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Awareness, acceptance, and adoption of Gen-AI by K-12 mathematics teachers: an empirical study integrating TAM and TPB

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Abstract
In the 21st century, the variety of instructional media for mathematics has significantly diversified. Generative AI (Gen-AI) is one technology that K-12 teachers can utilize for teaching mathematics. However, as a new instructional medium, Gen-AI presents its own set of usage challenges. Research into the factors influencing mathematics teachers' usage behavior of Gen-AI is crucial. This study integrates the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), incorporating a factor of AI awareness to explore the determinants of teachers' usage behavior in employing Gen-AI for mathematics instruction. Data from 230 mathematics teachers who agreed to participate were analyzed using the partial least squares structural equation modeling (PLS-SEM) approach. The results indicate that teachers' attitudes toward Gen-AI, subjective norms, and perceived behavioral control (PBC) have a direct effect on mathematics teachers' usage behavior. AI awareness was found to directly affect perceived usefulness (PU), perceived ease of use (PEOU), and attitudes, and it also has an indirect effect on mathematics teachers' usage behavior. This research provides new insights into enhancing the adoption of Gen-AI as an instructional medium by improving mathematics teachers' attitudes toward Gen-AI, with AI awareness playing a pivotal role in this enhancement.

Keywords Theory of planned behavior, Technology acceptance model, Gen-AI, SEM, AI awareness

Introduction

In recent years, Generative AI (Gen-AI) has evolved rapidly, with a notable acceleration following OpenAI's release of ChatGPT in 2023. Powered by large language models, Gen-AI processes vast amounts of data and learns the structure and patterns within datasets, enabling it to generate relevant responses and handle complex tasks based on user input [1]. In China, the adoption of Gen-AI and growing AI awareness have become hot topics across various sectors. Officials have stated that the AI offers numerous opportunities and facilitates educ ational activities.

In mathematics education, Gen-AI has demonstrated significant potential through its flexible responses and vivid contextualization. Empirical studies suggest that it not only helps educators generate personalized educational content and assists teachers in designing lesson plans and assessing student work, but also enhances student engagement, motivation, and academic performance through timely problem guidance, personalized learning pathways, or interactive tutoring features [2].

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However, while educators are excited about the potential of Gen-AI as a powerful teaching tool, there are also concerns regarding its limitations. Due to the constraints of language models, Gen-AI might misinterpret user inputs or generate inaccurate or even incorrect responses [3–5]. This issue may result in failures in visual mathematical content, logical and reasoning errors in mathematical proofs, or incompatibility with complex mathematical notation, equations, or specialized symbols beyond basic text representations, which presents numerous challenges for teachers in utilizing AI in the classroom. Such obstacles could negatively impact frontline teachers' awareness and willingness to adopt AI in their teaching practices. The question of whether Gen-AI should be used in mathematics teaching, and how to use it effectively, is one that math educators need to critically consider.

In teaching, regardless of how effective and powerful a technology may be, the extent to which it is utilized largely depends on the willingness of teachers [6, 7]. As providers of education and guides for student learning, teachers' perceptions and use of technology significantly impact the classroom teaching experience [8, 9]. Therefore, the successful integration of Gen-AI into mathematics education, which brings positive teaching experiences and outcomes for both teachers and students, undoubtedly hinges on the role of teachers. Currently, research on the application of Gen-AI in mathematics education mainly centers on three aspects: technical traits, teaching influences, and practical uses. For technical traits, researchers have looked into ways to better combine Gen-AI with teaching by considering its pros and cons [10]. Regarding teaching influences, they've assessed how Gen-AI affects classroom teaching and students' thinking through studies, and given useful tips for bringing AI into education [11]. Finally, based on existing challenges in mathematics teaching, the researchers applied Gen-AI to design targeted interventions, and shared practical teaching cases for reference [12]. However, there has been limited attention directed toward mathematics teachers, who are crucial users of Gen-AI. In this context, understanding the factors that influence mathematics teachers' usage behavior of Gen-AI for teaching warrants further exploration in the academic field. Based on this, the purpose of this study is identifying factors that significantly influence K-12 mathematics teachers to use Gen-AI for teaching, aiming to further expand and refine the current body of research.

While the Technology Acceptance Model (TAM) primarily focuses on the intrinsic characteristics of technology [13], and the Theory of Planned Behavior (TPB) considers the influence of the social environment and individual psychology [14], both models may not sufficiently address the complexities of Gen-AI adoption in educational settings. These traditional frameworks have demonstrated reliability and validity across diverse contexts and are frequently employed in educational research to examine technology usage behaviors among teachers and students [15–18]. However, the rapid evolution of Gen-AI technologies and their profound impact on educational practices suggest that a broader psychological and environmental perspective is crucial.

Our study poses the refined research question: How do teachers' perceptions and attitudes influence their adoption of Gen-AI in K-12 mathematics education? This inquiry seeks to explore beyond the conventional variables examined in models like TAM and TPB, by delving into how emerging factors specific to Gen-AI, such as AI awareness and the dynamic nature of technological evolution, affect teachers' willingness to integrate these technologies into their teaching practices. By focusing on these aspects, our approach not only maintains clarity and readability but significantly enhances the theoretical grounding of our study, providing a deeper understanding of the factors driving Gen-AI adoption among educators.

Literature review and hypothesis development

The role of Gen-AI in mathematics education

With the rapid advancement of the new technological and industrial revolutions, artificial intelligence (AI) technologies have gained significant attention and widespread application across various fields in recent years. Gen-AI, as a cutting-edge branch of AI, employs advanced algorithms to learn patterns and generate new content in diverse forms, including text, images, sound, video, and code [19]. A typical example of Gen-AI is ChatGPT, which can handle highly complex conversations and tasks while providing meaningful responses based on context [20].

The rise of Gen-AI has brought significant changes to the field of mathematics education, with one of the most notable shifts being the symbiotic relationship between teaching and technology. This has led to a rapid increase of computer-based instructional tools, bringing significant changes to mathematics teaching methods and reshaping the landscape of mathematics education [21, 22]. In typical learning environments, Gen-AI can support personalized instruction by generating engaging simulated learning environments for learners and assisting with creative tasks in scientific fields [23]. In the context of mathematics education, Gen-AI can effectively reduce students' learning difficulties through two key approaches. It offers targeted learning resources that bridge abstract mathematical concepts and real-world applications, and provides personalized diagnostics and formative assessments that support timely learning adjustments [2, 24].

Gen-AI brings many conveniences and benefits to mathematics education; however, it also presents new challenges for teachers. As the use of generative AI becomes increasingly widespread, its involvement in teaching has grown significantly—taking on tasks that were once the exclusive domain of teachers, such as personalized instructional guidance [25]. Moreover, due to the positive role Gen-AI plays in education, students may begin to view it as an authoritative source of knowledge, which could, to some extent, undermine the authority and professional status of teachers [26]. This development places new demands on teachers to redefine and adjust their roles. To maintain their core position and create effective classroom experiences, teachers must focus on their unique pedagogical functions. At the same time, the use of Gen-AI has also raised concerns among teachers regarding their careers and personal lives [27, 28]. How to properly understand and handle the relationship between traditional classroom teaching and Gen-AI, and how to fully leverage the positive role of Gen-AI to create a better mathematics learning environment for students, are questions that every mathematics educator must consider.

Although Gen-AI can provide students with personalized mathematics learning resources, addressing many educational issues such as insufficient instructional guidance, researchers emphasize that artificial intelligence should only serve as a complement to traditional mathematics teaching, not as a replacement for schools and teachers [10, 29]. As UNESCO stated in 2021, "while teachers cannot be replaced by machines, and human interaction between teachers and learners should remain at the core of education, the potentials of AI tools for 'human-machine collaboration' should be further mined to support teachers' high-skill pedagogical responsibilities in different learning settings. Equipping teachers with the skills they need for both their own professional development and the delivery of quality technology education across contexts."

How Gen-AI benefits mathematics teachers and AI awareness

Building on the transformative role of Gen-AI in mathematics education outlined in Sect. 2.1, it is pivotal to explore how this technology specifically benefits mathematics teachers in their instructional practices. The integration of Gen-AI into mathematics teaching not only revolutionizes educational approaches but also significantly empowers teachers.

