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TPACK-based professional development for the AI era: fostering pre-service teachers' acceptance of generative AI in mathematics classrooms

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Abstract

As Generative AI (GenAI) becomes more prevalent, the need to prepare pre-service teachers (PSTs) for its use is a critical challenge for mathematics teacher educators (MTEs). Yet, little is known about how to best foster PSTs' adoption and critical use of GenAI in mathematics classrooms. This study addresses this gap by exploring the influence of a 90-minute professional development workshop, grounded in the Technological Pedagogical Content Knowledge (TPACK) framework, on PSTs' technology acceptance in mathematics education. A mixed-methods design was employed, using pre- and post-surveys based on an extended Unified Theory of Acceptance and Use of Technology (UTAUT) model for quantitative data and semi-structured interviews and workshop discussions for qualitative data. Quantitative analysis observed statistically significant positive shifts in many aspects of technology acceptance, except for PSTs' perceived risks of the technology. Qualitative analysis identified key facilitators to adoption, such as GenAI's utility for instructional efficiency, alongside notable barriers, including the lack of institutional AI policies. This study offers actionable implications for MTEs on designing pedagogically grounded training that addresses the practical applications and ethical complexities of GenAI in mathematics classrooms.

Keywords Generative AI · Pre-service teachers · Mathematics education · Professional development · TPACK · Technology acceptance

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Introduction

The emergence of Generative Artificial Intelligence (GenAI) presents a significant pedagogical challenge for mathematics teacher educators (MTEs): how to prepare pre-service teachers (PSTs) to critically and effectively use this technology to support mathematical learning? GenAI is rapidly transforming education through increasing integration of AI-powered resources into instruction. GenAI systems can support differentiated instruction (Getenet, 2024) and promote student-centered learning (Song et al., 2025). Educators are adopting GenAI chatbots, like ChatGPT, alongside education-specific GenAI tools, like Magic School AI, to streamline instructional responsibilities and provide tailored learning experiences (Baidoo-Anu & Ansah, 2023; Kasneci et al., 2023; Yilmaz & Yilmaz, 2023). In mathematics education, GenAI is being used for developing instructional content (Ellis & Slade, 2023), solving math problems (Guler et al., 2024), and providing personalized feedback (Li et al., 2023). PSTs have recognized instructional benefits of GenAI tools for planning lessons and designing assessments (Wang et al., 2024).

However, the nature and use of GenAI differ substantially from earlier educational technologies. Unlike digital mathematics tools, such as algebra systems (e.g., Wolfram Alpha) and dynamic geometry environments (e.g., GeoGebra), which primarily execute pre-determined algorithms to compute or visualize, GenAI systems are conversational content-creating partners (Mishra et al., 2023) that respond probabilistically to open-ended tasks. These systems can generate novel mathematical tasks, explanations, and feedback in real time, producing different outputs for the same input (Walkington, 2025). This shift from deterministic tools to probabilistic, natural-language-based systems raises new pedagogical questions about how teachers should monitor and curate AI-generated content within students' learning experiences.

While calculators and algebra systems primarily automate computational procedures, GenAI also automates aspects of mathematical reasoning and problem-solving, often in ways that are error-prone (Walkington, 2025). PSTs have expressed apprehensions about GenAI's reliability and its potential to undermine teacher agency (Yang & Appleget, 2024). Together with findings that many teacher educators lack the competencies to facilitate AI literacy for PSTs (Nyaaba & Zhai, 2024), these concerns from PSTs highlight a significant gap in teacher preparation. Thus, it is imperative to develop structured training frameworks that equip PSTs with the knowledge and skills needed to thoughtfully and effectively incorporate GenAI tools into teaching practices (Sánchez-Ruiz et al., 2023; Wang et al., 2024).

Despite the rising adoption of GenAI in mathematics classrooms, a significant research gap remains regarding the motivations that drive teachers to adopt these tools for teaching mathematics. Most studies on GenAI technology acceptance in education focus on student usage (Strzelecki, 2023; Faruk et al., 2023; Yilmaz et al., 2024). In contrast, relatively few studies explore how pre-service and in-service teachers perceive the integration of GenAI into their pedagogical activities (Wang et al., 2024; Li, 2024). Given teachers' crucial role in determining technology adoption in classrooms, understanding the perspectives and competencies of PSTs regarding GenAI is vital for developing effective training programs.

Educators tend to find technology easier to use as they become more proficient (Mukuka & Alex, 2024). However, many teacher education programs lack hands-on opportunities for PSTs to develop and implement GenAI knowledge in classroom settings (Macdowell et al., 2024). This gap in teacher education is mirrored by limited empirical research. Prior work establishes that PD rooted in pedagogical frameworks like the Technological Pedagogical Content Knowledge (TPACK) model (Mishra & Koehler, 2006) effectively enhances teacher confidence and willingness to adopt new technologies (Daher et al., 2021; Jaipal-Jamani & Figg, 2015). However, there is a scarcity of studies that systematically evaluate such learning programs for GenAI adoption.

