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Their Structural Relationships with Pre-Service Teachers' Behavioral Intention to Engage in AI-Assisted Teaching

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The integration of AI technology into teaching addresses profound changes in the contemporary education system and the trend towards increasingly diversified student learning needs. As the future backbone of education, pre-service teachers' technology acceptance, readiness, and shaping of educational concepts will directly determine future education models' direction. Although the state has issued numerous relevant policies and provided substantial resources, pre-service teachers' behavioral willingness to integrate AI into future teaching remains below expectations. This phenomenon suggests that external support alone—such as facilitating conditions (FC)—may be insufficient to stimulate their intrinsic motivation; instead, internal factors like performance expectancy (PE) and AI-TPACK are likely to play a more critical role. This scenario underscores the need to explore the internal mechanisms linking FC, PE, and AI-TPACK. Through a questionnaire survey of 291 pre-service teachers, our research shows that FC, AI-TPACK, and PE all have a significant positive impact on pre-service teachers' behavioral intention (BI) to use AI. Further tests on mediating effects show that FC not only directly affects behavioral intention but also indirectly influences BI through a chain mediating path (FC→AI-TPACK→PE→BI), with the β value of this chain mediation being 0.193. In addition, this study conducted thematic analysis through in-depth interviews with 15 pre-service teachers. Based on these findings, several suggestions are proposed to enhance pre-service teachers' willingness to integrate AI into teaching.

Keywords: artificial intelligence, pre-service teachers, facilitating conditions, AI-TPACK, performance expectancy

INTRODUCTION

Artificial intelligence has increasingly permeated educational environments and teaching processes, and its importance in education is widely recognized. The European Commission's High-Level Expert Group defines AI as a system with autonomy that analyzes environments and takes actions to achieve goals. In education, AI applications

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include personalized tutoring, intelligent assessment, and profiling. AI optimizes learning environments, stimulating students' enthusiasm, initiative, and creativity. However, AI-driven education's future depends on technological advances and user acceptance, which directly impacts educational effectiveness in the AI era.

The deep integration of AI in education presents new challenges to teachers' professional competencies. As the core driving force behind future educational reforms, pre-service teachers' AI literacy and their willingness to integrate AI into teaching are directly linked to the advancement of educational digitalization. Pre-service teachers face AI education challenges, yet studies on their AI adoption are limited (Chiu & Chai, 2020*)*. However, existing empirical studies have predominantly focused on in-service teachers, with relatively insufficient attention paid to pre-service teachers (Zhang et al., 2023). Concurrently, educational practice faces the common reality of "high technological expectations but low application implementation": although many countries have formulated policies and invested a lot of resources to integrate AI into education(Ma & Lei, 2024), pre-service teachers generally lack intrinsic motivation to effectively integrate AI into teaching practices(Guan et al., 2025). To bridge the gap between theory and practice, this study aims to systematically explore the key factors influencing pre-service teachers' intention to use AI-assisted teaching and further clarify the interaction mechanisms among these factors. Aims to provide insights into enhancing pre-service teachers' willingness to integrate artificial intelligence into teaching.

LITERATURE REVIEW

Application of Artificial Intelligence in Education

Artificial Intelligence, a formidable force, is transforming fields like education and research unprecedentedly. Its application in education is a pivotal development of this century. AI invigorates traditional education with powerful data processing and intelligent analysis. This integration alters learning, teaching, and institutional operations, crafting a distinct educational ecosystem.

The deep fusion of AI and education heralds a new era of change. One of the most prominent applications of AI in education is the intelligent tutoring system, which analyzes vast amounts of students' learning patterns and performance data to deliver timely interventions and support. Additionally, AI-powered learning platforms leverage natural language processing and sentiment analysis to offer more personalized and interactive learning experiences for both students and educators(Aldraiweesh & Alturki, 2025).Preparing educators to integrate AI into education is a key prerequisite for the seamless integration of AI into educational environments(Zhang et al., 2023).

Utaut

The Unified Theory of Acceptance and Use of Technology (UTAUT) explains technology use intention and behavior. Given its widespread use in educational technology research(Barakat et al., 2025a), we chose it as our theoretical foundation. The UTAUT model includes four core concepts: performance expectations, effort expectations, social influences, and FC. The relative importance of these predictors is expected to vary across different contexts(Venkatesh et al., 2003). Given that pre-service teachers lack the social norms and workplace pressures of professional educators, their decisions regarding technology adoption are primarily driven by curriculum requirements and personal career development motivations. Additionally, the usability of current AI teaching tools has reached a high level, meaning teachers are more concerned with whether these tools can enhance teaching effectiveness (PE) rather than operational difficulty (EE). Therefore, PE and FC were ultimately retained as core independent variables.UTAUT models often include context-specific variables to explain teacher technology acceptance (Dindar et al., 2021).