Gen-AI tools provide teachers with advanced capabilities for personalizing instruction, enabling them to tailor lessons according to the unique learning styles and needs of each student [30, 31]. By automating the generation of engaging and contextually relevant materials, Gen-AI allows teachers to focus more on interactive and high-impact teaching strategies. This is particularly useful in mathematics, where the abstraction of concepts often poses significant challenges for student comprehension. Gen-AI supports teachers by offering diagnostic tools and formative assessments that help identify learning gaps and track student progress in real-time.

Furthermore, Gen-AI enhances the ability of teachers to facilitate complex problem-solving and critical thinking skills by providing simulations and interactive scenarios that relate mathematical theories to practical applications [30, 32]. This not only aids in reducing mathematics anxiety among students but also enriches the teaching toolkit available to educators, making the learning process more engaging and effective [33, 34].

While Gen-AI offers many benefits, its integration into mathematics education has brought significant changes to teachers' role positioning, task allocation, and resource planning. The rapid pace of these transformations has raised concerns about how teachers can balance emerging technologies with traditional pedagogical approaches [35]. Although teachers are encouraged to use Gen-AI as a complementary tool that enhances—rather than replaces—the human elements of teaching, their varied responses to Gen-AI add complexity to its effective implementation. To address this complexity, researchers have proposed the concept of AI awareness, which refers to individuals' perceptions of how emerging technologies like artificial intelligence may impact their future professional development [36]. AI awareness comprises several dimensions: (1) Knowledge and Understanding—teachers' awareness and understanding of Gen-AI technologies and their educational applications, (2) Engagement and Communication—the extent to which teachers discuss and engage with AI topics among peers, enhancing collective knowledge, and (3) Critical Analysis—the ability to read, analyze, and understand the challenges and issues associated with AI in education. Existing studies suggest that AI awareness can act as a double-edged sword. On one hand, heightened awareness may foster intrinsic motivation, increase technology acceptance, and improve teachers' capacity to adapt. On the other hand, it may also amplify concerns about job security and lead to pessimism regarding future career prospects [37, 38]. Given AI's potential impact on teaching practices, this study examines how these dimensions of AI awareness influence K-12 mathematics teachers' acceptance and adoption of Gen-AI.

Technology acceptance model (TAM)

In the evolving landscape of computer and information technology, user acceptance of technology remains a key area of study within modern information systems (IS) research. Historically, several theoretical models have been developed to analyze the factors that influence users' adoption of information technology. Among these, the Technology Acceptance Model (TAM), introduced in 1989 by [13] specifically for the IS context, has been particularly influential. TAM is designed to predict the acceptance and use of information technology in workplace settings, and extensive theoretical and empirical research has supported its validity and applicability across various technologies and user demographics [39, 40]. Theoretical and Empirical studies have demonstrated that TAM has shown good validity and applicability across different information technologies and user types [41].

In studies focused on teachers, the Technology Acceptance Model (TAM) has proven to be a powerful research framework [42, 43]. TAM is built on two key constructs [13]: perceived usefulness (PU)—"the degree to which a person believes that using a particular system would enhance their job performance"—and perceived ease of use (PEOU)—"the degree to which a person believes that using a particular system would be free of effort." Within TAM, these two factors, influenced by external variables, together shape users' attitudes toward using a technology (ATT). ATT represents an individual's positive or negative feelings about performing the target behavior [44]. These attitudes then influence usage intention, which ultimately determines actual usage behavior [13].

Our research model omits behavioral intention and directly examines the effects of the constructs on actual usage behavior. In behavioral models, researchers often choose to measure usage intention rather than actual behavior. This is primarily due to practical constraints—such as limited time, resources, and ethical considerations—which make it difficult to obtain accurate behavioral data from participants in many research settings. However, this perspective has faced criticism. For example, a previous study [45] identified several limitations of relying solely on behavioral intention: (1) it overlooks the gap between intention and the actual achievement of goals; (2) it fails to consider the time lag between forming intentions and taking actions; and (3) it does not recognize that for decision-makers, intention and action represent fundamentally different orientations. In our case, the research is embedded in a long-term educational project, allowing direct access to participants' actual usage behavior. Therefore, to avoid potential biases arising from the intention–behavior gap, we chose to directly measure actual usage behavior. This decision provides a more accurate and reliable foundation for drawing conclusions. Usage Behavior refers to the actual employment of technology by users, encompassing not just frequency or duration of use, but how effectively the technology is integrated into daily tasks, thus providing a direct measure of technology's utility in real-world settings [13].

In this study, we consider AI awareness as an external factor that may influence PU and PEOU. Since some studies have pointed out that higher AI awareness can lead to more positive attitudes towards AI integration in learning or teaching, we also take into account the influence of AI awareness on attitude [46].Based on the aforementioned theoretical and empirical studies, the following hypotheses are proposed:

H1: AI awareness have a significant influence on PU.

H2: AI awareness have a significant influence on PEOU.

H3: AI awareness have a significant influence on ATU.

H4: PU have a significant influence on UB.

H5: PEOU have a significant influence on UB.

H6: ATU have a significant influence on UB.

In this study, we also introduced the construct of facilitating conditions (FC) to extend the validity of TAM [47, 48]. Facilitating conditions refer to the degree to which users perceive the presence of technical and organizational infrastructure that supports system usage [48]. In this study, facilitating conditions refer to the extent to which teachers feel supported in terms of equipment, technology, and decision-making when using Gen-AI. In other words, facilitating conditions are factors in the environment that affect an individual's perception of how easy or difficult it is to perform a task [49]. If individuals expect to have sufficient facilitating conditions (such as well-equipped devices) when using a technology, they are more likely to adopt it; otherwise, it may hinder their usage.

H7: FC have a significant influence on UB.

The theory of planned behaviour (TPB)

Drawn from social psychology, Fishbein and Ajzen proposed the Theory of Reasoned Action (TRA) to predict human behavior [44]. TRA includes two core constructs: attitude toward behavior and subjective norm. Due to limitations in the original model when dealing with behaviors not completely under volitional control, Ajzen further developed the Theory of Planned Behavior (TPB) on the basis of TRA, introducing the construct of perceived behavioral control. He noted that while some behaviors are entirely determined by an individual's motivation, most behaviors are at least partially influenced by non-motivational factors such as money, time, skills, etc. These factors represent the actual control people have over their behaviors. Therefore, when predicting behavior, considering people's perceived ease or difficulty in performing the behavior is crucial, which is defined as perceived behavior control [14].

Subjective norm is defined as a person's perception that most people who are important to them think they should or should not perform the behavior in question

[44]. If an individual believes that significant others expect them to use a particular technology, they will have a higher intention to use it, even if their personal preference for it is moderate. The establishment and refinement of this core construct is consistent with the revised TAM model. Building on TAM, Venkatesh and Davis [41] proposed TAM2, incorporating, which, into the TAM model. Their research indicated that subjective norm has a significant direct influence on usage intentions. Subsequent empirical studies related to the TAM model have incorporated the variable of subjective norm and support the idea that adding subjective norm to TAM could be beneficial [40].

Currently, TPB has been widely applied in various business environments, including online procurement, banking, telemedicine, and more [50–52]. In the field of education, TPB has been extensively used in research on professional development and teaching practices and is considered a conceptually suitable model for explaining teachers' instructional practices. From the perspective of information technology, researchers have explored behavior intentions of both pre-service and in-service teachers based on the TPB model. Based on the above discussion, the following hypotheses are proposed:

H8: SN have a significant influence on UB.

H9: PBC have a significant influence on UB.

Given the respective strengths and focuses of TAM and TPB, we have combined the two models in this study, with certain extensions and refinements, to construct the theoretical model for this research. In educational settings, the adoption of Gen-AI is a complex process that depends not only on the ease of use and usefulness of the technology itself, but also on a range of social and psychological factors [53]. Specifically, TAM highlights perceived usefulness and perceived ease of use, which reflect teachers' rational judgments about how Gen-AI might improve the efficiency or effectiveness of teaching. This underscores TAM's technology-centered perspective, but also reveals its tendency to overlook the broader educational context in which teachers operate. In contrast, TPB introduces subjective norms and perceived behavioral control, which help explain how social expectations and perceived constraints influence teachers' adoption behaviors. By integrating TAM and TPB, our research model captures the combined effects of technological features, internal beliefs, and social pressures, offering a more realistic and holistic explanation for the application of Gen-AI in teaching. Based on the above discussion, we have developed the final research model, as shown in Fig. 1.

