australian J Educ 66(2):189–205
73. Tondeur J, Scherer R, Baran E, Siddiq F, Valtonen T, Sointu E (2019) Teacher educators as gatekeepers: Preparing the next generation of teachers for technology integration in education. Br J Edu Technol 50(3):1189–1209. https://doi.org/10.1111/bjet.12748
74. Tondeur J, Scherer R, Siddiq F, Baran E (2020) Enhancing pre-service teachers' technological pedagogical content knowledge (TPACK): A mixed-method study. Education Tech Research Dev 68(1):319–343. https://doi.org/10.1007/s11423-019-09692-1
75. Trust T, Carpenter JP, Krutka DG, Kimmons R (2020) #RemoteTeaching & #RemoteLearning: Educator tweeting during the COVID-19 pandemic. J Technol Teacher Educ 28(2):151–159

76. UNESCO (2021) AI and education: Guidance for policy-makers. UNESCO Publishing. https://unesdoc.unesco.org/ark:/48223/pf0000376709
77. Venkatesh V, Bala H (2008) Technology acceptance model 3 and a research agenda on interventions. Decis Sci 39(2):273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x
78. Venkatesh V, Morris MG, Davis GB, Davis FD (2003) User acceptance of information technology: Toward a unified view. MIS Q 27(3):425–478. https://doi.org/10.2307/30036540
79. Voogt J, Fisser P, Pareja Roblin N, Tondeur J, van Braak J (2013) Technological pedagogical content knowledge – A review of the literature. J Comput Assist Learn 29(2):109–121. https://doi.org/10.1111/j.1365-2729.2012.00487.x
80. Wang B, Rau PLP, Yuan T (2023) Measuring user competence in using artificial intelligence: Validity and reliability of artificial intelligence literacy scale. Behav Inform Technol 42(5):617–634. https://doi.org/10.1080/0144929X.2022.2027678
81. Wang Y, Liu X, Zhang J (2021) Technology integration in music education: Perspectives from Chinese music teachers. J Music Technol Educ 14(2–3):175–195. https://doi.org/10.1386/jmte000311
82. Webster PR (2002) Computer-based technology and music teaching and learning. In R. Colwell & C. Richardson (Eds.), The new handbook of research on music teaching and learning: A project of the Music Educators National Conference (pp. 416–439). Oxford University Press
83. Young PA (2020) The culturally responsive-sustaining design framework: A tool for designing culturally relevant instructional materials. In M. J. Bishop, E. Boling, J. Elen, & V. Svihla (Eds.), Handbook of research in educational communications and technology (5th ed., pp. 407–429). Springer. https://doi.org/10.1007/978-3-030-36119-819
84. Zawacki-Richter O, Marín VI, Bond M, Gouverneur F (2019) Systematic review of research on artificial intelligence applications in higher education – Where are the educators? International Journal of Educational Technology in Higher Education, 16, Article 39. https://doi.org/10.1186/s41239-019-0171-0
85. Zhang C, Schießl J, Plößl L, Hofmann F, Gläser-Zikuda M (2023) Acceptance of artificial intelligence among pre-service teachers: A multigroup analysis. Int J Educational Technol High Educ 20:49. https://doi.org/10.1186/s41239-023-00420-7

Figures

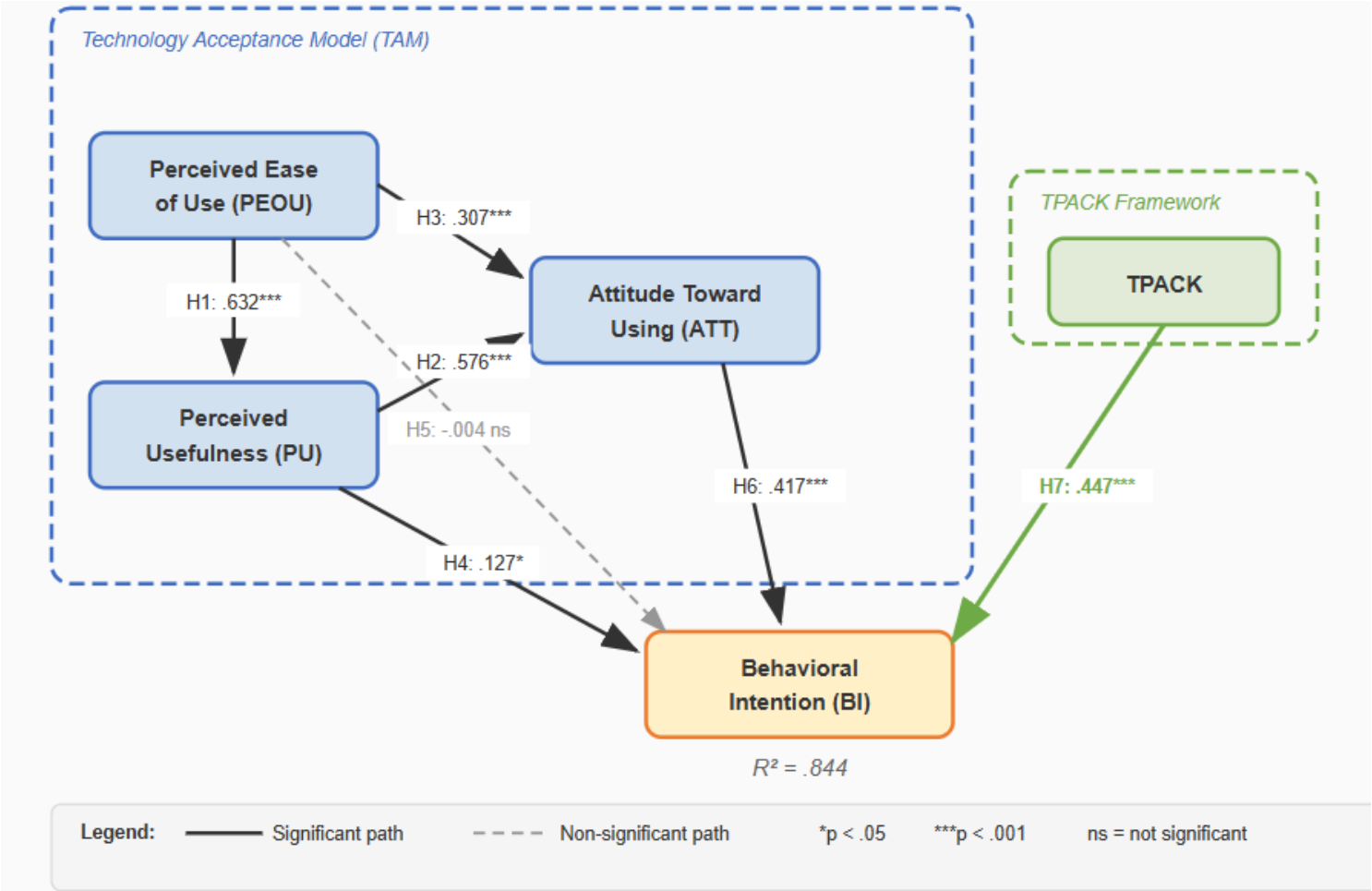


Figure 1

Research Model and Hypotheses with Path Coefficients