Technology acceptance frameworks like the Unified Theory of Acceptance and Use of Technology (UTAUT) model (Venkatesh et al., 2003) are frequently used to investigate technology adoption among educators (Gurer, 2021; Perienen, 2020), but few apply these models to understand PSTs' adoption of GenAI, particularly within mathematics classrooms. The UTAUT model serves as a robust foundation for studying technology adoption. However, it does not fully account for the unique challenges introduced by GenAI. In this AI era, teachers must not only decide whether to use GenAI but also how much to trust its suggestions, how to maintain student agency with AI-supported learning, and how to mitigate potential risks in classroom contexts. Therefore, this study employs an extended UTAUT framework that integrates the constructs of Trust, Perceived Risk, and TPACK. These additions are based on research identifying them as critical factors in the acceptance of AI-driven and educational technologies (Xiong et al., 2023; Yildiz & Arpaci, 2024). This enhanced model provides a more holistic lens for analyzing how PSTs perceive the adoption of GenAI tools.

This study addresses the gaps in the literature by designing and implementing a TPACK-based PD workshop to build PSTs' technological and pedagogical knowledge for integrating GenAI tools into mathematics instruction. Using a mixed-methods approach, it quantitatively explores the program's influence on PSTs' acceptance of GenAI in mathematics education and qualitatively elaborates the factors shaping their perceptions. Specifically, the research questions for this study are:

1. How does a TPACK-based PD workshop influence PSTs' perceptions of GenAI's adoption in mathematics classrooms?
2. What factors influence PSTs' willingness to adopt GenAI tools in mathematics education contexts?

This study offers an extended UTAUT framework for future GenAI adoption studies in educational contexts. For MTEs, the findings may guide the design of pedagogically-grounded GenAI training programs. Ultimately, this work informs strategies to enhance PSTs' GenAI competencies in navigating the pedagogical and ethical challenges of GenAI adoption in mathematics instruction.

Theoretical perspectives

The successful integration of technology in education begins with user acceptance (Appavoo, 2020). Technology acceptance explains how and why individuals embrace new technologies. While several models explain this phenomenon, this study builds upon the Unified Theory of Acceptance and Use of Technology (UTAUT) model introduced by Venkatesh et al. (2003), which presents four key constructs predicting acceptance:

- Performance Expectancy (PE): Degree of belief that technology enhances job performance.
- Effort Expectancy (EE): Perceived ease of using the technology.
- Social Influence (SI): Social pressure an individual feels to use the technology.
- Facilitating Conditions (FC): Perceived availability of organizational or technical support to use the technology.

PE, EE, and SI directly determine Behavioral Intention (BI), which is a user's intention to use the technology. This intention, with support of FC, can predict the actual Use Behavior (UB), i.e., the genuine adoption of the technology. UTAUT has been validated in various education research studies (Aytekin et al., 2022; Yee et al., 2021) and in assessing the acceptance of AI technologies like prediction and recommendation systems (Menon & Shilpa, 2023). However, GenAI's unique aspects for educators require an extension of the UTAUT model. Unlike traditional digital math tools that are deterministic and computational, Mishra et al. (2023) argue that GenAI behaves as a "psychological other", as it interacts through natural language in a way that feels like a social interaction to the user. This social dimension, combined with GenAI's tendency to hallucinate, i.e., generate misinformation (Weidinger et al., 2023), undermines user trust (Menon & Shilpa, 2023). Trust is crucial for enhancing user acceptance, while perceived risks can hinder it (Ajenaghughrure et al., 2021; Choung et al., 2022). Thus, their inclusion in UTAUT is critical for understanding GenAI adoption, an approach adopted and validated by Xiong and colleagues (2023). Similarly, pedagogical competence is a critical determinant of technology adoption for educators. TPACK, introduced by Mishra and Koehler (2006), illustrates the vital interplay among technology, pedagogy, and content knowledge for effective technology integration in education. Research (Kiyici & Övez, 2021; Mayer & Girwidz, 2019) has consistently established the significant influence of TPACK on PSTs' and mathematics teachers' technology acceptance. Additionally, Wang et al. (2024) found that PSTs' self-perceived TPACK enhanced their acceptance of GenAI by improving their perceptions of its usefulness and ease of use. Therefore, this study employs an extended UTAUT framework, represented in Fig. 1, that integrates these three key constructs of Trust (TR), Perceived Risk (PR), and TPACK to create a more nuanced understanding of GenAI acceptance among PSTs.

Literature review

This section synthesizes literature to establish the foundation for this research. It explores GenAI affordances and challenges in mathematics education, key factors influencing technology acceptance in educational contexts, and PD's role in enhancing PSTs' technology adoption.

GenAI in mathematics education

GenAI offers significant potential for mathematics education but also presents considerable challenges. It supports educators in generating course materials and lesson plans (Bazelais et al., 2024; Ellis & Slade, 2023). For students, it enhances learning by assisting in solving problems, explaining concepts, and providing personalized feedback (Guler et al.,