Methodology

Instruments

This study adopted a quantitative research method to explore the factors influencing K-12 mathematics teachers' use of Gen-AI tools in teaching. The Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) were employed because they are widely used in generational AI research to analyze behavioral intentions and actual usage. Based on the TAM and the

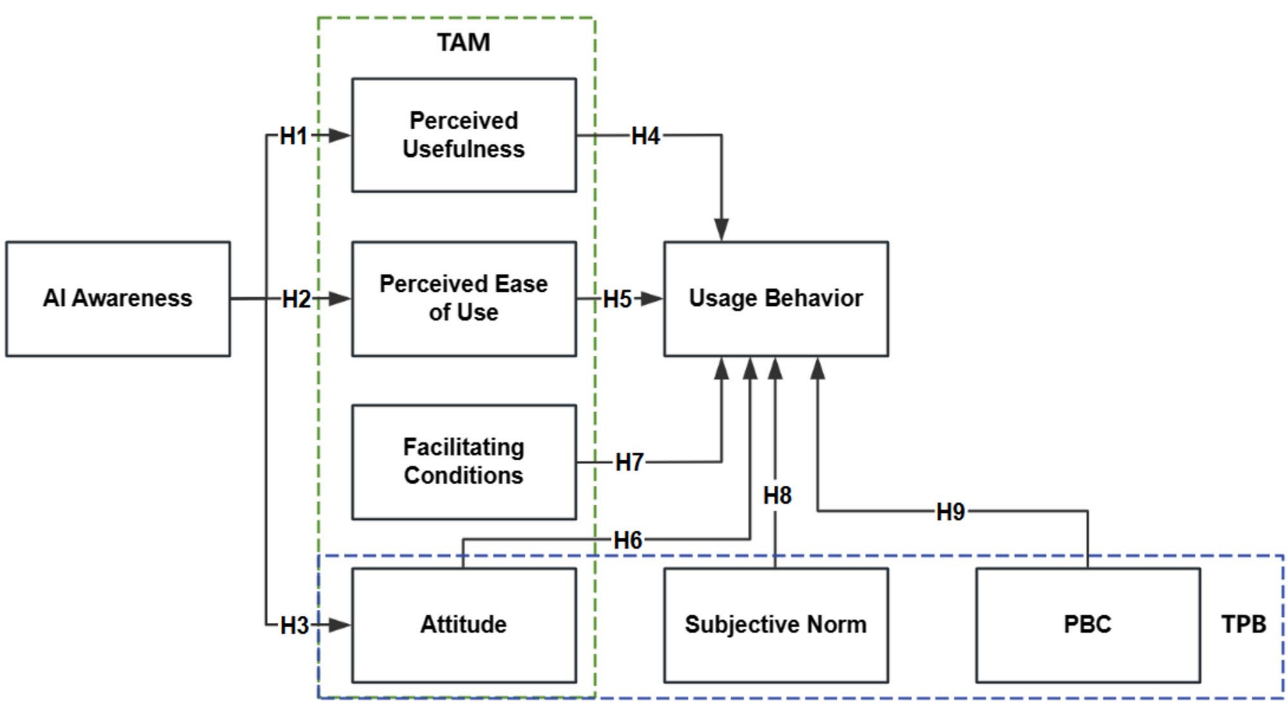

Fig. 1 The research model

Theory of Planned Behavior models, the research incorporated seven constructs, including perceived usefulness, perceived ease of use, facilitating conditions, subjective norm, PBC, attitude and usage behavior. Additionally, AI awareness had been added as a new dimension to the model, in line with the research objectives. All questionnaires utilized in this study were meticulously adapted from established scales used in prior research on AI awareness, as well as the TAM and the TPB. This adaptation process included carefully revising the items to ensure relevance to the specific context of Gen-AI tool usage by K-12 mathematics teachers. The questionnaires were pre-tested with a small sample of target participants to refine wording, scale consistency, and item relevance, thereby enhancing the overall reliability and validity of the instruments. Furthermore, statistical validation techniques, such as confirmatory factor analysis, were employed to assess the reliability of the scales before their final implementation in the study.

On this basis, a corresponding questionnaire was designed. The questionnaire consisted of two parts. The first part gathered basic personal information, investigating the participants' gender, age, years of teaching experience, frequency of Gen-AI use, etc. The second part was the main section of the questionnaire, comprising 26 items measured on a five-point Likert scale, where 1 represented "strongly disagree" and 5 represented "strongly agree."

Two mathematics education experts translated the original English TAM and TPB questionnaire into Chinese. A native Chinese-speaking expert then reviewed and refined the Chinese version, adjusting the vocabulary and sentences to make it easier to read and understand. After the revisions were completed, the questionnaire was distributed to the research participants.

Data collection

In July 2024, Beijing Normal University collaborated with the Tencent WeChat Mini Program team to launch the "Mini Program + Mathematics" Innovation Course Research Group. This initiative brought together approximately 250 K-12 mathematics teachers from across the country to explore the integration of AI technology into mathematics education through project-based practices.

Using this research group as the foundation, this study adopted a purposive sampling method to ensure the most relevant data collection. We targeted teachers who either had a basic understanding of Gen-AI or had already implemented it in practice, as their perceptions and experiences would provide authentic responses to our research questions. Since the participating teachers came from various regions across China, this sampling method helped avoid data concentration from specific schools or regions, enhancing the study's comprehensiveness and representativeness. The Research Ethics Committee of the School of Mathematical Sciences, Beijing Normal University, approved the study on June 10, 2024.

Throughout the research group's three-month activities, we identified suitable participants through information gathering, discussions, and exchanges of ideas. Then an online questionnaire was distributed to these selected participants using the survey platform "Wenjuanxing" (https://www.wjx.cn). To ensure data authenticity, the survey was conducted anonymously. In the questionnaire's introduction, we clearly informed respondents that there were no right or wrong answers and that all data would be used exclusively for this study.

A total of 246 respondents completed the questionnaire. To ensure data quality, we conducted a thorough cleaning process by examining the dataset for missing values, highly regular response patterns, response times under 90 s, and responses from non-mathematics teachers. After removing 16 invalid questionnaires, our final dataset comprised 230 participants. Table 1 presents a detailed breakdown of the respondents' demographic data.

Data analysis

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM) for data analysis. Generally, there are two common methods for evaluating structural equation models, namely PLS-SEM and CB-SEM, which are based on variance and covariance, respectively, to explain the structural equation model. We chose PLS-SEM for the following three reasons.

First, data collected in social science research often do not follow a normal distribution, and PLS-SEM can transform the data to prevent errors [54]. Additionally, compared to CB-SEM, PLS-SEM can be used with smaller sample sizes, even in cases of very complex models, and typically demonstrates higher levels of statistical power and convergence behavior than CB-SEM [55]. Third, PLS-SEM is considered to emphasize the predictive nature of the estimated model and provide causal explanations among structures, making it more suitable for theoretical model development [56]. For these reasons, we selected PLS-SEM for data analysis.

