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A Study on the Factors Influencing the Acceptance of Generative Artificial Intelligence Among Primary and Secondary School Teachers

Abstract: At present, a technological revolution has unfolded in the education sector due to the rapid development of generative artificial intelligence. What makes a profound impact on the quality of educational transformation is whether primary and secondary school teachers are willing to integrate generative artificial intelligence into teaching practices. Against this backdrop, the Unified Theory of Acceptance and Use of Technology (UTAUT) model is applied in this study to investigate the determinants influencing generative artificial intelligence adoption among 448 primary and secondary school teachers. This model incorporates four additional factors: personal innovativeness, self-efficacy, perceived risk, and Technological Pedagogical Content Knowledge (TPACK). It is revealed by this study that personal innovativeness and facilitating conditions have significant positive effects on behavioral intention, while TPACK and behavioral intention exert a significant positive influence on usage behavior. Self-efficacy makes a significant positive impact on TPACK, whereas TPACK exerts a significant negative effect on performance expectancy. Both social influence and TPACK are found to significantly enhance effort expectancy, while social influence, effort expectancy, and self-efficacy are shown to exert significant positive effects on performance expectancy collectively. This study illustrates the moderating role of specific variables. In practice, those teachers with different educational backgrounds vary significantly disparities in performance expectancy, despite the persistent statistical insignificance of other moderating effects. Finally, targeted recommendations are made according to these results to promote the effective integration and development of generative artificial intelligence technology in K-12 educational practices.

Keywords: Generative Artificial Intelligence; Primary and Secondary School Teachers; Influencing Factors; UTAUT Model

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1 Introduction

With the release of DeepSeek-R1 large model in January 2025, generative artificial intelligence was propelled to a new peak. Represented by DeepSeek, generative artificial intelligence tools can fulfill various functions, such as generating teaching content, designing teaching plans, and providing teaching resources. Due to these functions, there are some new opportunities created for education. From the perspective of teachers, they can benefit from it in many ways, including the effective implementation of teaching methods, the production of course content, the improvement of evaluation methods and the enhancement of management efficiency(Kikalishvili, 2024). So far, the application of generative artificial intelligence has been studied in various educational scenarios, such as enhancing teaching efficiency(Hooda et al., 2022), improving the effectiveness and efficiency of reviewing and grading

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students' assignments(Chen et al., 2020). Besides, great application potential in the teaching of science (Lee & Zhai, 2024). However, it is noteworthy that the acceptance and adaptability of front-line teachers determine whether the value of generative artificial intelligence empowering education can be fully realized. There are many practical challenges encountered by the acceptance of generative artificial intelligence among primary and secondary school teachers, including the role positioning of teachers and the transformation of teaching models and methods. In addition, teachers are concerns about educational equity and ethical risks in practice. Therefore, it is crucial to understand the acceptance of generative artificial intelligence by primary and secondary school teachers and its influencing factors, as required to promote the application of generative artificial intelligence in primary and secondary schools and to guide teachers towards the effective application of it.

Further with previous research, the scope of investigation is broadened in this study. The primary objective of this study is a twofold one. On the one hand, it is to understand teachers' "initial impression" of generative artificial intelligence. On the other hand, it is to identify the key factors that drive or hinder their "acceptance". Those teachers who have taken the first step in using it are the only group from whom valuable insights can be gained into "what factors prompt them to continue using it" or "what obstacles might cause them to give up". Therefore, this study focuses on K-12 teachers across all disciplines who have experiences in using generative artificial intelligence. Through a questionnaire survey, an analyze is conducted to explore the influencing factors of primary and secondary school teachers' use of generative artificial intelligence. Then the UTAUT model is applied to construct an acceptance model of primary and secondary school teachers towards generative artificial intelligence. Additionally, the structural equation model is used to analyze the relationship between variables. On this basis, our hypotheses are proposed and verified. This study aims to reveal the key drivers and underlying mechanisms influencing the use of generative artificial intelligence among primary and secondary school teachers. Also, countermeasures and suggestions are proposed to promote the acceptance and application of generative artificial intelligence by primary and secondary school teachers, thus providing a practical reference for empowering primary and secondary education with generative artificial intelligence.

2 Literature review

2.1 Generative artificial intelligence in K-12 Education

Generative artificial intelligence has multiple functions, such as text generation, image generation, and video generation. Its rapid development has accelerated the transformation in the field of education. Many researchers have focused on the application of generative artificial intelligence in K-12 educational scenarios. Generative artificial intelligence can play an important role in supplementing the imbalance of the teacher−student ratio, improving the effect of after-school personalized tutoring, and expanding the depth of knowledge while significantly shortening the time for teachers to prepare lessons and design lesson plans(Shouqian et al., 2025); the quality of teaching plans can also be improved(Hu et al., 2025); the teaching plans generated by LLMs excel in setting instructional objectives, identifying teaching priorities, organizing problem chains and teaching activities,

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articulating subject content, and selecting methods and strategies(Hu et al., 2024). Besides, generative artificial intelligence offers instant and targeted feedback. This provides personalized support to students, helping those who struggle with writing to improve their work(X. Zhang et al., 2025); when utilized thoughtfully, artificial intelligence/LLM technological interventions and co-creation in secondary schools have the potential to be high-quality, interest-creating tools for writing instruction(Spitsberg et al., 2025); and reduce students' cognitive load(J. Chen et al., 2025). Generative artificial intelligence plays a role in personalized learning, as well as in visualization, program simulation, feedback, and evaluation efficiency(B. Liu et al., 2025). This highlights the usefulness of ChatGPT in supporting structured learning activities. Teachers can also reflect on teaching practices and modify evaluations based on the annotations of generative artificial intelligence(Nguyen & Hayward, 2025). With the assistance of generative artificial intelligence, teaching skills training for pre-service teachers can enhance their self-efficacy and higher-order thinking ability(Lu et al., 2024). For primary school students, generative artificial intelligence can enhance their confidence and reduce anxiety in oral English learning(Tai & Chen, 2024); for middle school students, generative artificial intelligence can help them write more efficiently(Levine et al., 2025).

Some scholars have paid attention to the challenges brought by the application of generative artificial intelligence, such as lack of transparency, lack of reliability of the results, and lack of originality of the generated content(Lee, 2024). Primary school teachers worried that the information provided by generative artificial intelligence lacks accuracy, thereby bringing negative impacts(Uğraş et al., 2024). Primary school teachers are more willing to let students use generative artificial intelligence than junior high school teachers, while senior high school teachers are more cautious about the use of generative artificial intelligence(R. Chen et al., 2025). In previous studies on teachers' acceptance of generative artificial intelligence, many have focused on a specific teaching scenario, a particular subject, or a certain region. This may lead to the research results being applicable only to a small scope. Therefore, this study no longer focuses on a single teaching scenario or subject and further expands the investigation area. As the main venue for implementing systematic education, schools should undertake the task of cultivating students' technical literacy from the stage of basic education. And teachers, as the practitioners of education and teaching, their acceptance and application of generative artificial intelligence technology are of great significance for the cultivation of students' technical literacy.

2.2 Research on Technology acceptance

The research on technology acceptance has achieved abundant results. In terms of research methodologies, most scholars adopt quantitative approaches, while a minority employ qualitative or mixed methods. In quantitative studies, structural equation modeling (SEM) is widely utilized. For instance, they analyzed the influencing factors of pre-service teachers' use of generative artificial intelligence in teaching through the structural equation model(SEM)(K. Wang et al., 2024); analyzed the influencing factors of artificial intelligence chatbot use by pre-service mathematics teachers through the structural equation model(SEM) (Wijaya et al., 2025); used the structural equation model to explore the behavioral willingness of middle school English teachers to use artificial intelligence in teaching(An et al., 2023); and explore the influence of multiple factors on the acceptance of artificial intelligence

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by pre-service teachers through structural equation model(SEM)(C. Zhang et al., 2025). A few scholars still adopt qualitative methods. For instance, there is a study that explores the factors influencing K-12 teachers' integration of artificial intelligence into the educational environment through qualitative methods(Filiz et al., 2025). In addition, some scholars have adopted a mixed approach. For instance, they explored the use and experience of artificial intelligence by EFL learners through questionnaires and interviews(G. L. Liu et al., 2025); and used mixed methods to explore the use of chatbots by college students(Ebadi & Amini, 2024).