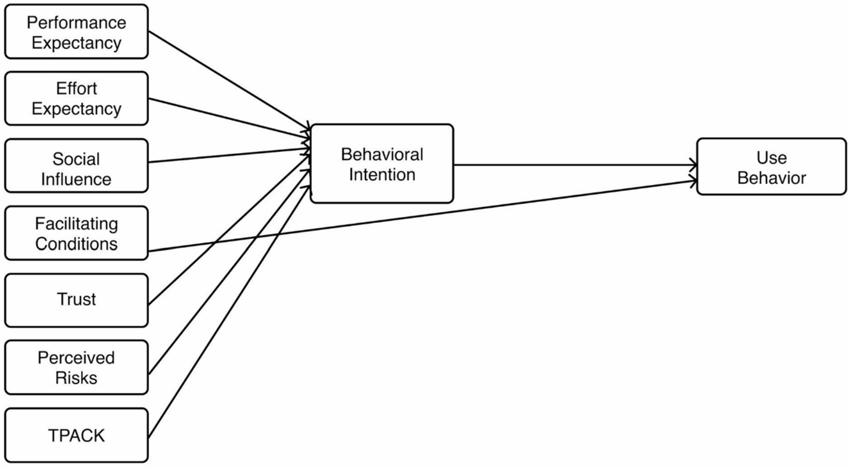

Fig. 1 Extended UTAUT Model

2024; Dasari et al., 2024; Li et al., 2023). GenAI-powered agents can foster student-centered learning by improving engagement and conceptual understanding (Song et al., 2025). Gattupalli et al. (2023) found that PSTs sometimes prefer GenAI's step-by-step guidance over human-crafted hints in online math learning. Furthermore, GenAI enables differentiate instruction (Getenet, 2024), creates engaging tasks (Sánchez-Ruiz et al., 2023), and complements traditional tools like Computer Algebra Systems (CAS) (Matzakos et al., 2023), with research highlighting its promise in teaching specific topics like geometry (Wardat et al., 2023) and its positive reception among students (Sánchez-Ruiz et al., 2023). However, these advantages are contested by ethical and pedagogical concerns, such as academic dishonesty (Rahman & Watanobe, 2023), misinformation due to hallucinations (Athaluri et al., 2023), reinforcement of biases (Gross, 2023), and possible exacerbation of the digital divide (Chan & Hu, 2023). In the context of mathematics education, particular limitations involve questionable computational accuracy (Matzakos et al., 2023), student overreliance, and pedagogical gaps such as the lack of adaptability to diverse learning styles (Sánchez-Ruiz et al., 2023).

Segal and Klemer (2025) found that dialogic teacher-GenAI interactions during geometry lesson planning led to substantive revisions in task structure that promoted inquiry, critical thinking, and creativity. Improvements in teaching practice, however, depended on teachers' ability to evaluate and adapt AI-generated suggestions. Similarly, Segal and colleagues (2025) showed that MTEs using iterative dialogue with ChatGPT to design teacher training, produced novel task ideas and representations for challenging topics (e.g., fraction division, number-line operations) and strategies to overcome teachers' resistance to new instructional approaches. These studies indicate that when teachers and teacher educators engage in sustained, iterative use of GenAI to design instruction, they reconfigure mathematical tasks, representations, and pedagogical practices, that requires a transformation of content and pedagogical knowledge to fit the affordances and challenges of GenAI. Thus, to design meaningful mathematical learning experiences with GenAI necessitates professional learning that support teachers to balance mathematics knowledge and pedagogical strategies within affordances and constraints of GenAI.

Technology acceptance in educational contexts

The acceptance of technologies in education is widely studied through frameworks like the UTAUT model (Venkatesh et al., 2003) and its variants. This section reviews the factors influencing the acceptance of GenAI and other technologies in general and math-specific educational settings.

GenAI acceptance research in higher education has shown that several key factors drive students' intention to use these tools. Across multiple studies, performance expectancy—the perceived usefulness of technology—consistently emerges as a primary determinant of adoption (Bazelais et al., 2024; Faruk et al., 2023; Strzelecki, 2023; Wang et al., 2024). Similarly, Strzelecki (2023) identified facilitating conditions (e.g., technical support and resources) as a critical driver. From students' psychological standpoint, personality traits such as openness can positively affect usage, while neuroticism may act as a barrier (Faruk et al., 2023). Researchers have also developed standardized instruments like the Generative Artificial Intelligence Acceptance Scale (GAIAS) (Yilmaz et al., 2024) to better measure these constructs for educational contexts.

While student adoption studies are extensive, research on educators is less common. A notable study by Wang et al. (2024) examined PSTs' intention to use GenAI, finding that performance expectancy (i.e., perceived usefulness) and social influence were the strongest predictors. Their extended UTAUT model also incorporated TPACK, which boosted confidence and reduced GenAI anxiety. Interestingly, some studies have found constructs like effort expectancy (i.e., the perceived ease of use) and facilitating conditions, to have no significant impact on behavioral intention to use GenAI in learning and teaching (Bazelais et al., 2024; Wang et al., 2024). This suggests that the perceived benefits of GenAI may sometimes outweigh ease-of-use and support availability concerns.

For mathematics teachers and PSTs, perceived usefulness consistently predict their intention to use technology (Al-zboon et al., 2021; Gurer, 2021; Philemon, 2022; Wong, 2015). Effort expectancy was also found to be an important factor influencing adoption (Gurer, 2021; Perienen, 2020; Philemon, 2022). Additionally, facilitating conditions and social influence are often cited as powerful influences on technology adoption (Wong, 2015; Gurer, 2021; Al-zboon et al., 2021). A study by Perienen (2020) noted that, despite recognizing technology's pedagogical value for mathematics instruction, teachers' actual integration was minimal, with effort expectancy and facilitating conditions being the primary factors influencing its use. This highlights a persistent need for PD focused on pedagogical integration of technology in classrooms. Furthermore, factors such as teacher pedagogical beliefs and technology self-efficacy are crucial in predicting technology acceptance (Wong, 2015; Gurer & Akkaya, 2022), as is the alignment of the technology with instructional goals, i.e., task-technology fit (Philemon et al., 2022). As GenAI tools enter mathematics education, early research shows positive perceptions among US college students (Li et al., 2024), but teacher adoption remains complex. A recent study on Chinese primary mathematics teachers by Li (2024) found that positive teacher attitudes significantly impacted GenAI adoption.