The PLS-SEM process is divided into two main parts: measurement model evaluation and structural model evaluation [54]. The purpose of measurement model evaluation is to ensure that the indicators used reliably and validly reflect the latent variables, including reliability analysis and validity analysis. In this part, each variable needs to be analyzed individually. Typically, Cronbach's alpha and composite reliability (CR) are used to assess the reliability of each latent variable, specifically its internal consistency. High internal consistency indicates that the observed variables reliably measure the

Table 1 Demographic information of the participants ($N=230$)

Demographic	Type	N	Percentage
Gender	Female	153	66.52
	Male	77	33.48
Age	≤ 20	1	0.43
	21–25	18	7.83
	26–30	43	18.70
	31–35	30	13.04
	36–40	34	14.78
	>40	104	45.22
Teaching level	Primary	136	59.13
	Middle	52	22.61
	High	42	18.26
School type	Public	222	96.52
	Private	8	3.48
School location	Rural	16	6.96
	Township	20	8.70
	Country Town	77	33.48
	City	117	50.87
Teaching experiences	0–3	29	12.61
	4–6	28	12.17
	7–10	27	11.74
	11–15	33	14.35
	> 15	113	49.13
Professional title	Senior	1	0.43
	Advanced	58	25.22
	First-Class	91	39.57
	Second-Class	64	27.83
	Third-Class	1	0.43
	Unranked	15	6.52
Education level	Undergraduate	188	81.74
	Postgraduate	40	17.39
	Doctorate	2	0.87
Familiarity with Gen-AI	Not familiar	104	45.22
	Somewhat familiar	109	47.39
	Very familiar	15	6.52
	Extremely familiar	2	0.87
Experience using Gen-AI in teaching	No relevant experience	107	46.52
	Tried a few times	104	45.22
	Regular use	19	8.26
Programming experience	No experience	172	74.78
	Basic understanding	53	23.04
	Intermediate programming skills	5	2.17
	Advanced programming skills	0	0

latent variable and that the measurement items within the same latent variable exhibit high correlations. This ensures that the scale measurements are stable and reliable. External consistency is assessed using average variance extracted (AVE) from the observed variables. Good external consistency indicates that each latent variable independently measures its specific concept, demonstrating good discriminant validity. When both internal and external consistency meet the required standards, the measurement model is considered to have good reliability and validity, making the results more robust.

On the other hand, structural model evaluation assesses the research model by examining the relationships within the structural model and conducting statistical tests of the hypotheses, with a focus on reporting the strength of path coefficients (Beta), explanatory power of the model (R^2), and statistical significance (p-value). Through a comprehensive analysis of these indicators, structural model evaluation serves two key purposes. First, it helps determine whether the model's pathways are reasonable and assists researchers in identifying necessary adjustments. Second, it evaluates the model's explanatory and predictive power, making it an essential approach for testing the model's robustness and validity. These two evaluation steps ensure the robustness and theoretical soundness of the PLS-SEM model, allowing researchers to distill effective predictions and explanations from complex causal relationships.

Limitations

This study faces certain limitations that affect the generalizability of its findings. First, the sample of participants mainly comes from public schools at primary level in urban districts of China, which may not fully represent K-12 mathematics teachers in diverse settings. However, it still is one step closer to the truth and provides some insights into teachers' perceptions and attitudes towards their adoption of Gen-AI in K-12 mathematics education, though the results should not be overgeneralized. Second, the research instruments used in this study only collect self-reported information, in which situation the data may have some bias, since the participants are likely to present a positive image of their behaviours, could be willing or unwilling to tell the truth, or might forget some details of their experiences. To minimize those effects, further studies can employ various research tools, such as classroom observation, and involves the relevant parties, such as students, to triangulate the data. Moreover, the absence of qualitative data in this study restricts a deeper understanding of the subjective factors influencing teachers' usage behavior. Incorporating qualitative methods such as interviews or focus groups in future studies could provide richer insights into the dynamics behind teachers' acceptance or resistance to using Gen-AI tools. Lastly, while the predictors used in our study explained a substantial portion of the variance in usage behavior, they may not capture all possible factors. Identifying additional variables, such as personal innovativeness, technology training, external pressures, or institutional support, could further enhance our understanding of how teachers adopt and integrate Gen-AI into their teaching practices.

Table 2 Measurement model analysis

	Cronbach's alpha	Composite reliability	AVE
AI AWARENESS	0.955	0.971	0.917
ATTITUDE	0.784	0.833	0.649
FC	0.953	0.970	0.915
PEOU	0.878	0.925	0.804
PU	0.912	0.945	0.852
SN	0.926	0.947	0.818
PBC	0.954	0.970	0.915
UB	0.964	0.974	0.902

Findings

To effectively meet the research objective of identifying the key factors that significantly influence mathematics teachers' usage behavior of Gen-AI tools in their teaching practices, we utilized smartPLS 4.0 software to examine the conceptual model in two areas: the measurement model and the structural model.

Measurement model

The measurement model was assessed by examining construct reliability, convergent validity, and discriminant validity for all constructs. Construct reliability in PLS-SEM was evaluated by examining Cronbach's alpha (α), average variance extracted (AVE), and composite reliability (CR) values. As shown in Table 2, all Cronbach's Alpha values exceed 0.7, indicating that the data in this study is accurate and reliable.

Furthermore, as depicted in Table 2, the composite reliability (CR) values exceed 0.7, indicating strong internal consistency among all variables. Additionally, the average variance extraction (AVE) approach is used for the convergent validity test, where AVE values must not be below 0.5 [57]. It can be observed that all AVE values in our study are above 0.5.

For discriminant validity testing, this study utilized the Fornell-Larcker criterion [58] and the Heterotrait-Monotrait (HTMT) ratio (see Table 3). Previous researchers have suggested that the HTMT is more effective than the Fornell-Larcker criterion for assessing differences between variables. As shown in Table 4, both Fornell-Larcker and HTMT values are excellent.

Structural model

After the measurement model was assessed and all constructs demonstrated satisfactory values, the structural model was analyzed using SmartPLS software. This study employs PLS-SEM to determine the direct and indirect effects for all hypotheses, where Hair [54] suggests that this technique is appropriate for investigating structural interactions allowing for both full and partial mediation. Furthermore, it is recommended that the Variance Inflation Factor (VIF) be analyzed to test for multicollinearity among constructs, where a VIF value below 5 indicates that the research model is significantly correlated.

Table 5 demonstrates the effects across various constructs. Six out of ten hypotheses were supported, indicated by significant P values (less than 0.05). Notably, pathways from AI awareness to attitude, perceived ease of use, perceived usefulness and usage behavior all show strong and statistically significant effects. Similarly, the

Table 3 Heterotrait-Monotrait ratio (HTMT)

	AI AWARENESS	ATTITUDE	FC	PEOU	PU	SN	PBC	UB
AI AWARENESS								
ATTITUDE	0.666							
FC	0.709	0.574						
PEOU	0.551	0.797	0.566					
PU	0.398	0.774	0.443	0.564				
SN	0.590	0.711	0.589	0.725	0.732			
PBC	0.739	0.640	0.758	0.612	0.473	0.589		
UB	0.635	0.709	0.646	0.631	0.707	0.818	0.721	

Table 4 Fornell–Larcker criterion

	AI AWARENESS	ATTITUDE	FC	PEOU	PU	SN	PBC	UB
AI AWARENESS	0.958							
ATTITUDE	0.525	0.806						
FC	0.677	0.468	0.956					
PEOU	0.506	0.611	0.519	0.897				
PU	0.372	0.739	0.413	0.506	0.923			
SN	0.555	0.746	0.553	0.654	0.675	0.904		
PBC	0.704	0.528	0.724	0.562	0.446	0.558	0.957	
UB	0.609	0.772	0.620	0.581	0.664	0.776	0.695	0.950

Table 5 Outcomes of hypothesis testing for direct and indirect effects

Path	Beta	Mean	STDEV	T statistics	*P* values	Significance ($p < 0.05$)
H1: AI AWARENESS -> PU	0.372	0.373	0.061	6.097	0.000	Yes
H2: AI AWARENESS -> PEOU	0.506	0.506	0.065	7.721	0.000	Yes
H3: AI AWARENESS -> ATTITUDE	0.525	0.525	0.057	9.282	0.000	Yes
H4: PU -> UB	0.081	0.080	0.058	1.396	0.163	No
H5: PEOU -> UB	-0.073	-0.070	0.062	1.191	0.234	No
H6: ATTITUDE -> UB	0.329	0.329	0.079	4.178	0.000	Yes
H7: FC -> UB	0.090	0.091	0.066	1.352	0.177	No
H8 SN -> UB	0.315	0.312	0.078	4.039	0.000	Yes
H9 PBC -> UB	0.286	0.284	0.066	4.308	0.000	Yes
Indirect effect						
AI AWARENESS-> UB	0.166	0.167	0.049	3.360	0.001	Yes