In summary, the Unified Theory of Acceptance and Use of Technology (UTAUT) model has been widely adopted in technology acceptance research. However, existing studies predominantly focus on teachers within specific disciplines or educational stages. Although some research has addressed primary and secondary school teachers, it largely prioritizes the original variables of the UTAUT model while paying limited attention to additional contextual factors. The UTAUT accounts for usability and usefulness factors pertaining to technology from users' perspectives(An et al., 2023). Therefore, this model is particularly valuable for examining how external factors, such as its usefulness, simplicity, and support from organizations and social networks, impact individuals' inclination toward technology adoption(Chao, 2019). Meanwhile, the UTAUT model, renowned for its high predictive accuracy, has been found to be approximately 70% effective in predicting technology acceptance(Oye et al., 2014), establishing it as a key theory in the field of technology adoption(Agyei & Razi, 2022). Therefore, this study extends the UTAUT framework by incorporating variables specific to generative artificial intelligence-empowered educational contexts, aiming to conduct a multidimensional analysis of the factors influencing generative artificial intelligence adoption among primary and secondary school teachers.

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3 Theoretical model and Hypothesis development

3.1 Theoretical model

The Unified Theory of Acceptance and Use of Technology (UTAUT) model was proposed by Venkatesh in 2003(Venkatesh et al., 2003) as a comprehensive framework integrating models such as the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Theory of Reasoned Action (TRA). The original model comprises four core constructs--performance expectancy, effort expectancy, social influence, and facilitating conditions--and four moderating variables: gender, age, experience, and voluntariness. Due to its robust explanatory power in predicting technology adoption and usage behaviors, UTAUT has been widely applied in technology acceptance research.

This study retains the four core constructs of the UTAUT model and introduces four new variables based on the pedagogical characteristics of primary and secondary school teachers: Personal Innovativeness: Studies have pointed out that people with higher personal innovation are more inclined to try new technologies and new ideas(Al-Adwan et al., 2023). Therefore, adding the variable of individual innovativeness can not only make up for the deficiency of the original UTAUT model in explaining the differences in individual cognitive abilities but also

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reflect the psychological characteristics of primary and secondary school teachers when using new technologies. Self-Efficacy: Bandura emphasized that high self-efficacy is critical for acquiring skills, retaining knowledge, and maintaining task focus(Bandura, 1997). Therefore, adding self-efficacy compensates for the UTAUT model's inadequacy in accounting for individual belief variations and enables analysis of teachers' intrinsic motivations when confronting emerging technologies. Perceived Risk: The risks associated with applying generative artificial intelligence in education primarily include ethical risks, content risks, and occupational risks. Therefore, incorporating the variable of perceived risk not only addresses the UTAUT model's limitations in reflecting barriers to technology adoption but also elucidates teachers' decision-making mechanisms when encountering emerging technologies. TPACK (Technological Pedagogical Content Knowledge): TPACK represents the integration of technological, pedagogical, and content knowledge. Studies have found that in the TAM model, TPACK has a significant impact on behavioral intentions through perceived usefulness and perceived ease of use(Hsu, 2016). Since UTAUT was developed based on TAM, integrating TPACK into the UTAUT framework compensates for its inadequacy in capturing teachers' professional competencies while revealing their domain-specific needs when adopting new technologies.

Furthermore, in this study, the moderating variables were processed based on the UTAUT model, and the two moderating variables, "experience" and "voluntariness" were deleted. Retain the variables of "gender" and "age". Since teachers with different teaching years and educational qualifications have different practical demands for generative artificial intelligence, the variables of "teaching years" and "educational qualifications" have been newly added. The adjusted theoretical model is illustrated in **Figure 1**.

(Insert Figure 1 here)

3.2 Hypothesis development

Based on the theoretical framework above, this study proposes the following hypotheses across ten dimensions: performance expectancy, effort expectancy, social influence, facilitating conditions, personal innovativeness, self-efficacy, perceived risk, TPACK (Technological Pedagogical Content Knowledge), behavioral intention, and usage behavior.

Performance Expectancy

Performance Expectancy refers to an individual's perception of the potential benefits a technology offers in enhancing their job performance(Venkatesh et al., 2003). In this study, it is defined as the extent to which primary and secondary school teachers believe that using generative artificial intelligence can improve their work efficiency. Studies have shown that performance expectations significantly influence students' behavioral intentions in using generative artificial intelligence(Du & Lv, 2024). Accordingly, the following hypothesis is proposed:

H1: Performance expectancy positively influences primary and secondary school teachers' behavioral intention to use generative artificial intelligence in teaching.

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Effort Expectancy

Effort expectancy refers to the perceived ease of use or degree of effort required when utilizing a technology or system(Venkatesh et al., 2003). In this study, it is defined as the level of effort that primary and secondary school teachers perceive as necessary to expend when using generative artificial intelligence. The research by An et al. demonstrated that effort expectancy positively influences the performance expectancy of middle school English teachers in adopting artificial intelligence technologies(An et al., 2023). Based on this, the following hypotheses are proposed in this study:

H2: Effort expectancy has a positive effect on primary and secondary school teachers' behavioral intention to use generative artificial intelligence in teaching.

H3: Effort expectancy has a positive effect on primary and secondary school teachers' performance expectancy in using generative artificial intelligence in teaching.

Social Influence

Social influence refers to the degree to which individuals important to a person believe they should use a particular technology(Venkatesh et al., 2003). In this study, it is defined as the extent to which primary and secondary school teachers are affected by surrounding community members when using generative artificial intelligence technologies. Research shows that social influence has a positive impact on both the behavioral intention and effort expectancy of university teachers when using ChatGPT(Khlaif et al., 2024; Strzelecki et al., 2024). And it also has a positive impact on the learning performance of college students(Nuseir et al., 2023). Based on these findings, the following hypotheses are proposed:

H4: Social influence has a positive effect on primary and secondary school teachers' behavioral intention to use generative artificial intelligence in teaching.

H5: Social influence has a positive effect on primary and secondary school teachers' performance expectancy in using generative artificial intelligence in teaching.

H6: Social influence has a positive effect on primary and secondary school teachers' effort expectancy in using generative artificial intelligence in teaching.

Facilitating Conditions

Facilitating conditions denote the perceived availability of resources and support required to complete a task(Venkatesh et al., 2003). This study defines it as the support accessible to primary and secondary school teachers when using generative artificial intelligence technologies, encompassing relevant equipment resources, knowledge reserves, and policy support. Studies have found that facilitation conditions have a positive impact on the behavioral intention of college teachers to adopt mobile technologies(Hu et al., 2020). Based on this, the following hypothesis is proposed:

H7: Facilitating conditions have a positive effect on primary and secondary school teachers' behavioral intention to use generative artificial intelligence in teaching.

Personal Innovativeness

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Personal innovativeness refers to the propensity to accept technological innovations, reflecting a risk-taking tendency associated with experimenting with new technologies(Farooq et al., 2017). This study defines it as primary and secondary school teachers' inclination to explore and utilize generative artificial intelligence technologies. Research has found that an individual's innovation has a significantly positive impact on the behavioral intention of college teachers to use ChatGPT(Strzelecki et al., 2024). Based on this, the following hypothesis is proposed:

H8: Personal innovativeness has a positive effect on primary and secondary school teachers' behavioral intention to use generative artificial intelligence in teaching.

Self-Efficacy

Self-efficacy refers to an individual's confidence in their ability to execute necessary behaviors to achieve specific performance levels(K. Wang et al., 2024). This study defines it as primary and secondary school teachers' confidence in their capability to proficiently use generative artificial intelligence technologies. Previous studies have indicated that self-efficacy positively influences teachers' performance expectancy and TPACK(K. Wang et al., 2024). Based on this, the following hypotheses are proposed:

H9: Self-efficacy of primary and secondary school teachers has a positive effect on performance expectancy.