Facilitating conditions

Facilitating conditions refer to individuals' perception of supportive environments for technology use, including technology, resource availability, and organizational /environmental support, impacting technology's successful application (Venkatesh et al., 2003).In addition, FC refers to a person's belief in the technological capabilities of the organization(Barakat & Elmaghraby, 2025). Buraimoh et al. (2023)show they influence teachers' willingness to use technology. The results of Fathi and Ebadi(2020), Kim and Lee(2022), and Wong(2015) all show that FC has a significant impact on the willingness of pre service teachers to use AI in teaching. Ronny Scherer (2019) and Barakat et al. (Barakat et al., 2025b) emphasized that FC is the key factor affecting teachers' technical efficiency. Based on this, we hypothesize:

H1: FC positively impacts pre-service teachers' intention to use AI in future teaching.

H2: FC influences pre-service teachers' PE for AI use in future teaching.

Performance Expectation

Performance Expectation (PE) refers to an individual's perception of technology's potential to improve job performance (Venkatesh et al., 2003). In this study, it refers to pre-service teachers' belief in AI's ability to enhance teaching effectiveness. In the UTAUT model, PE is a key factor influencing intentions (Xue et al., 2024). A study on interactive whiteboards found PE alone highly explained behavioral intentions, with other factors like effort expectations insignificant (Bardakcı & Alkan, 2019). Based on this, we hypothesize:

H3: PE positively affects pre-service teachers' intention to use AI in future teaching.

AI-TPACK

TPACK is a theoretical framework developed by Mishra and Koehler to help

teachers successfully integrate technology in the classrooms (Wangdi et al., 2023). TPACK is a crucial external factor in the technology acceptance model and complements UTAUT (Lai Wah & Hashim, 2021). In AI education, AI-TPACK (Celik, 2023) extends TPACK by incorporating AI technologies. Studies show AI-TPACK positively impacts teachers' PE (An et al., 2023). K. Wang et al. (2024) found GenAI TPACK significantly affects pre-service teachers' expectations. A study links FC, PE, and TPACK positively (Cheung et al., 2016). Tram's(2025) research indicates that AI-

TPACK is a key factor affecting PE, and FC is an important predictor of AI-TPACK. While existing studies have focused on AI-TPACK and numerous others have explored pre-service teachers' technology adoption, few have integrated AI-TPACK as a core antecedent variable into technology adoption models to systematically examine how it influences pre-service teachers' willingness to use AI. For pre-service teachers, mastery of specific technical and pedagogical knowledge (AI-TPACK) is essential to effectively incorporating AI into their teaching practices(Ning et al., 2024). To understand the intention of pre service teachers to use artificial intelligence, this study innovatively introduces the AI-TPACK framework.Hence, we hypothesize:

H4: AI-TPACK positively affects pre-service teachers' intentions to use AI in future teaching.

H5: AI-TPACK influences pre-service teachers' PE to use AI in future teaching.

H6: FC affects pre-service teachers' AI-TPACK for future AI use.

Behavioral Intention

Behavioral intention (BI) to use technology refers to a user's plan to adopt and use a tool in the future (Venkatesh & Brown, 2001), and it's the main predictor of technology use (Mousa Jaradat & Al Rababaa, 2013). In this study, BI focuses on pre-service teachers' intention to use AI in teaching. Teachers' BI to use AI affects their daily teaching adoption (Davis, 1989).

Therefore, we consider PE, FC from UTAUT, and AI-TPACK as key factors influencing pre-service teachers' BI.

Theoretical framework and research questions

Theoretical framework

In this study, we adopt Ternary Reciprocal Determinism (TRD) as the theoretical framework to explore how AI-TPACK, PE, BI, and FC interact to influence behavior and development. TRD, proposed by Bandura(1978), emphasizes the interrelationships among individuals, behavior, and the environment. In TRD, individual determinants focus on awareness, thinking, judgment, and emotions; behavioral determinants are reflected in specific responses to the environment; and environmental determinants consider the influence of conditions on development (Zeng et al., 2020). PE refers to the degree to which an individual believes that technology can improve job performance, which belongs to intrinsic psychological motivation. Therefore, we have identified PE as an individual dimension. AI-TPACK refers to the knowledge of artificial intelligence technology teaching content, which reflects an individual's ability to integrate artificial intelligence technology with teaching. Therefore, we have identified AI-TPACK as an individual dimension. FC refers to external conditions such as organizational resources and technical support, therefore we define FC as the environmental dimension. BI refers to the degree of willingness of individuals to use technology, therefore we have identified it as a behavioral dimension.