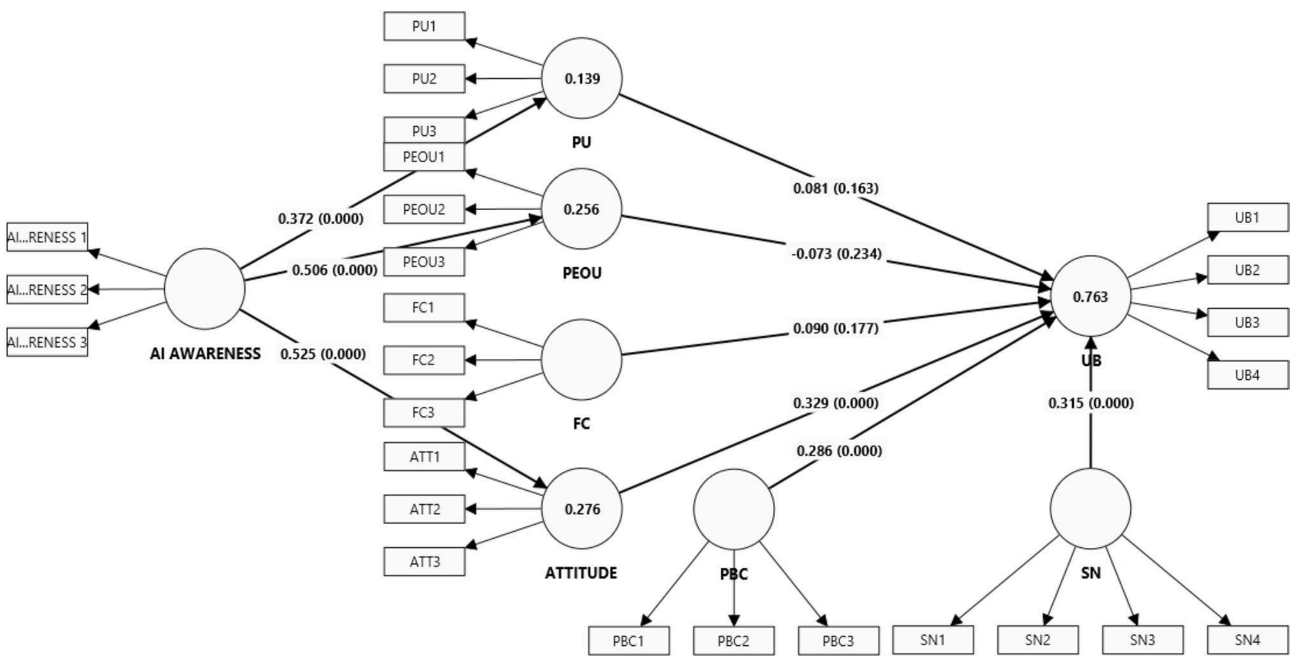

Fig. 2 Structural Model Test Results with Beta Coefficients and R^2 Values

influence of attitude, subjective norms, and perceived behavioral control on usage behavior is also significant. This analysis highlights the critical impact of AI awareness and positive attitudes towards fostering the use of AI in educational settings. Furthermore, our findings reveal that AI awareness has a positive indirect effect on UB, with a beta coefficient of 0.166 and a P-value of 0.001, T-value of 3.360.

To investigate the values of R^2 and structural path coefficients, we employed the bootstrapping technique with 5000 resamples and a 95% bias-corrected confidence interval. As illustrated in Fig. 2, the R2 values for usage behavior is 76.3%, which indicates that the factors included in our research model can explain up to 76.3% of the variance in teachers' usage of Gen-AI as a medium for teaching mathematics.

Discussion

The purpose of this study is to identify factors that significantly influence usage behavior of Gen-AI tools in their teaching practices. The research framework integrates the Technology Acceptance Model, the Theory of Planned Behavior, and AI awareness as an additional predictor. The results of the PLS-SEM analysis indicate that the proposed measurement model in this study meets the reliability requirements, and the structural model demonstrates good validity.

The results show that all hypotheses related to AI awareness were supported. AI awareness has a significant positive impact on attitudes, PU, and PEOU, which in turn indirectly influence usage behavior. This suggests that when mathematics teachers have higher AI awareness, they may more likely to view Gen-AI as an effective and easy-to-use teaching tool, and they may tend to hold more positive attitudes towards its use. This might be because AI awareness provides teachers with a deeper and more positive understanding of Gen-AI. Teachers who recognize how Gen-AI can enhance their teaching practices, such as simplifying complex mathematical concepts and generating personalized learning tasks, are more aware of AI's potential roles and benefits in education, reducing their uncertainty and fear about integrating AI into mathematics teaching, thereby fostering more positive attitudes. Additionally, AI awareness typically reduces the perceived difficulty in using the technology, directly influencing the perceived ease of use. When teachers have prior knowledge of how AI works, they are less likely to feel intimidated by technical barriers [59, 60]. This knowledge might come from professional development, peer discussions, or exposure to AI tools in everyday life, all of which contribute to lowering the learning curve associated with using AI in the classroom. This finding not only integrates the context of the AI era and effectively extends the TAM and TPB models, but also offers a new perspective for IT-related educational training. It emphasizes that in the context of technological transformation in education, training must focus on raising awareness of AI's educational applications, rather than merely concentrating on technical skills.

Among the three hypotheses (H4, H5, H6) related to the original TAM, only the significant influence of attitude on usage behavior was supported. This can be explain with when mathematics teachers have a positive feeling towards using technology, they are more likely to adopt it in their teaching practices, which is consistent with previous research [61, 62]. Unexpectedly, the results indicated that PU did not have a significant effect on teachers' usage behavior. This finding aligns with some previous study but contradicts others [63], which suggest that PU should strongly predict users' intention to use technology. This result may be attributed to the specific characteristics of the study participants and culture norm. First, the study participants were predominantly middle-aged teachers and elder, who may not find technology as immediately applicable or essential to their teaching compared to younger people. Prior research has shown that gender expectations and varying levels of technological exposure and training can influence teachers' perceptions of usefulness [64, 65]. Second, influenced by the collectivist cultural context, teachers tend to be more affected by policies and directives from superiors during the process of technology adoption. Compared with perceived usefulness, factors such as subjective norms and self-efficacy exert a stronger influence on their behavioral intentions [66]. Finally, this result may also be related to the fact that teachers express valid concerns about technology disrupting classroom instruction. Research on mobile technology in teaching shows that while teachers recognize its benefits, they worry about potential misuse, student distraction, and classroom disruption [67, 68]. These concerns hinder perceived usefulness from becoming a key factor in teachers' decisions to adopt new technology.

These observations suggest that even if teachers perceive technology as useful, their overall attitude towards using technology in their teaching practice may be a more critical determinant of actual technology use. Future research should focus on identifying which components of attitude most significantly affect technology integration. This could involve targeted professional development and the fostering of positive experiences with technology to enhance teachers' attitudes and, consequently, their usage behavior.

Interestingly, our results show that Perceived Ease of Use had no significant influence on mathematics teachers' adoption of Gen-AI. This result may be related to two main aspects. First, China's K-12 education system is characterized by rigid curriculum standards and policy constraints, which limit the degree of autonomy teachers have in their instructional practices [69]. In such a highly structured system, even if teachers personally perceive Gen-AI as valuable for teaching, they may lack the flexibility and space to incorporate the technology into their classrooms due to constraints imposed by policies and school regulations [26]. Second, tThis resistance also aligns with Markus's theory in "Power, Politics, and MIS Implementation" [70]. Mathematics teachers who perceive a loss of authority in their interactions with Gen-AI often reject the technology—the stronger their sense of power loss, the greater their resistance. This erosion of teachers' influence stems from the unique relationship between AI technology and education. The rapid advancement of AI has sparked debates about its potential to replace teachers, especially in subjects like mathematics and physics where content is clearly defined. These discussions have intensified teachers' concerns about job security. Additionally, as AI begins providing targeted student guidance, it diminishes teachers' traditional classroom authority and control. Consequently, despite Gen-AI's ease of use, teachers may view it as a threat, leading to lower adoption rates.