H10: Self-efficacy of primary and secondary school teachers has a positive effect on TPACK.

Perceived Risk

Bauer first proposed perceived risk theory, defining it as "the anticipation of risks associated with behavioral outcomes prior to action implementation"(Bauer, 1967). This study operationalizes it as the extent to which primary and secondary school teachers expect uncertain risks when using generative artificial intelligence technologies. Previous research has shown that perceived risk negatively affects users' behavioral intention(Pavlou, 2003). Based on this, the following hypothesis is proposed:

H11: Perceived risk has a negative effect on primary and secondary school teachers' behavioral intention to use generative artificial intelligence in teaching.

TPACK

Technological Pedagogical Content Knowledge (TPACK) represents the integration of technological, pedagogical, and content knowledge, encompassing four distinct types: Technological Content Knowledge (TCK), Pedagogical Content Knowledge (PCK), Technological Pedagogical Knowledge (TPK), and Technological Pedagogical Content Knowledge (TPACK)(Koehler et al., 2014). In the research on the digital teaching behaviors of primary school mathematics teachers, TPACK is the most significant factor influencing digital teaching behaviours(Tang et al., 2024). Furthermore, studies have found that TPACK has a significant impact on the perceived usefulness and perceived ease of use of K-12 teachers(Yang et al., 2021), where perceived usefulness corresponds to performance expectancy and perceived ease of use aligns with effort expectancy. Based on this theoretical foundation, the following hypotheses are proposed:

H12: TPACK has a positive effect on primary and secondary school teachers' performance expectancy.

H13: TPACK has a positive effect on primary and secondary school teachers' effort expectancy.

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H14: TPACK has a positive effect on primary and secondary school teachers' usage behavior.

Behavioral Intention

Behavioral intention refers to an individual's likelihood to adopt a specific technology in the future(Venkatesh et al., 2012). This study defines it as primary and secondary school teachers' intent to utilize generative artificial intelligence technologies. Studies have found that students' behavioral intentions in using artificial intelligence have a significant impact on their use behaviors(Arthur et al., 2025). Based on this, the following hypothesis is proposed:

H15: Behavioral intention has a positive effect on primary and secondary school teachers' use behavior of generative artificial intelligence technologies.

Moderating Variables

This study referred to the UTAUT model and adjusted the moderating variables to gender, age, educational attainment and teaching experience. To explore whether gender, age, educational attainment and teaching experience have a moderating effect on the relationship between performance expectations, effort expectations, community influence and facilitating conditions of primary and secondary school teachers' use of generative artificial intelligence and behavioral intentions.

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4 Methodology

4.1 Research measurement

This study refers to the research scales of Venkatesh(Venkatesh et al., 2003), Venkatesh(Venkatesh et al., 2012), Wijaya(Wijaya et al., 2025), and Nikou(Nikou & Economides, 2017), and combines the practical situation of primary and secondary school teachers' participation in generative artificial intelligence education. The final questionnaire was divided into two parts: The first section gathered demographic information (gender, age, educational background and other items); The second part is the investigation of influencing factors, including ten dimensions such as performance expectation, effort expectation, community influence and enabling conditions, and a total of 35 questions. The questionnaire survey in this study utilized a 5-point Likert scale ranging from 1(strongly disagree) to 5(strongly agree).

4.2 Reliability and validity test of the questionnaire

In order to ensure the reliability and validity of the questionnaire, the author conducted a pre-survey to test the reliability and validity of the questionnaire, and optimized the questionnaire items based on the test results until the reliability and validity were good. In this study, Cronbach's α coefficient was used to test the reliability of the self-compiled questionnaire. Through SPSS 27.0 statistics, it was found that the reliability coefficients of each variable were all higher than 0.8, and the overall reliabilitycoefficient was 0.968, indicating that the questionnaire had good reliability (Table 1). The data were obtained from a single source (participants or interviewees) using a self-reported approach with a fixed-response format. However, this data collection methodis susceptible to common method bias (CMB). CMB refers to the potential distortion caused by factors such as a shared measurement

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environment, item context, and item characteristics. To minimize potential sources of bias, when designing the questionnaire,we placed the questions for different variables on different pages(C. Wang et al., 2024). Meanwhile, this study utilized Harman's single-factor test technique. The results showed that the first common factor accounted for 43.6% of the variance, which was lower than the 50% threshold proposed by Hair et al.(F. Hair Jr et al., 2014). Therefore, based on the indices from Harman's single-factor test, it was concluded that there was no significant common method bias among the variables.

To ensure the good validity of the questionnaire, this study first conducted exploratory factor analysis (EFA), The KMO value was 0.943, and the $\chi 2$ value of Bartlett's sphericity test was 6565.044 ($p=0.000<0.001$), indicating that the questionnaire met the conditions for factor analysis (Table 2). Subsequent confirmatory factor analysis revealed all factor loading values are above 0.7, the AVE values above 0.5 and composite reliability (CR) values above 0.7, indicating good convergent validity. Furthermore, the square roots of the AVE for all variables are all greater than the maximum absolute value of the correlations between factors, indicating good discriminant validity.

Table 1 Results of Questionnaire reliability Analysis

Item	**PE**	**EE**	**SI**	**FC**	**PI**	**SE**	**PR**	**TPACK**	**BI**	**UB**
Cronbach's α	0.877	0.926	0.880	0.908	0.900	0.925	0.858	0.935	0.933	0.928
Overall Cronbach's α	0.968									

Table 2 Results of Exploratory Factor Analysis

KMO & Bartlett		
KMO		0.943
Bartlett's test	χ^2	6565.044
	df	435
	p	.000

4.3 Research procedure and samples

During the formal investigation stage, this study utilized the Chinese online survey platform "Wenjuanxing" (https://www.wjx.cn/) to collect data. The research relies on schools in Shaanxi, Gansu, Hebei, Beijing, Guangdong, Shanxi, Sichuan, Chongqing and other provinces to carry out the survey. The survey covers both economically developed areas with rich educational resources and economically backward areas with scarce educational resources. The time frame for questionnaire distribution was three weeks. From February 26, 2025 to March 17, 2025. Before answering the questionnaire, participants were provided with detailed information about the study. They only proceeded with the survey after providing informed consent and had the option to withdraw if they desired. Snowball sampling was used during data collection in this study. Our research subjects are primary and secondary school teachers who have used generative artificial intelligence. In the questionnaire, one of the questions

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inquires about whether teachers have used generative artificial intelligence. If the teacher has not used generative artificial intelligence, then we treat it as an invalid questionnaire. In addition, pre-test determined that it would normally take a participant 2 – 5 min to complete the questionnaire. Participants who completed the survey in <80 s were considered to have irresponsibly rushed through the questionnaire, and their data were deemed invalid. After the survey, a total of 588 questionnaires were distributed, of which 448 were valid, with an effective rate of 76.19%.

5 Data analysis

Based on the research model of generative artificial intelligence acceptance, SPSSAU and AMOS 24.0 were used to analyze the influencing factors of primary and secondary school teachers' generative artificial intelligence acceptance and the structural relationship between these factors. At the same time, the methods of moderating effect test were used to explore the moderating effects of four moderating variables: gender, age, education background and teaching age.

5.1 Participants

Among the 448 primary and secondary school teachers who participated in the survey, 105 were male and 343 were female. Among them, those with more than 10 years of teaching experience (42.2%) accounted for the highest proportion. 93.5% of the teachers are aged between 20 and 50. 52.2% of the teachers come from schools in ordinary cities (cities, counties). 50.0% of the teachers are primary school teachers. 66.1% of the teachers have a bachelor's degree. The subject distribution is mainly composed of teachers of Chinese (15.4%), mathematics (15.8%), English (22.8%) and information technology (17.6%). There are biases in the gender and subject distribution of the samples in this study. The proportion of female teachers is too high, which may lead to inference results favoring the female group. The relatively high proportion of information technology teachers may lead to an overall assessment of the acceptance of technology being overly optimistic. The specific demographic data are shown in Table 3.