Thus, a significant gap persists in technology acceptance studies at the intersection of GenAI technology, teachers, and mathematics education. Research on GenAI has predominantly centered on students, while studies in mathematics education have only begun exploring GenAI. Consequently, the factors influencing the adoption of GenAI tools among pre-service mathematics teachers remain largely unexplored.

Enhancing technology acceptance of PSTs with PD

Literature consistently emphasizes PD's crucial role in facilitating technology integration into instruction (Mistretta, 2005; Ndlovu et al., 2020). While many studies examine the factors influencing technology acceptance among educators, few focus on PD designed to improve this acceptance (Kale, 2018).

Daher and colleagues (2021) conducted a noteworthy investigation into targeted PD to enhance PSTs' acceptance of digital tools in mathematics and science. Their TPACK-based model emphasized technical proficiency and pedagogical understanding through collaborative discussions, digital content creation, and reflective practices. Analysis using paired samples t-tests revealed significant increases in pre- and post-intervention scores across several dimensions, including perceived ease of use, perceived usefulness, attitudes, intent to use, actual usage, and self-efficacy. Another study by Özbek et al. (2023) demonstrates that PSTs engaging hands-on with new digital tools or reading tool-specific information both increased intentions to incorporate it into lesson plans. Furthermore, Yang and Appleget (2024) underscored the importance of structured integration of GenAI within teacher education programs. In their study, PSTs utilized GenAI tools to generate and assess read-aloud questions during a literacy methods course, applying their pedagogical and content knowledge in a practical learning setting. The findings indicated that 91% of PSTs recognized GenAI as a valuable instructional tool, though concerns persisted about teacher agency, creativity, and reliability. Engagement positively correlated with future use intentions, underscoring needs for AI literacy and pedagogical adaptation within teacher preparation curricula. Overall, the literature suggests that educational interventions are vital in fostering PSTs' acceptance of technology.

Methods

Research design

This study employed a sequential mixed-methods design (Creswell, 2021) to understand PSTs' attitudes toward using GenAI in mathematics education. This approach is effective in technology acceptance research in educational settings (Creswell & Clark, 2018; Venkatesh et al., 2013), as it integrates the strengths of quantitative data to measure outcomes with qualitative data to explore the underlying processes driving them. As illustrated in Fig. 2, the quantitative part addressed Research Question 1 (RQ1) by exploring the TPACK-based workshop's influence on PSTs' perceptions. The qualitative part addressed Research Question 2 (RQ2), examining the underlying factors that shaped these perceptions. Quantitative results informed qualitative data collection, including the semi-structured interview guide.

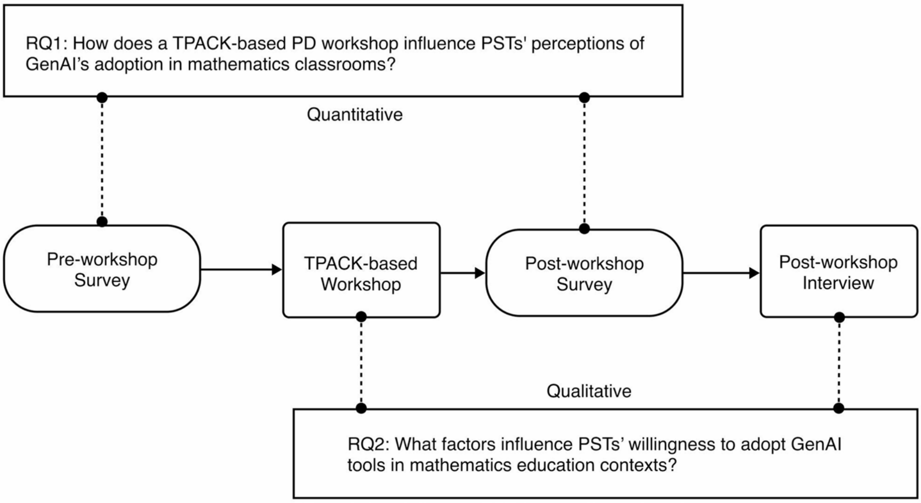

Fig. 2 Research Design

Context and participants

This study occured at a large public university in the Midwest United States, in two teacher education courses: a mathematics methods, consisting 12 students, and an educational technologies course with 15 students in one section and 14 students in another. The first author facilitated three 90-minute workshops, one in the mathematics methods course and two in each section of the learning technologies course as regular coursework. All 41 PSTs enrolled in these courses attended the workshops and were invited to participate in the research. A total of 28 PSTs (8 male, 20 female) consented to participate, representing various academic levels: six sophomores, 12 juniors, eight seniors, and two master's students. Aggregate course records showed a similar distribution of gender, majors, and academic year as the participant pool. This suggests the 28 participants were representative of the broader course cohorts.

Following the workshop, all 28 participants were invited for follow-up interviews. The first five PSTs who responded and aspired to serve as mathematics educators were selected for the interviews, including three females and two males, representing a range of academic levels: one junior, three seniors, and one master's student. The group comprised four secondary mathematics PSTs and one elementary education PST pursuing a secondary mathematics endorsement. This purposive sub-sample focused on PSTs whose career paths aligned directly with the study's focus on mathematics education.