Research Questions

Based on the above research background, this study endeavors to explore how FC affect pre-service teachers' willingness to integrate AI technologies into their future teaching and learning, and furthermore, it endeavors to provide an in-depth analysis of the interrelationships between such willingness and a range of influences with a view to revealing potential causal and interdependent pathways. Specifically, the following research questions were answered:

1. To what extent does FC influence pre-service teachers' use of AI for BI and do AI-TPACK and PE influence pre-service teachers' use of AI for BI?

2. What are the complex mechanisms behind FC, AI-TPACK, and PE on the BI of pre-service teachers' use of AI, and what correlations exist between these factors?

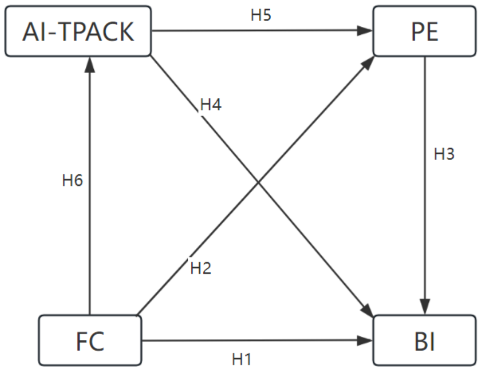

Figure 1
Research hypotheses.

METHOD

Quantitative phase

Background and participants

This study was conducted in mid-June 2024 at four teacher education universities in central China. Participants were second-year pre-service teachers from various majors, selected because this stage occurs after foundational courses (e.g., Modern Educational Technology) and before full-time internships, making it ideal for examining initial technology acceptance intentions. Questionnaires were distributed via the Wenjuanxing platform (https://www.wjx.cn/) to students across different majors.

Ethical approval was obtained from the University Ethics Committee, and informed consent was secured. In a pre-test with 30 participants, the average completion time was 90 seconds, with effective and focused response times ranging from 60 to 150 seconds.Data were collected online, with 400 questionnaires returned. After screening, 109 invalid responses were excluded due to short completion times (less than 60 seconds), monotonous response patterns, or incorrect answers to trap questions, yielding

291 valid questionnaires (an effective response rate of 72.8%). The final sample comprised 88.7% female and 11.3% male participants. Clear instructions were provided to ensure response authenticity and data quality.

Item design

The questionnaire consisted of two parts, the first of which contained demographic information about pre-service teachers, including information on gender and specialization, and the second of which was a survey of pre-service teachers' perceptions of PE, FC, AI-TPACK, and BI. Specifically, (1) FC subscales (items 1-5) for pre-service teachers: for the assessment of the facilitation condition part of the scale, reference was made to the scales of(Venkatesh et al., 2003) and (Chen et al., 2024). (2) PE subscales (items 6-9) for pre-service teachers: modifications were made based on (Venkatesh et al., 2003)framework in designing the scales for the PE section. (3) AI-TPACK subscales (items 10-14) for pre-service teachers: adapted from the scale designed by (Celik, 2023). (4) BI subscale (items 15-19) for pre-service teachers: based on (Davis, 1989)' scale and with reference to scales by (Xuemei Bai et al., 2024) to finalize the subscale for BI. The questionnaire as a whole was in the form of a five-point Likert scale ranging from "1-strongly disagree" to "5-strongly agree". For the specific items of the scale, please refer to the Appendix.

Data analysis

In this study, SPSS 26.0 was used for descriptive statistical analysis, while Amos 28.0 was employed to establish a structural equation model for in-depth verification. Subsequently, the PROCESS macro—capable of analyzing mediating and moderating effects and handling multiple models simultaneously—was utilized, with 5,000 samples and the bias-corrected percentile bootstrap method, to test the significance of the mediating effect(Hayes & Andrew, 2012).

Qualitative phase

Participants

To further explore and interpret the results of the quantitative phase, a follow-up survey with open-ended questions was conducted after the initial quantitative study(Yu, 2009). Fifteen participants from the initial quantitative phase were invited to participate in the current qualitative phase, all of whom were required to have at least one year's experience using AI technology. To ensure depth and diversity of perspectives, participants completed an open-ended interview in small groups.

Interview outline design

The design of the open-ended interview outline for the qualitative phase was based on the results of the initial quantitative study, where two open-ended questions explored students' perceptions of AI technology-assisted teaching and learning, two more open-ended questions explored students' perceptions in terms of PE arising from the application of AI technology, and two more open-ended questions explored students' perceptions of FC and AI-TPACK, respectively.