Table 3 Demographic statistics

Item	Category	Quantity	%
Gender	male	105	23.4
	female	343	76.6
Age of teaching	0-3 years	102	22.8
	3-6 years	91	20.3
	6-10 years	66	14.7
	⩾10 years	189	42.2
Age	20-30 years	159	35.5
	30-40 years	147	32.8
	40-50 years	113	25.2

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	⩾50 years	29	6.5
Level of school	Provincial Model Schools	40	8.9
	Municipal Exemplary Schools	34	7.6
	District/Country Key Schools	88	19.6
	Regular Public Schools	234	52.2
	Rural-serving Schools	33	7.4
	Other School Types	19	4.2
Educational stage	Primary School	224	50.0
	Junior High School	149	33.3
	Senior High School	58	12.9
	Other Stages	17	3.8
Educational background	Junior College Education	14	3.1
	Bachelor's Degree	296	66.1
	Master's Degree	130	29.0
	Doctor's Degree	8	1.8
Subject	Chinese	69	15.4
	Math	71	15.8
	English	102	22.8
	Physics	13	2.9
	Chemistry	12	2.7
	Politics	18	4.0
	Science	7	1.6
	Information Technology	79	17.6
	History	8	1.8
	Geography	3	0.7
	Physical Education	11	2.5
	Music	7	1.6
	Art	14	3.1
	Biology	13	2.9
	Other Subjects	21	4.7

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5.2 Normality test and descriptive statistics

The normality test was conducted on the scale items in the questionnaire to analyze the group's recognition degree of the measurement items as a whole. The results show (Table 4) that the average values of each measurement item vary between 3.67 and 4.426. The absolute values of skewness of each variable's measurement item are all

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less than 2, and the absolute values of kurtosis are all less than 3, indicating that the data distribution is approximately a normal distribution(Cai et al., 2024; Wijaya et al., 2025).

Table 4 Normality Test

Dimention	Item	Mean	SD	Skewness	Kurtosis
PE	PE1	4.261	0.817	-0.91	0.537
	PE2	4.426	0.774	-1.222	1.106
	PE3	4.259	0.854	-0.891	0.198
EE	EE1	3.85	0.906	-0.389	-0.24
	EE2	3.719	0.97	-0.313	-0.432
	EE3	3.67	0.991	-0.283	-0.433
SI	SI1	4.248	0.882	-0.977	0.359
	SI2	4.217	0.825	-0.685	-0.36
	SI3	4.06	0.866	-0.428	-0.654
FC	FC1	3.703	1.063	-0.428	-0.4
	FC2	3.685	0.97	-0.221	-0.497
	FC3	3.786	1.016	-0.345	-0.748
PI	PI1	4.308	0.762	-0.736	-0.405
	PI2	4.254	0.779	-0.649	-0.531
	PI3	4.344	0.761	-0.822	-0.294
SE	SE1	4.112	0.862	-0.637	-0.223
	SE2	4.067	0.846	-0.551	-0.237
	SE3	3.933	0.915	-0.431	-0.485
PR	PR1	3.674	1.05	-0.309	-0.551
	PR2	3.342	1.152	-0.147	-0.76
	PR3	3.638	1.094	-0.429	-0.541
TPACK	TPACK1	3.665	0.946	-0.212	-0.308
	TPACK2	3.71	0.944	-0.177	-0.557
	TPACK3	3.853	0.903	-0.2	-0.85
BI	BI1	4.078	0.803	-0.246	-1.133
	BI2	4.172	0.788	-0.479	-0.758
	BI3	4.201	0.808	-0.56	-0.743
UB	UB1	3.913	0.948	-0.427	-0.542
	UB2	3.77	0.943	-0.267	-0.442
	UB3	3.973	0.917	-0.489	-0.297

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5.3 Result of Measurement model test

The tests of the measurement model include reliability, convergent validity and discriminant validity tests. As shown in Table 5, all factor load values are above 0.7, indicating that the measurement relationship between the factors and the measurement items is good. The CR values were all greater than 0.7 and the AVE values were all greater than 0.5, indicating good polymerization validity. Through Cronbach's alpha coefficient test, all items were above 0.7, indicating good internal consistency reliability. As shown in Table 6, the values of the square roots of each AVE item are all greater than the absolute values of the correlation coefficients between each item and the others, indicating good discriminative validity. Meanwhile, the fitting index of the measurement model also reached a good level (Table 7), indicating that the fitting degree of the measurement model is relatively good.

Table 5 Assessment of Reliability and Convergent Validity

Dimention	Item	Factor Loading	CR	AVE	α
PE	I believe that generative artificial intelligence can enhance my teaching effectiveness	0.879	0.905	0.760	0.904
	I believe generative artificial intelligence can enhance my work efficiency	0.864			
	I believe that generative artificial intelligence can promote my professional development	0.872			
EE	For me, learning how to use generative artificial intelligence is easy.	0.841	0.865	0.681	0.862
	I find it easy to use generative artificial intelligence in teaching	0.850			
	I have mastered various techniques for using generative artificial intelligence for teaching	0.784			
SI	My school administration supports the use of generative artificial intelligence in my teaching.	0.729	0.823	0.609	0.815
	My colleagues approve of my employing generative artificial intelligence in teaching.	0.855			
	My students prefer that I use generative artificial intelligence for teaching	0.751			
FC	I have the necessary equipment to use generative artificial intelligence.	0.843	0.865	0.682	0.862

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	I possess the knowledge and skills required to use generative artificial intelligence.	0.871			
	My use of generative artificial intelligence is supported by policies.	0.761			
PI	I like experimenting with new technologies	0.891	0.909	0.768	0.908
	I often focus on the latest development of the impact of new technology development on education	0.853			
	If I heard about a new technology, I would look for ways to experiment with it in my teaching.	0.885			
SE	If I work hard enough, I can use generative artificial intelligence for instructional design	0.865	0.902	0.754	0.899
	If I work hard enough, I can use generative artificial intelligence to assist classroom teaching	0.908			
	If I work hard enough, I can use generative artificial intelligence for teaching evaluation	0.831			
PR	I worried that the use of generative artificial intelligence will reveal personal information and violate privacy rights.	0.705	0.835	0.629	0.833
	I worried that the use of generative artificial intelligence in teaching will affect the emotional communication and interactive experience between teachers and students.	0.860			
	I think the use of generative artificial intelligence will weaken students' thinking ability and affect their independent thinking	0.806			
TPACK	I can teach the methods of using generative artificial intelligence to solve problems	0.824	0.915	0.782	0.910
	I know how to effectively use generative artificial intelligence for teaching activities	0.935			
	I know how to effectively integrate generative artificial intelligence, subject knowledge and teaching methods into	0.890			

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	classroom teaching				
BI	In future teaching activities, I am more inclined to apply generative artificial intelligence technology to carry out teaching design, implementation and evaluation activities	0.871	0.925	0.804	0.925
	If there are suitable conditions, I am willing to use generative artificial intelligence technology in the process of teaching design, implementation and evaluation	0.899			
	I am willing to recommend the use of generative artificial intelligence in instructional design, implementation, and evaluation to those around me.	0.919			
UB	I once used generative artificial intelligence to assist in teaching design, teaching implementation and teaching evaluation.	0.883	0.918	0.790	0.917
	I often apply generative artificial intelligence technology in teaching design, teaching implementation and teaching evaluation.	0.924			
	I once recommended that others use generative artificial intelligence in instructional design, implementation and evaluation.	0.858			

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Table 6 Discriminant Validity Test

	PE	EE	SI	FC	PI	SE	PR	TPACK	BI	UB
PE	0.872									
EE	0.585	0.825								
SI	0.661	0.587	0.780							
FC	0.436	0.627	0.640	0.826						
PI	0.584	0.501	0.654	0.570	0.876					
SE	0.508	0.590	0.561	0.666	0.696	0.868				
PR	0.143	0.315	0.225	0.282	0.199	0.271	0.793			

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TPACK	0.393	0.621	0.514	0.724	0.561	0.726	0.384	0.884		
BI	0.566	0.505	0.640	0.559	0.722	0.656	0.208	0.622	0.897	
UB	0.494	0.601	0.545	0.618	0.586	0.725	0.339	0.743	0.702	0.889

Table 7 Goodness-of-fit indices

Indicator	χ^2/df	RMR	RMSEA	GFI	AGFI	NFI	CFI	TLI
Recommended Criteria	＜3.0	＜0.05	＜0.08	＞0.8	＞0.8	＞0.9	＞0.9	＞0.9
P-value	2.561	0.034	0.059	0.880	0.845	0.923	0.951	0.941

5.4 Result of Structural model test

In this study, AMOS24.0 was used to test the fitting index of structural equation model. As shown in Table 8, the fitting degree of structural model of generative artificial intelligence acceptance is good, which is suitable for analyzing the influencing factors of primary and secondary school teachers' use of generative artificial intelligence. The detailed results of the structural model test are shown in **Figure 2**.