TPACK-based PD workshop

The 90-minute workshop was designed to enhance PSTs' competence and willingness to integrate GenAI in mathematics instruction. Its design was grounded in the TPACK-based Professional Learning Design Model (TPLDM), a framework developed by Figg and Jaipal-Jamani (2012, 2013, 2015) that moves beyond traditional, technocentric PD by providing a structured approach that systematically integrates technological, pedagogical, and content knowledge. Research has demonstrated the model's effectiveness in building TPACK competencies among diverse educators, from university faculty to K-12 teachers (Jaipal-Jamani et al., 2018; Tai, 2015). The workshop progressed through four main components:

Modeling a technology-enhanced activity type

The workshop started as the PSTs were asked to assume the role of a sixth-grade student tackling ratio practice problems on Khan Academy, an online educational platform. During this modeled activity, the PSTs worked through several ratio problems both with and without the support of Khanmigo, a GenAI chatbot integrated into Khan Academy. Khanmigo was chosen for this demonstration because of the widespread adoption of Khan Academy among U.S. school districts, making it a relevant and relatable example for PSTs. During the 2023–2024 school year, Khan Academy had nearly 975,800 licensed users across 577 U.S. school communities (Khan Academy, 2024).

The activity took PSTs through a series of Khan Academy screenshots that followed a narrative, allowing them to observe and critically assess the AI's ability to provide instant feedback, scaffold problem-solving strategies, and tailor instruction to meet student needs. For instance, during the Khanmigo interactions demonstrated in Fig. 3, some PSTs raised concerns that while Khanmigo effectively prompted the student to identify the correct numbers needed for a ratio problem (five turtles and eight total animals), it immediately provided the final answer. Instead of guiding the student to form the ratio themselves, the chatbot stated, "So, the ratio of turtles to total animals is 5 for every 8."

A volunteer PST then demonstrated live interactions with Khanmigo, engaging with Khanmigo in various manners typical of a sixth-grade student. They used the chatbot's suggested prompts, communicated with it using slang and spelling mistakes, and exhibited behaviors resistant to learning. This interactive demonstration enabled PSTs to closely examine how real-time interactions with a GenAI tutor resemble the experiences of their perceived impression of a sixth-grade learner. Thus, this activity, which lasted approximately 25 min, contributed to PSTs' understanding of the complex relationship between GenAI tools (Khanmigo), pedagogical strategies (scaffolding and differentiation), and math content (ratios).

Integrating pedagogical dialogue

After the modeling exercise, PSTs discussed the instructional implications of GenAI, drawing specifically on the ratio tasks and student-AI interactions they had just observed in the Khanmigo activity. First, they individually answered two prompts for one minute using a real-time interactive tool (Wooclap) that connects a presenter's screen with students' personal devices. The prompts were: (1) How can Khanmigo facilitate differentiation for mixed-ability classrooms? and (2) What could be some drawbacks to students engaging with GenAI bots like Khanmigo?

Figure 4 illustrates a subset of these individual Wooclap responses to the second prompt. Then, for each prompt, the facilitator projected individual responses (as shown in Fig. 4) and led small-group and whole-class discussions among the PSTs for two minutes each. This component specifically focused on the pedagogical aspect of the TPACK framework,

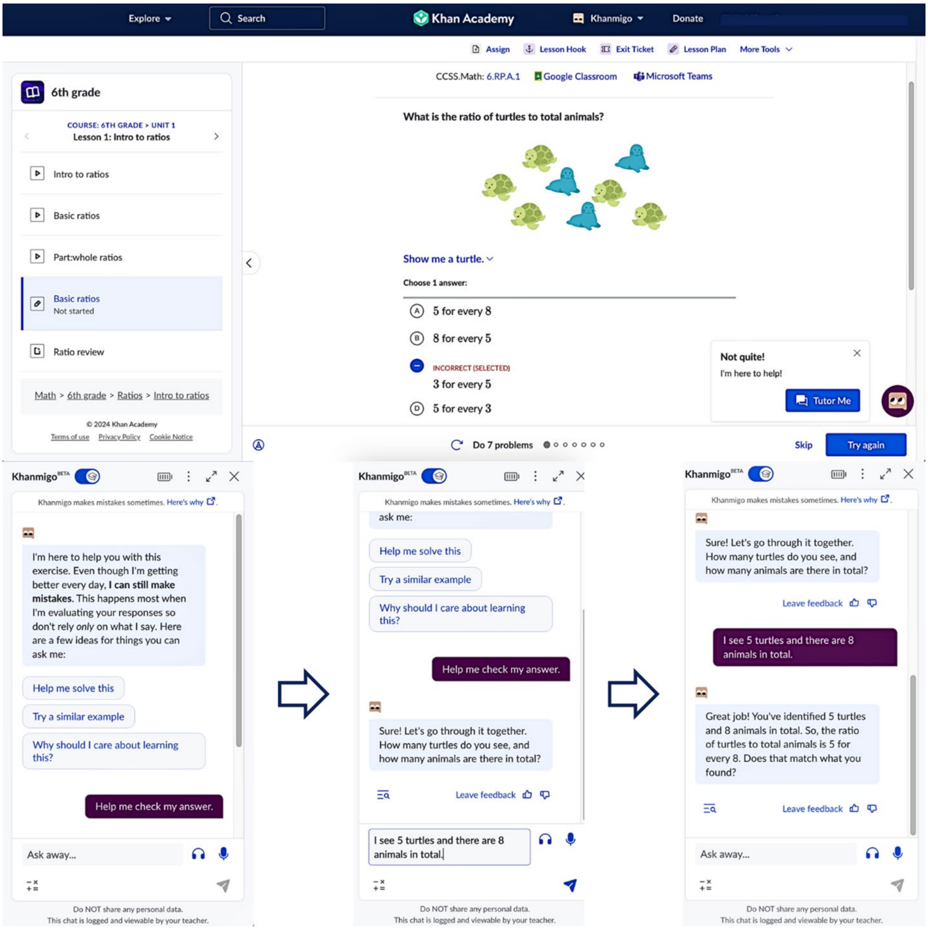

Fig. 3 Screenshots of Simulated Learning Activity with GenAI-powered Chatbot, Khanmigo