In this study, usage behavior was not significantly influenced by facilitating conditions. Although this is inconsistent with our research hypothesis, it is supported by many related studies [49, 71, 72]. This could be because the use of Gen-AI by teachers is influenced by multiple factors, making it a highly complex process [59]. Merely providing facilitating conditions, such as equipment or technical support, is not sufficient to motivate them to adopt Gen-AI in their teaching. In addition, the simple and convenient interface of Gen-AI also makes it easy for math teachers to use, thus reducing the impact of facilitating conditions.

Both hypotheses related to the original TPB model were supported, indicating that subjective norms and PBC (perceived behavioral control) had a significant positive impact on usage behavior, which aligns with findings from previous research [73, 74]. This suggests that when mathematics teachers decide whether to use Gen-AI in their teaching, the opinions of those around them and their perceived control over the technology are key factors. When education administrators, principals, colleagues, and students value the use of Gen-AI in mathematics teaching, or when teachers feel they have sufficient control over the use of Gen-AI, they are more likely to adopt it in practice.

Implications

Theoretical implications

Overall, the findings of this study offer the following theoretical contributions. First, by incorporating AI awareness as an external variable and adjusting the original models based on their strengths and weaknesses, this study extends the existing TAM and TPB models to explore the factors significantly influencing K-12 mathematics teachers' use of Gen-AI in teaching activities. The results show that the model has a high explanatory power for Chinese K-12 mathematics teachers' use of Gen-AI in teaching, suggesting that it is an effective theoretical framework. This provides a more comprehensive and in-depth understanding of the factors affecting teachers' technology adoption. Considering the commonality of variables across different contexts, the model offers valuable insights for other researchers investigating teachers' use of AI technologies.

Additionally, the results demonstrate that AI awareness is a key factor influencing mathematics teachers' use of Gen-AI in teaching indirectly, highlighting its positive role in K-12 teachers' adoption of Gen-AI for instructional purposes. Given AI's growing significance in today's fast-evolving technological landscape, further exploration is needed to understand how AI awareness affects teaching and learning activities. This study provides a new perspective on understanding and investigating the role and value of AI awareness and contributes to a deeper exploration of the intrinsic reasons and decision-making processes behind teachers' technology adoption.

This study also presents findings that differ from some previous research, encouraging further reflection on perceived usefulness and perceived ease of use. The results indicate that teachers' decisions to use AI in teaching activities involve a highly complex process. Policymakers and educational researchers must fully consider the nuanced and sometimes conflicting relationship between teachers and AI, especially in the era of rapid technological change, as well as the dynamic nature of teachers' evolving evaluations of AI's value as it increasingly integrates into the educational landscape.

Practical implications

As Gen-AI increasingly integrates with mathematics education, teachers need support to harness its full potential in creating dynamic and inclusive learning environments. Following our study's findings, we implemented several improvements to the "Mini Program + Mathematics" Innovation Course Research Group activities. We launched teacher training programs, designed mathematics courses, and created educational discussion platforms. Through months of refinement and collaboration, our research group developed exemplary teaching cases, which serves as important models that offer useful inspiration and guidance, particularly for new and early-career teachers. The exemplary teaching cases successfully boost teacher professional development and enhance students' innovation and information literacy skills. Overall, the adjustments have demonstrably improved the integration of AI technology in mathematics teaching. Based on these results, we recommend actions in three key areas.

First, teacher training programs should focus on cultivating AI awareness while providing AI technology training and showcasing exemplary lessons. Our result shows that AI awareness and attitudes are crucial factors in teachers' acceptance and adoption of AI—more so than perceived usefulness, ease of use, or available technology and equipment. Although robust teacher training programs exist at all educational levels, they often place excessive emphasis on teachers' mastery of AI technology, while neglecting to provide support for teachers' knowledge of AI and curriculum design skills [75]. Integrating AI into classroom teaching presents a complex challenge beyond traditional methods for teachers. Effective use of AI technology requires teachers to thoroughly understand its functions and value—without this awareness, classroom implementation suffers. Additionally, as classroom leaders and student guides, teachers must balance this with content delivery, student needs, and classroom management, adding to their responsibilities.

Hence, future teacher training should prioritize enhancing AI awareness through diverse methods: lectures, self-directed learning, and group discussions. This training should deepen teachers' understanding of how Gen-AI and mathematics education intersect, including AI's historical context, its benefits and drawbacks in mathematics teaching, and its role in professional development. Building on this foundation, targeted operational training can boost teachers' technical confidence. Particularly, sharing exemplary lessons helps teachers understand practical AI integration methods and fosters positive attitudes.

Second, course design should emphasize collaborative participation from diverse stakeholders to strengthen teachers' sense of support. Currently, curriculum development is primarily carried out independently by teachers, without a sufficient support structure in place [76]. In this context, teachers not only lack professional communication and guidance, but also fail to receive timely care and support from the teaching community. This leads to feelings of confusion and uncertainty during instruction, and weakens their sense of belonging [75]. Such isolation negatively affects teachers' perceived subjective norms, which can hinder their engagement with broader perspectives.

To address this, course design should actively involve mathematics education experts, school administrators, parents, and AI technology experts. This can be achieved in three ways: First, use mass media and campus initiatives to raise awareness about the value of AI integration in mathematics teaching, building support across different groups. Second, invite AI experts, administrators, and students to participate directly in course design through hands-on program interactions and discussions. Third, create open channels for communication between teachers, students, and parents to encourage dynamic feedback and enrich exemplary teaching cases. These steps will strengthen teachers' connection to their support network and increase their willingness to adopt AI technologies.

Finally, this study offers valuable insights for developing technology-supported course design platforms. While traditional course design and lesson planning occur offline, the complexity of integrating AI with mathematics education requires more dynamic solutions for real-time feedback and resource sharing. This highlights the importance of developing intelligent course design platforms. The findings on perceived behavioral control show that mere access to technology isn't enough—teachers need to feel confident and supported in using it.

The development of these platforms should address teachers' core needs, offering personalized teaching support and simplifying AI classroom integration. These platforms should leverage online interactivity to connect educational experts, technical specialists, and mathematics teachers in a professional yet flexible discussion space where teachers can quickly resolve practical challenges. For instance, GeoGebra incorporates AI features to help visualize mathematical concepts, create interactive geometric constructions, and solve complex problems. It also provides online resources shared by teachers worldwide. This boosts teachers' perceived behavioral control, encouraging them to embrace AI technology in their teaching and ultimately achieve more innovative and effective educational outcomes.

Conclusion

As artificial intelligence technologies continue to evolve, Generative AI—exemplified by tools like ChatGPT—is increasingly integrated into mathematics education. This integration is transforming the teaching and learning landscape. This study utilized the PLS-SEM method, drawing on an extended TAM and TPB model, to uncover the factors influencing K-12 mathematics teachers' adoption of Gen-AI in their teaching practices. The findings indicate that attitude, subjective norms, and perceived behavioral control (PBC) significantly positively impact K-12 mathematics teachers' use of Gen-AI. This insignificant result is primarily due to the influence of the characteristics of the educational system and cultural norms. Compared to the intrinsic features of the technology and environmental conditions, teachers are more focused on subjective norms and perceived behavioral control. In addition, AI awareness also played an indirect role in shaping usage behavior. This study closely aligns with the contemporary context by incorporating AI awareness into the theoretical model, constructing a reliable and effective framework. Additionally, based on the research findings and project implementation experience, this study provides practical recommendations for teacher training programs, mathematics course design, and the development of technology-supported course design platforms. These insights provide valuable guidance for policymakers, educators, and researchers striving to enhance AI integration in K-12 mathematics education.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40359-025-02781-2.

Supplementary Material 1

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Author contributions

Y.W. and Z.W. were responsible for the conceptualization and design of the study. T.T.W. managed the data collection and administration processes. Y.C. and Y.N. conducted the data analysis and verified the analytical methods. Y.W., Z.W., and T.T.W. wrote the main manuscript text. All authors reviewed the manuscript and contributed to the final version.

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Data availability
The datasets generated and analyzed in this study are not publicly available due to confidentiality and privacy-related issues but are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare no competing interests.