Table 8 Structural model fit index

Indicator	CMIN/DF	SRMR	RMSEA	GFI	NFI	IFI	TLI	CFI
Recommended Criteria	＜3.0	＜0.08	＜0.08	＞0.8	＞0.9	＞0.9	＞0.9	＞0.9
P-value	2.973	0.056	0.066	0.858	0.905	0.935	0.925	0.934

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(Insert Figure 2 here)

5.5 Result of Hypothesis test

The results of the hypothesis test are shown in Table 9. The P-values of H1, H2, H4 and H11 were all greater than 0.05, so none of these four paths had statistical significance. The P values of other paths were all less than 0.05, which are statistically significant. Therefore, H3, H5, H6, H7, H8, H9, H10, H12, H13, H14 and H15 were established, indicating that community influence, effort expectation and self-efficacy had a significant positive effect on performance expectation, and TPACK had a significant negative effect on performance expectation. Community influence has a significant positive impact on effort expectation. Personal innovation and facilitation conditions have a significant positive impact on behavioral intention. Self-efficacy has a significant positive impact on TPACK. TPACK has a significant positive impact on effort expectation and usage behavior. Behavioral intention has a significant positive impact on usage behavior. The final model of this study is shown in **Figure 3**.

Table 9 The results of the direct effects hypothesis

Hypothesis	Path	β	S.E.	C.R.	P	Conclusion

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H1	PE→BI	0.099	0.060	1.654	0.098	Not Supported
H2	EE→BI	0.013	0.052	0.243	0.808	Not Supported
H3	EE→PE	0.347	0.065	5.355	＜0.001	Supported
H4	SI→BI	0.176	0.100	1.755	0.079	Not Supported
H5	SI→PE	0.575	0.080	7.169	＜0.001	Supported
H6	SI→EE	0.526	0.067	7.858	＜0.001	Supported
H7	FC→BI	0.100	0.047	2.129	0.033	Supported
H8	PI→BI	0.587	0.066	8.891	＜0.001	Supported
H9	SE→PE	0.258	0.089	2.897	0.004	Supported
H10	SE→TPACK	0.905	0.048	18.900	＜0.001	Supported
H11	PR→BI	0.014	0.030	0.478	0.633	Not Supported
H12	TPACK→PE	-0.313	0.076	-4.133	＜0.001	Supported
H13	TPACK→EE	0.418	0.050	8.405	＜0.001	Supported
H14	TPACK→UB	0.571	0.042	13.743	＜0.001	Supported
H15	BI→UB	0.396	0.041	9.592	＜0.001	Supported

(Insert Figure 3 here)

5.6 Result of Moderation effect test

This study uses SPSSAU to test the moderating effect. The moderating effects of gender, age, educational attainment and teaching years on the relationship between performance expectation, effort expectation, community influence and facilitating conditions on behavioral intention were verified respectively. The results show that only one moderating effect is significant, that is, educational attainment significantly moderates the relationship between "performance expectations" and "behavioral intentions". The results indicated that higher educational levels strengthened the positive relationship between performance expectancy and behavioral intention, with education enhancing the predictive effect of performance expectancy on behavioral intention. Furthermore, no other moderating effects reached statistical significance (

Table 10).

Table 10 Moderation effect test

Path	β	T	P	Conclusion
Gender*PE→BI	0.012	0.296	0.768	No
Gender*EE→BI	0.096	1.674	0.095	No
Gender*SI→BI	-0.007	-0.198	0.843	No
Gender*FC→BI	-0.001	-0.015	0.988	No

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Age*PE→BI	-0.042	-1.054	0.292	No
Age*EE→BI	-0.011	-0.263	0.793	No
Age*SI→BI	0.016	0.432	0.666	No
Age*FC→BI	-0.014	-0.365	0.715	No
Age of teaching*PE→BI	-0.058	-1.478	0.140	No
Age of teaching*EE→BI	-0.051	-1.254	0.210	No
Age of teaching*SI→BI	-0.003	-0.089	0.929	No
Age of teaching*FC→BI	-0.028	-0.708	0.479	No
Education background*PE→BI	0.087	2.184	0.029	Yes
Education background*EE→BI	0.029	0.697	0.486	No
Education background*SI→BI	-0.005	-0.149	0.882	No
Education background*FC→BI	0.040	1.015	0.311	No

6 Discussion

In this study, the UTAUT model is used to explore the influencing factors of the acceptance of generative artificial intelligence among primary and secondary school teachers. This is purposed to promote the application of generative artificial intelligence in primary and secondary school education and teaching. In total, 15 hypotheses are proposed in this study, of which 11 are supported and 4 are rejected.

According to the research results, H1 is rejected, indicating that performance expectation exerts no significant influence on behavioral intention, which is similar to some other research findings. For instance, the research by Lin et al. found that performance expectations have no significant impact on users' behaviors when using artificial intelligence online e-learning products(Lin et al., 2022); Tan et al. 's research found that performance expectations have no significant impact on college students' willingness to continuously use ChatGPT(Tan et al., 2024); Razak et al. 's research found that performance expectations have no significant impact on graduate students' behavioral intentions in using artificial intelligence(Razak et al., 2025). This result indicates that performance expectation is not an important factor affecting the acceptance of using generative artificial intelligence among primary and secondary school teachers. The possible reasons are: The possible reasons are: (1) At present, primary and secondary schools may not have provided training for teachers on the use of new technologies, resulting in many problems encountered by teachers during the process of using new technologies, causing them to feel frustrated and thus reducing the effect of performance expectations; (2) Although generative artificial intelligence can empower multiple aspects of education and teaching, such as helping teachers design teaching plans and grade homework, thereby reducing their burden. However, the effective exertion of its functions depends on teachers' mastery of its usage skills. But currently, at the educational practice level, many generative artificial intelligence tools lack detailed application guidelines, which leads to teachers' inability to quickly master their operation

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methods and improve their work efficiency and teaching effectiveness in a short period of time, thereby weakening performance expectations. Furthermore, the results of the moderating effect test show that educational attainment significantly moderates the relationship between performance expectations and behavioral intentions, indicating that the behavioral intentions of teachers with different educational attainment levels using generative artificial intelligence are affected differently by performance expectations. The higher the educational attainment level, the stronger the positive relationship between performance expectations and behavioral intentions. That is to say, for teachers with high academic qualifications, strengthening performance expectations can enhance behavioral intentions even more.

In addition, H2, H4, and H11 are not supported, indicating that effort expectancy, social influence, and perceived risk have no significant impact on behavioral intention, which is different from the hypothesis in the original model. However, some studies have shown that effort expectancy, social influence, and perceived risks have no significant impact on behavioral intentions. For instance, the research by Wang et al. found that effort expectancy has no significant impact on the behavioral intention of pre-service teachers to adopt generative artificial intelligence(K. Wang et al., 2024). However, Wijaya et al.'s research found that effort expectancy, social influence, and perceived risk had no significant impact on the behavioral intention of pre-service mathematics teachers to use AI chatbots(Wijaya et al., 2025), which is similar to the findings in this study. The possible reasons are: (1) Our survey subjects are primary and secondary school teachers. For teachers, they may pay more attention to the effect of technology usage rather than the simplicity of its use. (2) When using new technologies, teachers may pay more attention to the benefits it brings to teaching or learning and seldom pay attention to its risks or consider them to be relatively small. (3) When teachers use new technologies for teaching, they may pay more attention to their own personal experiences and less to the opinions of others.