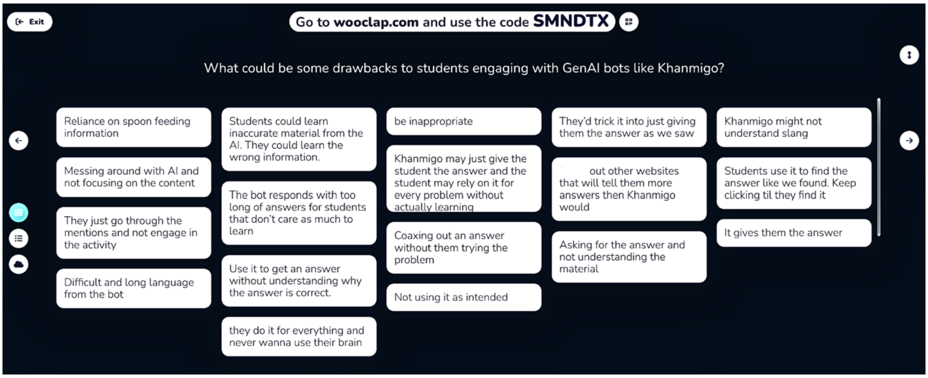

Fig. 4 Screenshot of PST Individual Responses on Wooclap for Second Discussion Prompt

encouraging PSTs to reflect on how technology and teaching methods intersect and affect student learning in mathematics education.

Developing technical skills through short tool demonstrations

In this part, PSTs were asked to individually respond, via Wooclap, to the prompt, "How are GenAI tools being used by teachers for mathematics instruction?" This exercise aimed to draw examples of practices PSTs' were seeing among in-service teachers. Then, the first author showed live demonstrations for about 40 min to showcase the instructional uses of various GenAI tools: ChatGPT, Microsoft Copilot, Google Gemini, and Anthropic Claude Sonnet. The workshop illustrated specific instructional applications pertinent to mathematics education, which included:

- Ideating interactive story-based problems for specific learning standards and goals.
- Adjusting a middle school-level percentage problem about discounts to an elementary-level addition/subtraction problem.
- Simplifying a mathematical word problem to improve the question's readability.
- Generating hints to provide students with scaffolding to solve math problems.
- Generating a graph that depicts the story of the race between the tortoise and the hare via piecewise linear functions.

Each instructional application was showcased using at least two distinct GenAI tools (e.g., ChatGPT and Google Gemini), prompting comparisons of their outputs based on the same prompt. Through these demonstrations, the PSTs witnessed how GenAI tools could support lesson planning, differentiation, and instructional scaffolding, providing them with essential technical skills to implement these technologies in their future classrooms. Thus, PSTs were shown fundamental technical skills, effectively merging technological and content knowledge crucial for real-world classroom applications.

Applying TPACK to design their own task

The workshop concluded with PSTs applying their integrated technological, pedagogical, and content knowledge by independently creating instructional materials using GenAI. The PSTs selected one or more GenAI tools that had been previously showcased to develop materials that were aligned with specific mathematics learning objectives. The tasks drew on earlier demonstrated use cases, which allowed the PSTs to transform the knowledge acquired during the workshop into tangible teaching resources.

Figure 5 illustrates the submitted work of a participating PST during this exercise, where the individual employed ChatGPT to generate hints for a mathematical word problem. This design activity enabled the PSTs to synthesize their learning by applying GenAI to enhance pedagogical strategies within the context of mathematics, thereby enabling an advancement in their TPACK competencies.

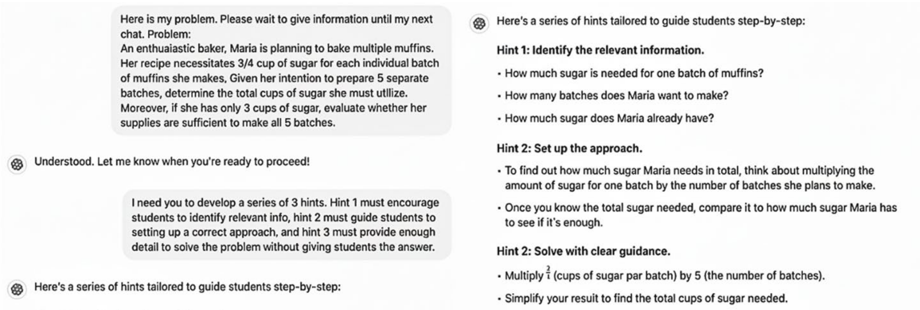

Fig. 5 Screenshot of a PST Using ChatGPT to Generate Hints for a Word Problem

Data collection and analysis

Pre- and post-surveys were administered via Qualtrics immediately before and after the workshop. The survey instrument included 29 items (see Appendix) measuring the nine constructs of the extended UTAUT model. The instrument was created by adapting items from previously validated instruments in recent, relevant literature (Ning et al., 2024; Xiong et al., 2023; Yildiz & Arpaci, 2024; Yilmaz et al., 2023) to ensure validity of the measured constructs. The instrument used a 7-point Likert scale, instead of five, to improve the scale's sensitivity (Preston & Coleman, 2000) and reduce bias (Garland, 1991).