Ethics approval and consent to participate
Ethical approval for this study was granted by the Institutional Review Board of Beijing Normal University on June 10, 2024, ensuring that all research involving human participants was conducted in accordance with the Declaration of Helsinki. All participants gave written informed consent in accordance with the Declaration of Helsinki.

Consent for publication
Not applicable.

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References
1. Chen J, Chen P, Wu X. Generating Chinese Event Extraction Method Based on ChatGPT and Prompt Learning. Applied Sciences. 2023;13(17):9500.
2. Wardat Y, Tashtoush MA, AlAli R, Jarrah AM. ChatGPT: A revolutionary tool for teaching and learning mathematics. Eurasia J Math Sci Technol Educ. 2023;19(7).
3. Dwivedi YK, Kshetri N, Hughes L, Slade EL, Jeyaraj A, Kar AK, Baabdullah AM, Koohang A, Raghavan V, Ahuja M, Albanna H, Albashrawi MA, Al-Busaidi AS, Balakrishnan J, Barlette Y, Basu S, Bose I, Brooks L, Buhalis D, Carter L, Chowdhury S, Crick T, Cunningham SW, Davies GH, Davison RM, Dé R, Dennehy D, Duan Y, Dubey R, Dwivedi R, Edwards JS, Flavián C, Gauld R, Grover V, Hu MC, Janssen M, Jones P, Junglas I, Khorana S, Kraus S, Larsen KR, Latreille P, Laumer S, Malik FT, Mardani A, Mariani M, Mithas S, Mogaji E, Nord JH, O'Connor S, Okumus F, Pagani M, Pandey N, Papagiannidis S, Pappas IO, Pathak N, Pries-Heje J, Raman R, Rana NP, Rehm SV, Ribeiro-Navarrete S, Richter A, Rowe F, Sarker S, Stahl BC, Tiwari MK, van der Aalst W, Venkatesh V, Viglia G, Wade M, Walton P, Wirtz J, Wright R. 'So what if ChatGPT wrote it?' Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. Int J Inform Manage. 2023;71.
4. Dempere J, Modugu K, Hesham A, Ramasamy LK. September, The impact of ChatGPT on higher education. Front Educ. 2023;8.
5. Athaluri SA, Manthena SV, Kesapragada VSRKM, Yarlagadda V, Dave T, Duddumpudi RTS. Exploring the boundaries of reality: investigating the phenomenon of artificial intelligence hallucination in scientific writing through ChatGPT references. Cureus No April, 2023.
6. Wijaya TT, Cao Y, Weinhandl R, Yusron E. Applying the UTAUT model to understand factors affecting Micro-Lecture usage by mathematics teachers in China. Mathematics. 2022;10(7):1–20.
7. Wang F, Wijaya TT, Habibi A. Predictors influencing urban and rural area students to use tablet computers as learning tools: Combination of UTAUT and TTF Models. Sustainability. 2022.
8. Morchid N. The determinants of use and acceptance of mobile assisted Language learning: the case of EFL students in Morocco. Arab World Engl J. 2019;5:76–97.
9. Yang J, Wang Q, Wang J, Huang M, Ma Y. A study of K-12 teachers' TPACK on the technology acceptance of E-schoolbag. Interact Learn Environ. 2021;29(7):1062–75.
10. Mai DTT, Van Da C, Van Hanh N. The use of ChatGPT in teaching and learning: a systematic review through SWOT analysis approach. Frontiers in Educ. 2024;9:1–17.
11. Habib S, Vogel T, Anli X, Thorne E. How does generative artificial intelligence impact student creativity? J Creat. 2024;34(1):100072.
12. Rizos I, Foykas E, Georgakopoulos SV. Enhancing mathematics education for students with special educational needs through generative AI: A case study in Greece. CONT ED Technol. 2024;16(4):ep.
13. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Q. 1989;13(3):319–40.
14. Ajzen I. From Intentions to Actions: A Theory of Planned Behavior in Action Control, in *SSSP Springer Series in Social Psychology*, 1985.
15. Stössel J, Baumann R, Wegner E. Predictors of student teachers' Esd implementation intention and their implications for improving teacher education. Sustain (Switzerland), 13, 16, 2021.
16. Al-Emran M, Arpaci I, Salloum SA. An empirical examination of continuous intention to use m-learning: an integrated model. Educ Inform Technol. 2020;25(4):2899–918.
17. Shen Y. Determinants of problem sports betting among college students: moderating roles of betting frequency and impulsive betting tendency. BMC Psychol. 2023;11(1):1–11.
18. Gellerstedt M, Babaheidari SM, Svensson L. A first step towards a model for teachers' adoption of ICT pedagogy in schools. Heliyon. 2018;4(9):e00786.
19. J. J. KK, Raghuram NV. Gen – AI integration in higher education: predicting intentions using SEM – ANN approach. Springer US; 2024. p. 0123456789.
20. Van Poucke M. ChatGPT, the perfect virtual teaching assistant? Ideological bias in learner-chatbot interactions. Computers and Composition. 2024;73:102871.
21. Wijaya TT, Su M, Cao Y, Weinhand R, Houghton T. Examining Chinese preservice mathematics teachers ' adoption of AI chatbots for learning: unpacking perspectives through the UTAUT2 model. Educ Inform Technol. 2024.
22. Lee D, Yeo S. Computers & Education Developing an AI-based chatbot for practicing responsive teaching in mathematics. Computers & Education. 2022;191:104646.
23. Wang N, Lester J. K-12 education in the age of AI: A call to action for K-12 AI literacy. Int J Artif Intell Educ. 2023:228–32.
24. Wu R, Yu Z. Do AI chatbots improve students learning outcomes? Evidence from a meta-analysis. British J Educ Technol. 2023:1–24.
25. Nyaaba M, Shi L, Nabang M, Zhai X, Kyeremeh P, Ayoberd SA, Akanzire BN. Generative AI as a learning buddy and teaching assistant: Pre-service teachers' uses and attitudes. ArXiv, 03-Jun-2024.
26. Zhai X. Transforming Teachers' Roles and Agencies in the Era of Generative AI: Perceptions, Acceptance, Knowledge, and Practices. arXiv, 03-Oct-2024.
27. Kim J. Leading teachers ' perspective on teacher – AI collaboration in education. Springer US. 2024;29(7).
28. Hung J, Chen J. The benefits, risks and regulation of using ChatGPT in Chinese academia: A content analysis. Social Sci. 2023;12(7).
29. Ng DTK, Leung JKL, Su J, Ng RCW, Chu SKW. Teachers' AI digital competencies and twenty-first century skills in the post-pandemic world. Education Tech Research Dev. 2023;71(1):137–61.
30. Rapaka A, Dharmadhikari SC, Kasat K, Mohan CR, Chouhan K, Gupta M. Revolutionizing learning– A journey into educational games with immersive and AI technologies. Entertainment Computing. 2025;52:2024.
31. Baillifard A, Gabella M, Lavenex PB, Martarelli CS. Effective learning with a personal AI tutor: A case study. Educ Inform Technol. 2024.
32. Joksimovic S, Ifenthaler D, Marrone R, De Laat M, Siemens G. Opportunities of artificial intelligence for supporting complex problem-solving: findings from a scoping review. Computers Education: Artif Intell. 2023;4:100138.
33. Villegas-Ch WE, Govea J, Gutierrez R, Mera-Navarrete A. Improving interaction and assessment in hybrid educational environments: an integrated approach in Microsoft teams with the use of AI techniques. IEEE ACCESS. 2024;12:93723–38.
34. Long D, Magerko B. What is AI Literacy? Competencies and Design Considerations, in *Proceedings of the* 2020 *CHI Conference on Human Factors in Computing Systems*, 2020, pp. 1–16.
35. Webb C, Luckin R, Ecoff E. Ethical principles for the development and application of artificial intelligence in K-12 education. In: Lee WO, Brown P, Goodwin AL, Green A, editors. International handbook on education development in Asia-Pacific. Singapore: Springer Nature Singapore; 2022. pp. 1–19.
36. Liang X, Guo G, Shu L, Gong Q, Luo P. Investigating the double-edged sword effect of AI awareness on employee's service innovative behavior, *Tourism Management*, vol. 92, p. 104564, Oct. 2022.
37. Mo Z, Liu MT, Ma Y. How AI awareness can prompt service performance adaptivity and technologically-environmental mastery, *Tourism Management*, vol. 105, p. 104971, Dec. 2024.
38. Kandlhofer M, Weixelbraun P, Menzinger M, Steinbauer-Wagner G, Kemenesi Á. Education and Awareness for Artificial Intelligence, in *Informatics in Schools. Beyond Bits and Bytes: Nurturing Informatics Intelligence in Education*, Cham, 2023, pp. 3–12.