Data collection and analysis

Fifteen invited participants were divided into two groups (one group of eight and one group of seven) to conduct focus group interviews, with strict consideration of research ethics, and all responses were voluntary. Thematic analysis of interview data helps to summarize key features and generate unexpected insights. We followed the six stages proposed by Braun and Clarke(Braun & Clarke, 2006): familiarizing with the data, generating initial codes, developing themes, reviewing themes, defining and naming themes, and producing the report.

Throughout the process, two well-trained research team members participated in manual data analysis to ensure the credibility and reliability of the procedure. Any discrepancies were discussed and resolved by the two authors. Inter-coder consistency was measured using Miles and Huberman's (Miles & Huberman, 1994) formula (reliability = number of agreements / (total number of agreements + number of disagreements)). Consistency among coders ranged from 84% to 95%, indicating that the coding and categorization were reliable(Saldaña, 2009).

FINDINGS

Quantitative findings

Reliability of the scale

Based on real data from 291 participants, the reliability of the scale was initially assessed using Cronbach's reliability coefficient. The results are shown in Table 1 below, and the reliability coefficients for all subscales exceeded 0.8, indicating good reliability.

Table 1
Reliability

Variable	Cronbach's alpha coefficient
PE	0.904
FC	0.854
AI-TPACK	0.872
BI	0.884

Confirmatory Factor Analysis

Confirmatory Factor Analysis (CFA) was used to assess model fit. CFA relies on a variety of metrics, including CMIN/DF, RMSEA, IFI, TLI, and CFI, to assess model fit(Pressley, 1990). As shown in the Table 2, all of these metrics typically meet the necessary criteria to indicate that the model demonstrates an acceptable fit(Browne & Cudeck, 1992).

Table 2
Model fit

Indicators	Reference standard	Measurement value
CMIN/DF	<5	2.452
RMSEA	<0.08	0.071
IFI	>0.8	0.953
TLI	>0.8	0.924
CFI	>0.8	0.935
SRMR	<0.08	0.057

To evaluate the explanatory power of the structural equation model for endogenous variables, this study calculated the R^2 values for PE, AI-TPACK, and BI. The results indicate that the R^2 value for PE is 0.191, meaning the independent variables in the model can explain 19.1% of the variance in PE. The R^2 value for AI-TPACK is 0.330, indicating that the model explains 33.0% of the variance in AI-TPACK. For BI, the R^2 value is 0.606, suggesting that the variables in the model account for 60.6% of the variance in BI.

Convergent validity and composite reliability

The model ensuring good fit is a prerequisite and the measurement model was assessed through convergent validity (AVE) and composite reliability (CR) as shown in Table 3. It is important to note that according to the criteria, the benchmark for ensuring good convergence and reliability of the model is an AVE value of 0.5 or above and a CR value of 0.7 or above(Hair et al., 2020). Therefore, it is shown that the measurement model in this study has robust convergent validity and composite reliability.

Table 3
Composite reliability and convergence validity

Path			Unstd.	S.E.	C.R.	P	Std.	AVE	CR
PE1	<---	PE	1				0.817	0.71	0.91
PE2	<---	PE	1.007	0.061	16.647	***	0.844		
PE3	<---	PE	1.021	0.058	17.745	***	0.886		
PE4	<---	PE	0.918	0.058	15.737	***	0.811		
FC1	<---	FC	1				0.651	0.55	0.86
FC2	<---	FC	1.07	0.106	10.098	***	0.696		
FC3	<---	FC	1.017	0.1	10.19	***	0.703		
FC4	<---	FC	1.492	0.13	11.488	***	0.824		
FC5	<---	FC	1.403	0.124	11.279	***	0.803		
AI-TPACK1	<---	AI-TPACK	1				0.691	0.58	0.87
AI-TPACK2	<---	AI-TPACK	1.004	0.092	10.874	***	0.704		
AI-TPACK3	<---	AI-TPACK	1.126	0.096	11.702	***	0.764		
AI-TPACK4	<---	AI-TPACK	1.125	0.089	12.697	***	0.843		
AI-TPACK5	<---	AI-TPACK	1.048	0.087	12.114	***	0.795		
BI1	<---	BI	1				0.747	0.61	0.89
BI2	<---	BI	0.989	0.072	13.751	***	0.809		
BI3	<---	BI	0.945	0.068	13.8	***	0.812		
BI4	<---	BI	0.948	0.072	13.126	***	0.775		
BI5	<---	BI	0.942	0.074	12.782	***	0.756		

Abbreviations: AVE, average variance extracted; CR, composite reliability; SE, squared error. ***$p < 0.001$.

Distinguishing validity

As shown in the Table 4, validity tests indicated that the standardized correlation coefficients for each pair of dimensions were less than the square root of the corresponding mean(Rönkkö & Cho, 2022). This finding indicates the discriminant validity of the measurement model in this study is sufficient.