The research results show that among the 11 valid hypotheses, the path coefficient value of H10 is 0.905, indicating that the influence of self-efficacy (SE) on TPACK is the most significant in the model. This finding confirms the research of Wang et al. and Kul et al.(Kul et al., 2019; Wang & Zhao, 2021). This indicates that teachers with high self-efficacy may have greater confidence in their knowledge and ability to integrate technologies. Therefore, we speculate that their willingness and possibility to try new technologies in teaching practice are also relatively higher. By using new technologies, teachers' technical knowledge will be enhanced, thereby improving their TPACK level. Furthermore, the path coefficient value of H12 is negative, indicating that TPACK has a negative impact on performance expectancy (PE). The possible reasons are: (1) Teachers with a high TPACK have a deeper understanding of new technologies, a stronger sense of criticism, and can be aware of the possible negative impacts of the use of new technologies, thereby reducing teachers' performance expectancy; (2) Teachers with high TPACK have a more accurate understanding of technical knowledge, subject knowledge, and teaching knowledge. Therefore, they can more clearly assess the costs required for using new technologies in education and teaching, such as time, equipment, and resources. Considering these costs, teachers' performance expectancy will be lower.

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The research results confirm that H3, H5, and H9 are supported, demonstrating that effort expectancy, social influence, and self-efficacy all significantly positively affect performance expectancy, which is consistent with the findings of previous studies(An et al., 2023; Nuseir et al., 2023; K. Wang et al., 2024). It indicates that teachers with high effort expectancy will consider new technologies easier to master and thus believe that using this technology can better achieve teaching goals and improve teaching effects. Therefore, they have higher performance expectancy. When school administrators advocate the use of new technologies or other teachers are all using new technologies, teachers will be more inclined to recognize the role of new technologies, thereby raising performance expectancy. Teachers with high self-efficacy may be more convinced that they can enhance teaching efficiency and effectiveness by using new technologies, thereby raising performance expectancy.

The research results show that H6 and H13 are supported, proving that both social influence and TPACK have a significant positive impact on effort expectancy, which is consistent with the previous research findings(Khlaif et al., 2024; Yang et al., 2021). It is indicated that when others use or recommend new technologies, teachers are more inclined to believe that the technology is easy to use, thereby reducing the expectation of the difficulty of using the technology and increasing the effort expectancy. Teachers with a high level of TPACK can accurately judge the adaptability of the application of new technologies, thereby reducing the difficulty of using new technologies and also increasing the effort expectancy. Furthermore, the establishment of H7 and H8 proves that both the facilitating conditions and personal innovativeness have a significant positive impact on behavioral intention, which is consistent with the previous research findings(Hu et al., 2020; Strzelecki et al., 2024). It indicates that under the guarantee of conditions such as equipment resources or policy support, teachers have a stronger behavioral intention to use new technologies. Teachers with higher personal innovativeness tend to show a risky tendency to use new technologies, thereby enhancing their behavioral intention to use new technologies. The establishment of H14 proves that TPACK has a significant positive impact on use behavior. It indicates that the higher the TPACK level of teachers, the more effectively they can integrate technology with teaching, solve teaching problems more accurately, and improve use behavior. The establishment of H15 proves that behavioral intention has a significant positive impact on use behavior. This discovery is consistent with the assumption of the original model. That is to say, if teachers have the intention to use new technologies, then this intention is very likely to be transformed into actual use behavior.

In conclusion, the findings of this study align with the research conducted by Lin et al., Tan et al., and Razak et al.(Lin et al., 2022; Razak et al., 2025; Tan et al., 2024), consistently demonstrating that performance expectancy has no significant effect on behavioral intention. Similarly, the result that effort expectancy, social influence, and perceived risk have no significant impact on behavioral intention is corroborated by the research of Wang et al. and Wijaya et al.(K. Wang et al., 2024; Wijaya et al., 2025). In addition, the result found in this study that self-efficacy has a significant impact on TPACK is corroborated by the research of Wang et al. and Kul et al.(Kul et al., 2019; Wang & Zhao, 2021). The result that effort expectancy, social influence, and self-efficacy all significantly positively affect performance expectancy is corroborated by the studies of Nuseir et al., Wang et al., and Xin et al.(An et al.,

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2023; Nuseir et al., 2023; K. Wang et al., 2024). The finding that both social influence and TPACK significantly and positively influence effort expectancy aligns with the studies by Jinzhong et al. and Khlaif et al.(Khlaif et al., 2024; Yang et al., 2021). Both facilitating conditions and personal innovativeness demonstrate a significant positive influence on behavioral intention; this outcome is consistent with the research of Hu et al. and Strzelecki et al.(Hu et al., 2020; Strzelecki et al., 2024).

7 Practical implications

The research results show that the facilitating conditions and individual innovativeness have a significant positive impact on behavioral intention, and TPACK and behavioral intention have a significant positive impact on usage behavior. Based on the above research findings, to promote the effective application of generative artificial intelligence in primary and secondary schools, we put forward the following suggestions:

(1) Improve the facilitation conditions for teachers to use generative artificial intelligence. First, provide policy guarantees for teachers to use generative artificial intelligence. The education administrative department has introduced corresponding policies and systems to ensure the application of generative artificial intelligence in primary and secondary schools. To promote the effective use of generative AI, schools should integrate its applications into teacher performance assessment and create aligned incentive mechanisms. Second, provide device resources for teachers to use generative artificial intelligence. The education administrative department should provide comprehensive support to schools. This support includes direct financial assistance. It also involves partnering with technology enterprises to establish a team of professional technicians dedicated to resolving unexpected issues, such as technical malfunctions. Schools should equip all teachers with terminal devices capable of running generative artificial intelligence tools and develop generative artificial intelligence toolkits specific to each educational stage and subject. Third, provide professional training for teachers on the use of generative artificial intelligence. The school offers stratified training courses and establishes data archives of teachers' use of generative artificial intelligence. Based on the data usage, it intelligently pushes relevant resources to enhance teachers' application capabilities gradually.

(2) Strengthen the learning and advancement of innovative thinking among primary and secondary school teachers. Innovative thinking is the cognitive competency to define a need or a problem, generate new or changed ideas, develop an outcome in accordance with new or changed ideas, implement a new or improved outcome for the addressee, and adopt a new or improved outcome with added value. The first step is to investigate how primary and secondary school teachers are currently applying innovative thinking. Based on the findings, the next steps are to develop targeted teacher training courses; and create an innovative resource library empowered by generative artificial intelligence to support education and teaching. Hold innovative achievement competitions and forums, and provide support for the improvement of innovative thinking among primary and secondary school teachers. Second, formulate evaluation standards based on international advanced evaluation concepts to assess teachers' performance in innovative thinking and provide guidance for the improvement of teachers' innovative thinking.

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Thirdly, traditional technology training often focuses primarily on "how to operate." Therefore, this study recommends transforming training to address "how to apply innovatively." Schools and training institutions can design workshops to guide teachers in using methodologies like design thinking and project-based learning to proactively explore the integration points between generative artificial intelligence and teaching scenarios. For instance, organizing a "Generative Artificial Intelligence-Powered Learning Solution Design Competition" can encourage teachers to utilize generative artificial intelligence for cross-curricular course design or personalized learning path planning, thereby honing their innovative thinking through practice.