39. Chen R-S, Tsai C-H. A study of the success of E-classroom system on the higher education expansion. Inf Technol J. 2011;10(2):257–66.
40. Zhu M, Zhang Y. Medical and public health instructors' perceptions of online teaching: A qualitative study using the technology acceptance model 2. Educ Inform Technol. 2022;27(2):2385–405.
41. Venkatesh MG, Morris GB, Davis, Davis FD. User acceptance of information technology: toward a unified view. Manage Inform Syst Q. 2003;27(3):425–78.
42. Ngafeeson MN, Sun J. The effects of technology innovativeness and system exposure on student acceptance of e-textbooks. J Inform Technol Educ. 2015;14(1):55–71.
43. Al-rahmi AM, Al-rahmi WM, Alturki U, Aldraiweesh A, Almutairy S, Al-adwan AS. Exploring the factors affecting mobile learning for sustainability in higher education. Sustain (Switzerland). 2021;13(14):1–22.
44. Fishbein M, Ajzen I. Belief, attitude, intention, and behavior: An introduction to theory and research, *Contemporary Sociology; Addison-Wesley: Reading, MA, USA*, 1975.
45. Balakrishnan J, Abed SS, Jones P. The role of meta-UTAUT factors, perceived anthropomorphism, perceived intelligence, and social self-efficacy in chatbot-based services? *Technological Forecasting and Social Change*, vol. 180, no. December 2021, p. 121692, 2022.
46. Milicevic N, Kalas B, Djokic N, Malcic B, Djokic I. Students' Intention toward Artificial Intelligence in the Context of Digital Transformation, *Sustainability*, vol. 16, no. 9, p. 3554, Apr. 2024.
47. Pal D, Patra S. University students ' perception of Video-Based learning in times of COVID-19: A TAM / TTF perspective. Int J Human–Computer Interact. 2021;37(10):903–21.
48. Venkatesh V, Davis FD. Theoretical extension of the technology acceptance model: four longitudinal field studies. Manage Sci. 2000;46(2):186–204.
49. Yuan Z, Liu J, Deng X, Ding T, Wijaya TT. Facilitating conditions as the biggest factor influencing elementary school teachers' usage behavior of dynamic mathematics software in China. Mathematics. 2023;11(6).
50. Zhao W, Mok IAC, Cao Y. Factors influencing teachers' implementation of a reformed instructional model in China from the theory of planned behavior perspective: A multiple case study. Sustain (Switzerland). 2020;12(1):1–21.
51. Yao Y, Wang P, Jiang YJ, Li Q, Li Y. Innovative online learning strategies for the successful construction of student self-awareness during the COVID-19 pandemic: merging TAM with TPB. J Innov Knowl. 2022;7(4):100252.
52. Yusop FD, Habibi A, Razak RA. Factors affecting Indonesian preservice teachers' use of ICT during teaching practices through theory of planned behavior. SAGE Open. 2021;11(2).
53. Al-Emran M, Al-Sharafi MA, Foroughi B, Al-Qaysi N, Mansoor D, Beheshti A, Ali N. Evaluating the influence of generative AI on students' academic performance through the lenses of TPB and TTF using a hybrid SEM-ANN approach, *Educ Inf Technol*, Mar. 2025.
54. Hair J, Black B, Babin B, Anderson RE, Tatham RL. Multivariate data analysis. 6th ed. Prentice Hall; 2006.
55. Hair JF, Ringle CM, Sarstedt M. Partial least squares: the better approach to structural equation modeling? Long Range Plann. 2012;45:5–6.
56. Hair JF, Anderson RE, Tatham RL, Black WC. Multivariate data analysis. Volume 87, 4no. ed. United Kingdom: Annabel Ainscow; 2019.
57. Hair JF, Hult GTM, Ringle C, Sarstedt M. A primer on partial least squares structural equation modeling (PLS-SEM). SAGE; 2016.
58. Fornell C, Larcker DF. Evaluating structural equation models with unobservable variables and measurement error. J Mark Res. 1981;18(1):39–50.
59. Du H, Sun Y, Jiang H, Islam AYMA, Gu X. Exploring the effects of AI literacy in teacher learning: an empirical study. Humanit Social Sci Commun. 2024;11(1):1–10.
60. Kim MJ, Hall CM, Chung N. The influence of AI and smart apps on tourist public transport use: applying mixed methods. Inform Technol Tourism. 2024;26(1):1–24.
61. Pando-Garcia J, Periañez-Cañadillas I, Charterina J. Business simulation games with and without supervision: an analysis based on the TAM model. J Bus Res. 2016;69(5):1731–6.
62. Jiang P, Wijaya TT, Mailizar M, Zulfah Z, Astuti A. How Micro-Lectures improve learning satisfaction and achievement: A combination of ECM and extension of TAM models. Mathematics. 2022;10(19):3430.
63. Tang X, Yuan Z, Kuang H, Qu H, Tang X. Using the UTAUT-TPACK model to explain digital teaching behaviour of elementary school mathematics teacher. Asia Pac J Educ. 2024;00(00):1–23.
64. Hu S, Laxman K, Lee K. Exploring factors affecting academics' adoption of emerging mobile technologies-an extended UTAUT perspective. Educ Inform Technol, pp. 4615–35, 2020.
65. Wang YS, Wu MC, Wang HY. Investigating the determinants and age and gender differences in the acceptance of mobile learning. Br J Edu Technol. 2009;40(1):92–118.
66. Zhao Y, Wang N, Li Y, Zhou R, Li S. Do cultural differences affect users' e-learning adoption? A meta-analysis. Brit J Educational Tech. Jan. 2021;52(1):20–41.
67. Testa N, Tawfik A. Mobile, but Are We Better? Understanding Teacher's Perception of a Mobile Technology Integration Using the Unified Theory of Acceptance and Use of Technology (UTAUT) Framework, *J Form Des Learn*, vol. 1, no. 2, pp. 73–83, Dec. 2017.
68. Nikolopoulou K. Secondary education teachers' perceptions of mobile phone and tablet use in classrooms: benefits, constraints and concerns J. Comput. Educ. 2020;7(2):257–275.
69. Chen D, Chen Y, Chi J. Early childhood teachers amid China's curriculum reforms: from a literature review. ICEP. Aug. 2024;18(1):8.
70. Markus ML. Power, politics, and MIS implementation. Commun ACM. 1983;26(6):430–44.
71. Kim J, Lee KS. Conceptual model to predict Filipino teachers ' adoption of ICT-based instruction in class: using the UTAUT model. Asia Pac J Educ. 2020;00(00):1–15.
72. Dahri NA, Yahaya N, Al-Rahmi WM, Vighio MS, Alblehai F, Soomro RB, Shutaleva A. Investigating AI-based academic support acceptance and its impact on students' performance in Malaysian and Pakistani higher education institutions. Volume 0123456789. Springer US; 2024.
73. Stols G, Kriek J. Why don't all maths teachers use dynamic geometry software in their classrooms? Australasian J Educational Technol. 2011;27(1):137–51.
74. Sobaih AEE, Hasanein A. Higher education in and after COVID-19: the impact of using social network applications for E-Learning on students ' academic performance. Sustain (Switzerland), 2022.
75. Chiu TKF, Chai C. Sustainable Curriculum Planning for Artificial Intelligence Education: A Self-Determination Theory Perspective. Sustainability. 2020;12(14):5568.
76. Tan X. Artificial intelligence in teaching and teacher professional development: A systematic review. Computers Educ. 2025.

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