Descriptive statistics, i.e., mean, median, and standard deviation (SD) were calculated to assess central tendency and variability. Among the 28 participating PSTs, three incompleted survey responses were excluded, resulting in a final sample of 25 for inferential analysis. Composite scores for each construct were computed by averaging their respective item scores, thus providing an overall assessment of each construct both pre- and post-workshop. The internal consistency and reliability of the adapted instrument were confirmed with the current study's data, with Cronbach's alpha coefficients (α) for each construct, with a reliability threshold set at 0.7. Before conducting inferential analyses, the Shapiro-Wilk test assessed the normality of each construct. Two-tailed inferential tests were employed to explore shifts from pre- to post-survey scores. Paired samples t-test was used for normally distributed data, and the Wilcoxon signed-rank test was utilized for non-normally distributed data, with a significance threshold set at $p < 0.05$. Given a small sample size $(n = 25)$, the Wilcoxon signed-rank test was also applied to normal constructs to check for statistical significance, ensuring statistical robustness.

Qualitative data were gathered from semi-structured interviews and workshop responses, to provide a deep and contextualized understanding of PSTs' perceptions. Following the workshop, in-depth semi-structured interviews, lasting 40 min to an hour, were conducted with five PSTs specializing in mathematics education. The interviews were audio-recorded and transcribed verbatim. The interview protocol was aligned with the study's theoretical framework to explore participants' attitudes towards adopting GenAI in educational contexts. Participants digitally submitted individual written responses to discussion prompts and images of hands-on tasks during the workshop via the Wooclap platform. For the three workshops' discussion prompts, 24 participating PSTs submitted their thoughts, collecting a total of 88 responses. The number of individual responses for each question was as follows: The first question, "How can Khanmigo facilitate differentiation for mixed-ability classrooms?" received 24 responses. The second question, "What could be some drawbacks to students engaging with GenAI bots like Khanmigo?" received 29 responses. Finally, the third question, "How are GenAI tools being used by teachers for mathematics instruction?" received 35 responses.

An integrated thematic analysis (Braun & Clarke, 2006) was conducted to synthesize findings from all qualitative data sources. The analysis, managed in the Dedoose software, followed a multi-phase coding process to ensure a robust and comprehensive interpretation. An initial coding phase was conducted using a deductive approach, where the constructs of the extended UTAUT model served as a priori parent codes. This step ensured that the analysis aligned with the study's theoretical framework. Then, a second inductive coding phase was conducted within and across the UTAUT constructs to identify emergent themes and patterns. This allowed for capturing nuanced perspectives not fully encompassed by the initial framework.

The analysis was primarily conducted by the first author, so many strategies were employed to ensure the trustworthiness and rigor of the findings. The qualitative findings from the interviews and workshop responses were systematically compared with each other and against the quantitative survey data. This methodological triangulation was used to identify areas of convergence, where both data types told the same story, and expansion, where the qualitative data provided a deeper explanation for the quantitative results. This process created a more valid and holistic interpretation of the PSTs' perceptions. Peer debriefing served as the primary strategy for ensuring analytical rigor. The first author regularly met with the second author to review the codebook, discuss analytical decisions, and challenge emerging interpretations. This critical dialogue helped validate the thematic structure and minimize potential researcher bias. A detailed audit trail was maintained, documenting every step of the analytical process, from creating and revising the codebook to developing the final themes.

Results

Shifts in PSTs' technology acceptance of GenAI in mathematics classrooms

To explore the influence of the PD workshop, shifts across eight constructs of the extended UTAUT model, except UB, were measured. The pre-workshop UB scores $(M = 5.92,\ SD = .81)$ captured a baseline of the PSTs' pre-existing use of GenAI tools. Since the pre- and post-surveys were administered immediately before and after the workshop, no change was anticipated in the use behavior of PSTs. So, inferential analysis was not performed on the UB scores. Internal consistency and reliability of the adapted instrument were confirmed with the study's data from pre- and post-workshop surveys, with Cronbach's alpha coefficients for constructs showing acceptable $(.70 < \alpha < .80)$, good $(.80 \leq \alpha < .90)$, or excellent $(\alpha \leq .90)$ reliability, as shown in Table 1.

The descriptive and inferential statistics, summarized in Table 1, reveal a significant positive shift in PSTs' perceptions of GenAI following the workshop. Participants reported statistically significant improvements in all measured constructs, except perceived risk. Wilcoxon signed-rank test performed on the normal constructs yielded results showing statistical significance $(p < .05)$, mirroring the results of the paired t-tests. The most substantial changes

Table 1 *Shifts in Pre- and Post-workshop survey scores for extended UTAUT constructs*