Table 4
Discriminant validity

	PE	FC	AI-TPACK	BI
PE	0.843			
FC	0.401	0.742		
AI-TPACK	0.372	0.575	0.762	
BI	0.638	0.649	0.535	0.781

Descriptive statistics and results of normality test

After descriptive statistics and normality tests, the results were obtained as shown in Table 5.Given the questionnaire's 1-5 scoring, descriptive stats showed mean scores of 3-4, indicating participants' moderate to above-average understanding. PE scored highest (4.22), followed by BI (3.846) and FC (3.534). This suggests pre-service teachers recognize AI's importance in education, believe it's practical, and are eager to integrate it into future teaching. Skewness and kurtosis tests, using Kline's criteria (skewness <3, kurtosis <8)(Kline, 1998), confirmed data normality, as all coefficients' absolute values fell within the range.

Table 5
Descriptive statistics and results of normality test

Variables	Items	M	SD	Skewness	Kurtosis	M	SD
PE	PE1	4.19	0.727	-0.855	1.336	4.22	0.698
	PE2	4.21	0.709	-0.787	1.252		
	PE3	4.21	0.684	-0.548	0.228		
	PE4	4.27	0.672	-0.651	0.468		
FC	FC1	3.73	0.866	-0.534	0.326	3.534	0.9114
	FC2	3.47	0.868	-0.223	-0.093		
	FC3	3.75	0.816	-0.497	0.274		
	FC4	3.35	1.021	-0.343	-0.379		
	FC5	3.37	0.986	-0.396	-0.118		
AI-TPACK	AI-TPACK1	3.30	0.832	-0.093	0.271	3.45	0.8048
	AI-TPACK2	3.34	0.820	-0.164	-0.198		
	AI-TPACK3	3.45	0.847	-0.083	0.129		
	AI-TPACK4	3.51	0.767	-0.225	0.379		
	AI-TPACK5	3.65	0.758	-0.122	0.210		
BI	BI1	3.81	0.819	-0.623	0.661	3.846	0.758
	BI2	3.87	0.748	-0.585	0.693		
	BI3	3.99	0.712	-0.62	1.084		
	BI4	3.8	0.748	-0.353	0.255		
	BI5	3.76	0.763	-0.416	0.266		

Path analysis results

The hypotheses of the path model were tested and the resultant data is shown in Table 6. The empirical verification of the research model shows that the 6 hypotheses are supported.

Table 6
SEM path relationship test

Hypothesis	Path	β	S.E.	t-value	P	Conclusion
H1	FC→BI	0.424	0.078	5.423	***	Supported
H2	FC→PE	0.295	0.086	3.43	***	Supported
H3	PE→BI	0.437	0.061	7.143	***	Supported
H4	AI-TPACK→BI	0.163	0.067	2.424	*	Supported
H5	AI-TPACK→PE	0.218	0.082	2.648	**	Supported
H6	FC→AI-TPACK	0.586	0.081	7.238	***	Supported

***p < 0.001; **p < 0.01; *p < 0.05.

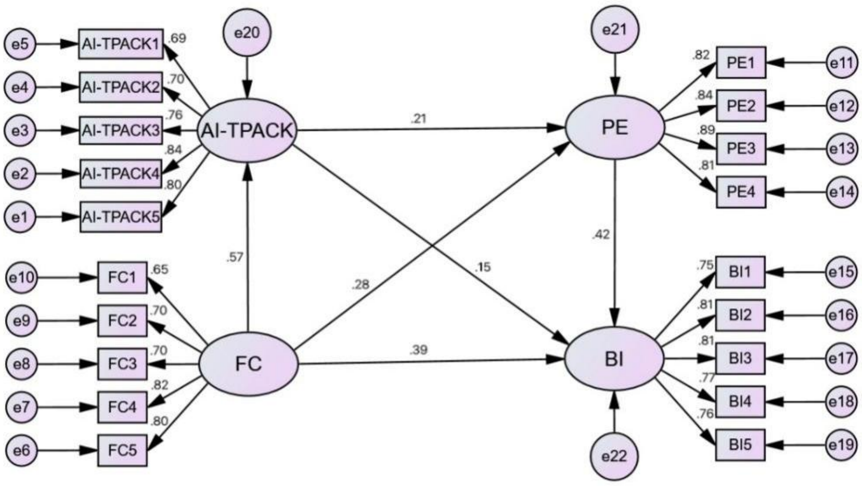

Figure 2
Path analysis results

Mediating effects

Mediating effect of AI-TPACK between FC and BI

Process distribution regression was used to test the mediating effect of AI-TPACK between FC and BI and the results are shown in the Table 7. In the initial step of the test, a significant relationship was observed between the independent variable FC and the dependent variable BI ($\beta = 0.513$, $p < 0.001$), indicating the presence of a total effect. In the subsequent step of the test, a significant relationship was observed between the independent variable FC and the mediating variable AI-TPACK ($\beta = 0.461$, $p < 0.001$). In the final step of the test, a significant effect of the independent variable on the dependent variable was established (β = 0.416, p < 0.001) and that AI-TPACK also had a significant effect on BI (β = 0.209, p < 0.001). These findings establish a mediating role for AI-TPACK in the model, indicating partial mediation.