(3) Enhance the TPACK proficiency of primary and secondary school teachers. First, at the level of technology integration, enhance teachers' understanding and operational capabilities of generative artificial intelligence. Set up workshops to systematically explain the basic functions of generative artificial intelligence tools, invite technical experts to conduct case teaching, and demonstrate the diverse applications of generative artificial intelligence. Including the generation of multimodal teaching resources, such as teaching courseware, micro-lessons, etc. In terms of developing learning scaffolds, such as pre-class study sheets, mind maps, gamified activities, etc. In the aspect of developing teaching evaluations, such as the scale design, question design, and test question design for process evaluation and performance evaluation; In addition, it also includes personalized learning feedback, etc. Second, in terms of teaching knowledge, promote the deep integration of generative artificial intelligence and instructional design. In combination with the characteristics of the discipline, develop teaching plan templates, prompt templates, etc. that include generative artificial intelligence teaching applications, guiding teachers to optimize teaching methods and strategies by using generative artificial intelligence. Third, at the level of subject knowledge, build teaching scenarios that integrate generative artificial intelligence with subject knowledge. Help teachers achieve the visualization of knowledge points and cross-disciplinary integration, reconstruct the knowledge transmission path, and realize personalized understanding of subject knowledge.

(4) Improve the quality of technical application by primary and secondary school teachers in multiple dimensions. First, educators should change their own educational philosophy. They should enhance the effectiveness of using generative artificial intelligence to empower education and teaching. This process should be guided by theories such as learning advancement, multiple intelligences, and the integration of teaching, learning, and assessment. Second, adopt advanced teaching models, such as large-unit teaching, project-based learning, and cross-disciplinary thematic learning, and use them as templates to have precise dialogues with generative artificial intelligence to enhance the efficiency of lesson preparation. Thirdly, enhance the ability of dialectical thinking and critical thinking, view the content generated by generative artificial intelligence in a balanced way, and make correct value judgments and choices under the guidance of correct values. Fourth, learn the prompt strategy of "human-machine" dialogue, improve the ability to ask advanced questions, such as the Socratic questioning method, etc. Through systematic and structured precise questioning, increase the probability of generating high-quality personalized content. Fifth, form a closed-loop identification strategy of multi-subject collaboration, such as the collaboration among teachers, students and generative artificial intelligence. Teachers can re-engage in dialogue

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with artificial intelligence based on the dynamic questions generated by students, and iteratively optimize the generated content.

8 Conclusion

This study, based on the UTAUT model, explores the influencing factors of primary and secondary school teachers' use of generative artificial intelligence and the structural relationships among these factors. Furthermore, this study analyzed the moderating effects. The moderating variables include gender, age, teaching experience, and educational attainment. This study has some limitations: (1) The data of this study were mainly collected through questionnaires, with a single data source. The lack of multi-dimensional data led to insufficient depth of the study. Therefore, to gain more understanding, in future research, the relationships among various structural elements in the UTAUT model can be verified by qualitative methods to understand the relationships among various structures in more detail; (2) The sample size of this study is not large enough, which may affect the universality of the research results. The proportion of female teachers is too high, which may lead to inference results favoring the female group. In future research, participants should be recruited using methods such as stratified or quota sampling. This will help ensure the sample is more representative and balanced in terms of gender and other relevant demographic variables. (3) The cross-sectional nature of this study imposes limitations on causal inference. Therefore, future research could employ longitudinal designs with measurements at multiple time points to better establish causal relationships. Additionally, incorporating interviews or observations would help elucidate the reasons behind the questionnaire data, thereby compensating for the limitations of quantitative research. And uncovering new variables not accounted for in the UTAUT model. For instance, contextual factors such as "teaching beliefs" could be integrated as new constructs to enhance the model's applicability to primary and secondary educational settings.

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Figure Legends

Figure 1. Theoretical model

Figure 2. Structural model test

Figure 3. Final model with standardized estimates

Ethical Approval

This study was approved by the Institutional Ethics Committee of Shaanxi Normal University, with the ethics appr oval number: SNNU-ETH-2025-Ed0218. The ethical approval date is January 6, 2025, which was prior to the com mencement of data collection. Throughout the entire research process, the research team adhered strictly to the ethi cal guidelines and principles established by Shaanxi Normal University to ensure that all participants were treated with fairness, respect, and confidentiality.

Informed Consent

All individuals participating in the study received informed consent. All participants were fully informed of the nature of the study, including its purpose, procedures, potential risks and benefits. They were guaranteed the right to withdraw from the research at any time without being punished. This online survey was conducted from February 27th to March 14th, 2025. Obtain the electronic informed consent form on the first page of the investigation. Consent was indicated by selecting "I agree" prior to completing the questionnaire, and the survey platform automatically recorded the submission time of each response.

Competing Interests

The authors declare no competing interests.

Author Contributions

Jinbo Hu was responsible for data curation, conducting the questionnaire survey, software operation, and writing the main manuscript text. Wenlan Zhang undertook the methodology design, supervised the entire research process, carried out the investigation work, and secured funding for the study. Lixia Zhao was in charge of creating the figures and tables, as well as participating in the writing of the manuscript. All authors have read and approved the final version of the manuscript.

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Data Availability

The data that support the findings of this study are not publicly available due to ethical and confidentiality restrict ions. Participants in this research were assured that their data would remain confidential and would not be shared with external parties. Therefore, supporting data are only available from the author upon reasonable request, subject to ethical approval and participants' consent.