Table 7
Mediation effect test using process distributed regression method

Step	Dependent variable	Independent variable	R	R^2	F	β	t
1	BI	FC	0.594	0.353	157.901***	0.513	12.566***
2	AI-TPACK	FC	0.511	0.261	102.2666***	0.461	10.113***
3	BI	FC	0.623	0.389	91.550***	0.416	9.002***
		AI-TPACK				0.209	4.080***

Abbreviations: R, correlation coefficient; R2, square of correlation coefficient; β, standardized regression coefficient. ***p < 0.001.

To further confirm the extent of the mediating role of AI-TPACK in the model, Bootstrap analysis was performed, and the results of this analysis are shown in the Table 8, with a calculated indirect effect value of 0.096 and a 95% confidence interval of [0.042, 0.160], and the fact that the confidence interval does not contain a zero suggests a significant indirect effect, establishing that AI-TPACK plays a crucial mediating role. Based on the effect ratio calculation, the effect of AI-TPACK accounted for 19% of the total effect.

Table 8
Mediation effect test of bootstrap analysis

Type of effect	Effect size	LLCI	ULCI	Relative effect size(%)
Total effect	0.513	0.432	0.593	100
Direct effect	0.416	0.325	0.507	81
Indirect effect	0.096	0.042	0.16	19

Abbreviations: LLCI, lower limit of confidence interval; ULCI, upper limit of confidence interval.

Mediating role of PE between FC and BI

Process distribution regression was used to test the mediating role of PE between FC and BI and the results are shown in the Table 9. In the initial step of the test, a significant relationship was observed between the independent variable FC and the dependent variable BI (β = 0.513, p < 0.001), indicating the presence of a total effect. In the subsequent step of the test, a significant relationship was observed between the independent variable FC and the mediating variable PE (β = 0.322, p < 0.001). In the final step of the test, a significant effect of the independent variable on the dependent variable was established (β = 0.382, p < 0.001) and that PE also had a significant effect on BI (β = 0.407, p < 0.001). These findings establish the mediating role of PE in the model, indicating partial mediation.

Table 9
Mediation effect test using process distributed regression method

Step	Dependent variable	Independent variable	R	R^2	F	β	t
1	BI	FC	0.594	0.353	157.901***	0.513	12.566***
2	PE	FC	0.38	0.144	48.656***	0.322	6.975***
3	BI	FC	0.7	0.49	138.219***	0.382	9.734***
		PE				0.407	8.775***

Abbreviations: R, correlation coefficient; R2, square of correlation coefficient; β, standardized regression coefficient. ***$p < 0.001$.

To further confirm the extent of the mediating role of PE in the model, Bootstrap analysis was conducted, and the results of this analysis are shown in the Table 10, with a calculated indirect effect value of 0.131 and a 95% confidence interval of [0.084, 0.182], and the fact that the confidence interval does not contain zero suggests a significant indirect effect and establishes that PE plays a crucial mediating role in the model. Based on the effect ratio calculation, the effect of PE accounted for 26% of the total effect.

Table 10
Mediation effect test of bootstrap analysis

Effect type	Effect size	LLCI	ULCI	Relative effect size(%)
Total effect	0.513	0.432	0.593	100
Direct effect	0.382	0.305	0.459	74
Indirect effect	0.131	0.084	0.182	26

Abbreviations: LLCI, lower limit of confidence interval; ULCI, upper limit of confidence interval.

Role of AI-TPACK and PE in chained mediated effects between FC and BI

Examining the role of chain mediated effects of AI-TPACK and PE between FC and BI, the confidence interval for the total effect was [0.432,0.593], excluding 0, proving the significance of the effect of FC on BI, with a β-value of 0.513. The confidence interval for the direct effect was [0.308,0.488] also excluding 0, indicating that the direct effect was significant. In addition, the confidence interval for the total indirect effect was [0.124,0.267], which did not contain 0. The fact that the total indirect effect was distributed across the three pathways, and that none of these pathways contained a confidence interval of 0, provides strong evidence for the role of the chained mediating effect of AI-TPACK and PE between FC and BI. As Table 11.

Table 11
Chain mediation effect of AI-TPACK and PE between FC and BI

			Bootstrap 95% CI	
Path	β	SE	Lower	Upper
Total effect	0.513	0.041	0.432	0.593
Direct effect	0.32	0.043	0.235	0.405
Total indirect effect	0.193	0.036	0.124	0.267
Path1	0.069	0.027	0.021	0.123
Path2	0.096	0.023	0.053	0.144
Path3	0.027	0.012	0.005	0.052

Abbreviations: Path1，FC→AI-TPACK→BI；Path2，FC→PE→BI；Path3，FC→AI-TPACK→PE→BI.

Qualitative findings

To further explore and interpret the findings from the quantitative phase, we categorized the results of the qualitative data analysis to reflect pre-service teachers' perspectives on FC, AI-TPACK, and PE:

Facilitating Conditions and Pre-Service Teachers' Willingness to Practice AI-Enhanced Teaching

Almost all pre-service teachers indicated that when they perceive the AI technology resources, training opportunities, and policy support (such as equipment and guidance) provided by the school, it directly alleviates their concerns about attempting AI-based teaching and enhances their willingness to practice. The more specific and timely the support, the stronger their willingness becomes.

> *"Without these supports, I definitely wouldn't dare to use AI in the classroom on my own, for fear of taking responsibility for any problems that may arise." (Student 3, Group 1)*

External support is the foundation for pre-service teachers to develop AI-TPACK. Only when teachers master the ability to integrate AI can they foresee the practical teaching value of AI, thereby directly stimulating their willingness to practice.

> *"The school invited experts to teach us how to design tiered homework using AI. I learned how to push different questions based on students' levels. After practicing a few times, I found that it can indeed help underachieving students improve their scores. Now, I really want to promote this method in the graduating class!" (Student 4, Group 2)*

AI-TPACK and Pre-Service Teachers' Willingness to Practice AI-Enhanced Teaching

Pre-service teachers who master how to deeply integrate AI technology with subject content and teaching methods (such as using AI to design differentiated tasks and analyze learning situations) will have the willingness to actively apply AI because they "know how to teach".

"I have learned how to use AI to analyze the weak points in students' compositions and then create questions based on these weaknesses. Now, I really want to test the effect and feel that it can truly help students." (Student 7, Group 2)

Most pre-service teachers indicate that with external support, they can directly promote the development of AI-TPACK abilities, and this knowledge growth further stimulates their willingness to use AI for teaching.

"The teacher took us to use AI tools to break down the text, and I finally understood how to integrate AI with reading classes. Now I really want to design an AI-assisted deep reading class!" (Student 2, Group 1)

"The AI teaching case library provided by the school has taught me interdisciplinary integration methods, which gives me the confidence to apply AI to project-based learning." (Student 3, Group 2)

Performance Expectancy and Pre-Service Teachers' Willingness to Practice AI-Enhanced Teaching

Pre-service teachers who believe they can handle AI tools (such as operating them proficiently and addressing unexpected issues) and anticipate positive teaching outcomes (such as improved efficiency and increased student engagement) will be more willing to take action due to their "expected success."

"I have practiced using AI for classroom interaction several times, and it went smoothly. Students should like it. I plan to use it during my internship next semester." (Student 2, Group 2)

When pre-service teachers, through external support such as resources and training, firsthand experience the potential of AI technology to improve teaching efficiency, student engagement, or their own professional growth, they will become more willing to actively try AI-based teaching.

"Professional teachers taught us step by step how to use AI to generate courseware. After practicing a few times, we became familiar with it. Now we feel that using AI in class is very easy, and we will definitely use it in our teaching in the future!" (Student 5, Group 1)

DISCUSSION

To answer research question (1), previous studies showed FC does not affect teachers' classroom technology use (Abd Rahman et al., 2021). In contrast, our study found a direct effect of FC on pre-service teachers' BI. TPACK and FC also positively influence digital teaching behaviors, with TPACK having the greatest impact (Tang et al., 2024). We revealed a direct effect of AI-TPACK on pre-service teachers' BI in using AI. Consistent with other studies, PE positively impact technology use intentions (Proctor & Marks, 2013).

For research question (2), we demonstrated that pre-service teachers' AI-TPACK mediates the effect of FC on their BI to use AI in teaching (FC→AI-TPACK→BI). This aligns with findings by Hang Khong et al. and An et al., showing FC influences TPACK, emphasizing the importance of technical and expert support (An et al., 2023). Adequate material bases and supportive environments motivate pre-service teachers to learn AI, enhancing their AI-TPACK. Higher AI-TPACK levels increase familiarity and trust in AI, boosting their willingness to use it in teaching. Some educators struggle to integrate AI into their technical pedagogical content knowledge (Wijaya et al., 2021). In the AI era, AI technologies have transformed teaching tools and teachers' cognitive structures and methods (Li, 2022). The AI-TPACK framework helps pre-service teachers recognize AI's potential in education. Current AI-TPACK research is still emerging, focusing on components without exploring intrinsic relationships (Ning et al., 2024). Our study not only shows AI-TPACK's direct impact on pre-service teachers' AI BI but also establishes its mediation between FC and BI.