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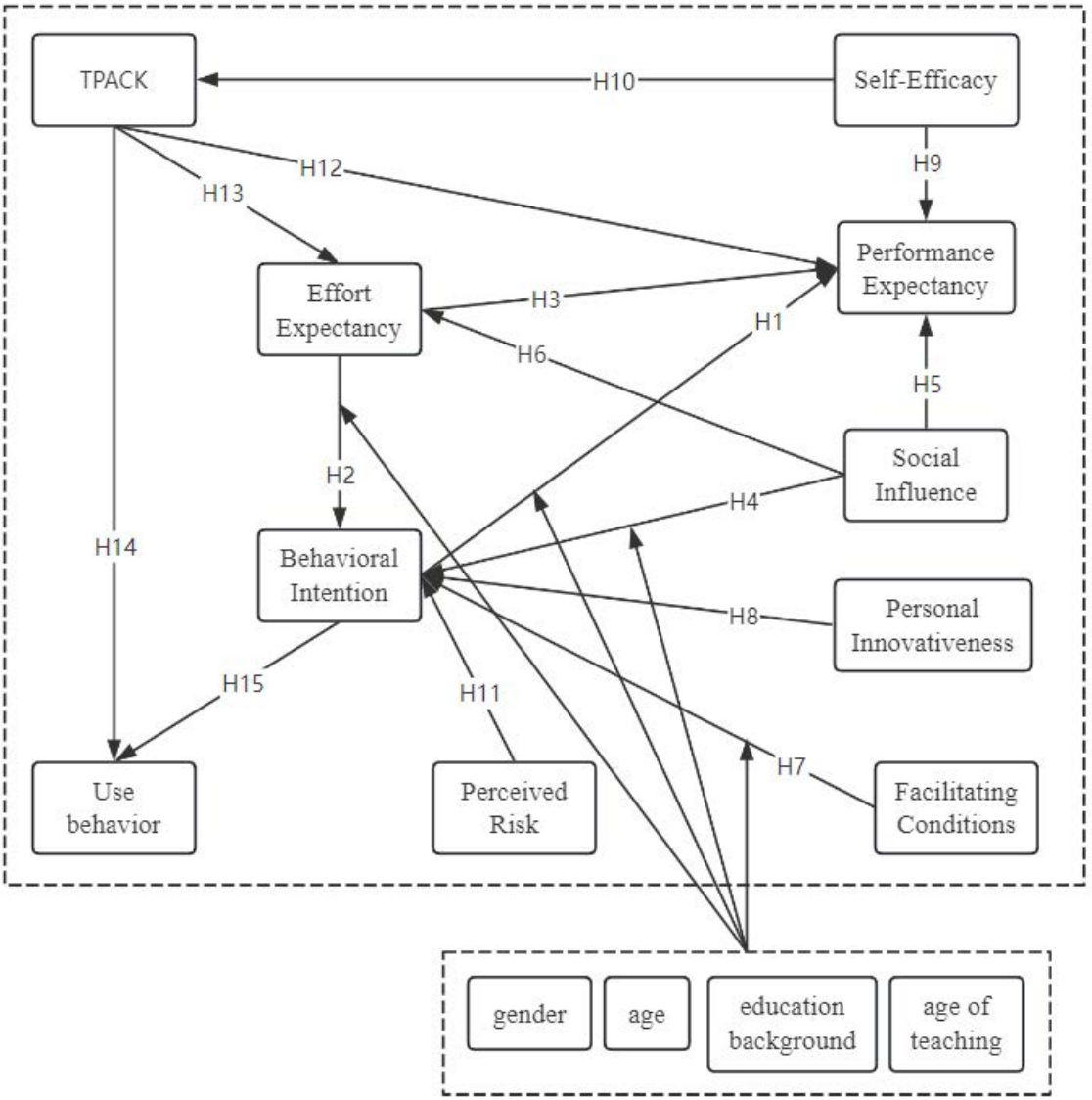
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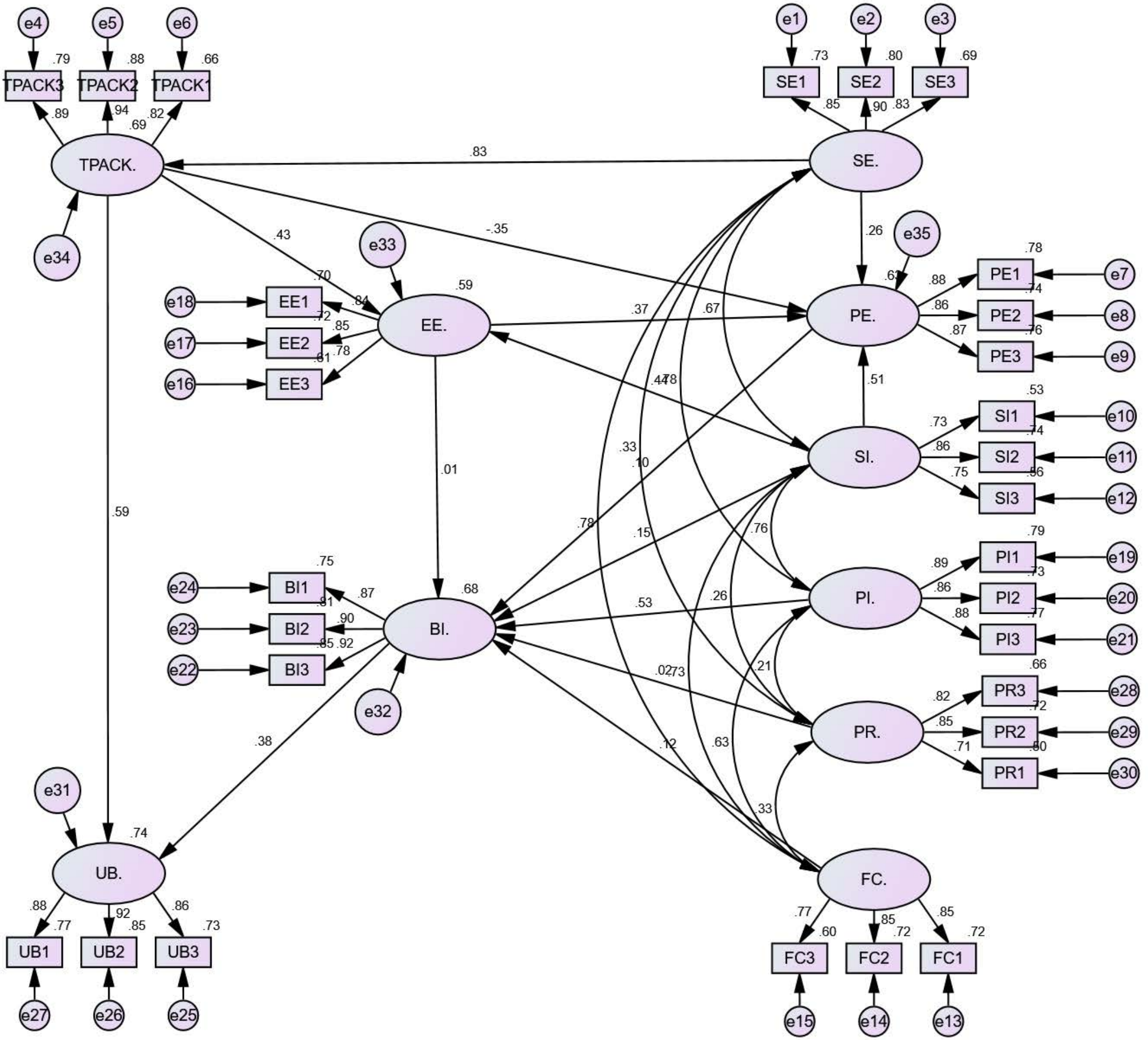
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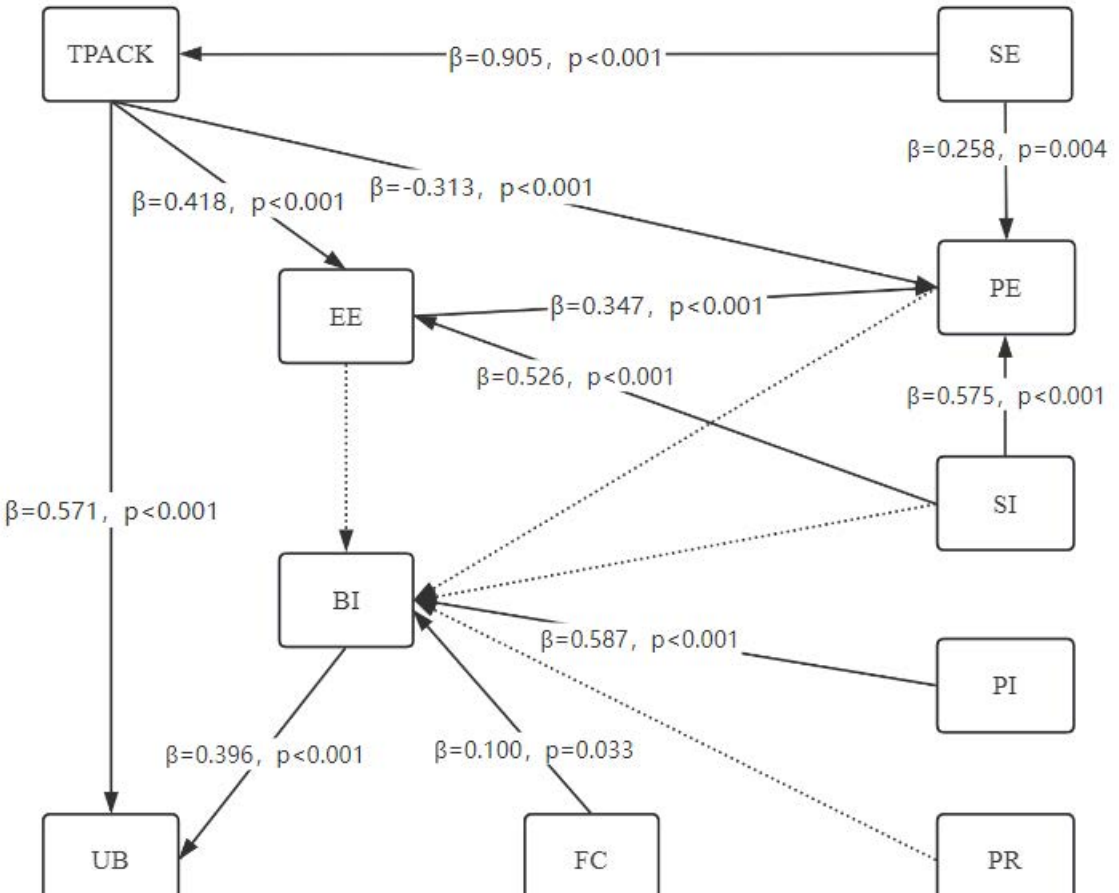
TPACK
β=0.905, p<0.001
SE
β=0.258, p=0.004
β=0.418, p<0.001
β=-0.313, p<0.001
EE
β=0.347, p<0.001
PE
β=0.526, p<0.001
β=0.575, p<0.001
β=0.571, p<0.001
SI
BI
β=0.587, p<0.001
PI
β=0.396, p<0.001
β=0.100, p=0.033
UB
FC
PR