Second, our study showed that pre-service teachers' PE mediated the effect of FC on their BI to teach with AI-assisted instruction (FC→PE→BI). This aligns with the findings of Hang Khong et al. (2023), who observed that FC are positively correlated with teachers' perceptions of technology effectiveness. Our study suggests FC indirectly affects BI by influencing PE. Better FC for AI in teaching (e.g., easy access, simple operation, sufficient support) raise expectations for teaching effectiveness and competence, increasing willingness to use AI. Consistent with Cabellos et al., school FC significantly affected teachers' willingness to use technology (Cabellos et al., 2024). Even with positive attitudes, lack of FC reduces IT use. This underscores the significance of FC in teachers' practice.

Our study also revealed a chain-mediating role of AI-TPACK and PE in the effect of FC on BI (FC→AI-TPACK→PE→BI). AI-TPACK and PE are mediators, forming a chain through which FC indirectly affects BI. AI-TPACK predicted PE, aligning with previous research (J. Yang et al., 2021) suggesting TPACK affects PU. Hang Khong et al. found FC positively affected PU and online learning TPACK (Khong et al., 2023). Consistent with prior studies, our study confirmed AI-TPACK and PE's mediating role. Analyzing these effects deepened our understanding of the complex relationship between FC, AI-TPACK, PE, and BI. The chain-mediating effect (FC→AI-TPACK→PE→BI) reveals how external FC are mediated by internal competence (AI-TPACK) and cognitive changes (PE) to influence BI.

The conclusions of this study are only applicable to pre-service teachers, and the technology acceptance mechanism of in-service teachers remains to be further verified.

CONCLUSION AND SUGGESTIONS

This study extends the UTAUT model and integrates AI-TPACK to explore the key factors influencing pre-service teachers' BI to use AI in teaching, with a specific focus on the complex relationships among FC, AI-TPACK, and PE. It provides empirical evidence and practical guidance for enhancing pre-service teachers' willingness to integrate AI into future teaching practices.

Based on the research findings, it is observed that the formation of pre-service teachers' willingness to engage in AI-assisted teaching follows a progressive process: environmental support (FC)→capacity building (AI-TPACK)→ cognitive transformation (PE) → behavioral intention (BI). AI-TPACK serves as a key hub connecting external support and internal motivation. For normal education school, several strategies can be adopted to improve pre-service teachers' BI:

Creating a robust FC environment: In the teacher education environment, improving technological infrastructure includes the following: in terms of hardware, building AI teaching laboratories equipped with high-performance computing devices and terminal tools (such as smart tablets and AR glasses); in terms of technical support, establishing an "AI Teaching Support Center" to provide real-time technical response and build an AI teaching knowledge base; in addition, providing pre-service teachers with stable artificial intelligence teaching platforms and tools, developing and integrating high-quality AI educational resources, forming an AI support team composed of technical experts and subject teaching experts, and providing opportunities for AI application in teaching design and practice.

Incorporating AI-TPACK as a core competency: Embedding AI-TPACK into the teacher education curriculum system to systematically develop pre-service teachers' integrated abilities in AI technology and pedagogy.

Enhancing PE: Utilizing methods such as model lessons and excellent lesson plan exchanges to showcase how AI can effectively address teaching challenges and improve instructional outcomes, thereby strengthening pre-service teachers' PE.

LIMITATIONS

This study has limitations requiring further research. First, while it examined FC, AI-TPACK, and PE on pre-service teachers' AI integration, other relevant factors may exist and deserve exploration. Second, This study's findings, derived from a sample of second-year pre-service teachers in central China, necessitate that the relevant conclusions be interpreted within the context of this specific demographic and regional background.Future studies should include educators from more regions and grades to enhance data sample and generalizability.Thirdly, the research data primarily relies on participants' self-reported questionnaires. While measures such as ensuring anonymity and utilizing validated scales were implemented to mitigate potential biases, some limitations remain unavoidable. Future studies should integrate more objective measurement methods to validate and supplement self-reported results.Fourthly, this study did not explore potential gender differences. Future research should prioritize rigorous tests of measurement invariance; based on confirming measurement equivalence, it should systematically examine the moderating effects of gender and other key background variables (e.g., disciplinary background and prior technical experience).

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