Construct	Pre-workshop		Post-workshop		Mean score Difference (M)	Test statistic (t)	p-value (p)
	Cronbach's Alpha (α)	Mean (SD)	Cronbach's Alpha (α)	Mean (SD)			
Paired samples t-test[a]							
Effort Expentancy (EE)	0.89	5.33 (1.06)	0.86	5.70 (0.87)	0.37	2.47	0.0212
Social Influence (SI)	0.80	4.57 (1.00)	0.75	5.05 (0.87)	0.48	2.41	0.0239
Trust (TR)	0.79	5.09 (1.13)	0.95	5.40 (1.09)	0.31	2.35	0.0272
Perceived Risks (PR)	0.79	3.96 (1.37)	0.83	3.73 (1.40)	-0.23	-1.80	0.0842
TPACK	0.86	5.29 (0.99)	0.79	5.85 (0.79)	0.56	2.99	0.0052
Behavioral Intentions (BI)	0.78	5.13 (0.90)	0.79	5.67 (0.80)	0.55	4.67	0.0001
Wilcoxon signed-rank test							
Performance Expectancy (PE)	0.85	5.33 (0.93)	0.90	6.00 (0.73)	0.67	9.50	0.0003
Facilitating Conditions (FC)	0.82	4.67 (1.21)	0.83	5.67 (1.05)	1.00	27.50	0.0199

[a] To ensure robustness of findings for the small sample size, the Wilcoxon signed-rank test was also applied to all normal constructs as a non-parametric alternative, which was found to be consistent with the paired t-test findings in terms of statistical significance $(p < .05)$

were observed in PSTs' intention to adopt GenAI (BI; $M = .55, t = 4.67, p = .0001$) and their perception of available resources and support for using GenAI in educational contexts (FC; $M = 1.00, W = 27.5, p = .0199$). This was complemented by highly significant gains in PSTs' perception of GenAI's usefulness (PE; $M = .67, W = 9.5, p = .0003$), indicating that after the workshop, PSTs more strongly believed that GenAI would help achieve their academic and instructional goals. Furthermore, participants' confidence in adapting GenAI to instructional activities that enhance teaching and learning approaches (TPACK) increased significantly $(M = .56, t = 2.99, p = .0052)$.

Significant improvements were also found in PSTs' perceived ease of use of GenAI (EE; $M = 0.37, t = 2.47, p = 0.0212$), perceived influence from important others to adopt GenAI in educational contexts (SI; $M = .48, t = 2.41, p = .0239$), and trust in the technology (TR; $M = .31, t = 2.35, p = .0272$). In contrast, the decrease in perceived risks was not statistically significant (PR; $M = -0.23, t = 1.80, p = .0842$), suggesting that while other perceptions became more positive, PSTs' sense of risk associated with using GenAI did not decrease significantly.

Factors influencing psts' willingness to adopt GenAI

The integrated thematic analysis of interview and workshop data revealed five overarching themes. These themes synthesize the constructs of the extended UTAUT model into a holistic narrative of the facilitators and barriers shaping the PSTs' perspectives. The themes are supported by excerpts from the interview and workshop, with participants referred to by pseudonyms.

Theme 1: GenAI as a collaborative partner for efficiency and creativity

This was the most dominant theme, identified by all five interviewees and heavily supported by the workshop data, where 57 out of 88 submitted responses were related to GenAI's utility. This theme encapsulates PSTs' views on GenAI's perceived usefulness and their current use behavior, framing GenAI not just as a tool, but as a partner that enhances their professional practice.

PSTs consistently described using GenAI to offload the repetitive, time-consuming aspects of teaching. This focus on efficiency was detailed in the workshop. In response to a question about how they think math teachers are using GenAI, participants identified the rapid generation of instructional materials as the key benefit, specifically highlighting its ability to create problems (11 responses), lesson plans (7 responses), and differentiated materials (7 responses). This sentiment was perfectly captured during an interview with Liberty, a junior in elementary education. She explained how she planned to use these tools to maintain a healthy work-life balance in her future career. She saw GenAI as a practical assistant that would "help me stay at school within my contracted hours."

Beyond simple efficiency, PSTs valued GenAI as a creative collaborator that could enhance the quality of their instruction. Caleb, a master's student, provided a vivid description of this dynamic process during his interview, sharing that he does not ask GenAI for a finished product but instead engages in a brainstorming session. He explained, "You can use it almost like a whiteboard; you just throw an idea to it, and it will throw an idea back, and you just keep bouncing back and forth until you get what you want." This concept of the "whiteboard" illustrates how GenAI tools serve as spaces for co-creation. Caleb utilizes his pedagogical and subject-matter knowledge along with natural language instructions to assess and guide the AI's outputs, rather than relying on a single, perfect prompt. This iterative dialogue with the AI allows Caleb to transform a generic instructional idea into a specialized mathematical task. Additionally, GenAI was viewed as a collaborative partner for students, a point that emerged from the workshop discussion on differentiation. Participants envisioned tools like Khanmigo acting as an intelligent, personalized tutor capable of "creating different tiers of problems for different tiers of learners" and providing instant scaffolding that "meets [students] where they are at with their knowledge." By offering "guided help" for struggling learners and novel challenges for advanced ones, PSTs saw GenAI as a direct partner in fostering a more creative and differentiated learning environment.

Theme 2: Navigating a learning curve with cautious engagement

This theme, central to the experience of all five interviewees, combines PSTs' perceived ease of use and trust in the GenAI technology and their developing TPACK. It captures the understanding that while GenAI is accessible, leveraging it effectively is a learned skill that requires critical oversight.

Caleb shared that the quality of the output is the user's responsibility, not the tool's. He explained, "GenAI is very dumb. It's as smart as you are. If you give it a well-detailed design prompt, it will give you a well-detailed answer. But if you give it a generic prompt, it'll give you a generic response." This sentiment was echoed by Amanda, a senior, who noted that getting a useful output "takes some practice" and that "you have to learn how to feed it the information so that you get what you want." This reframes ease of use not as a static property of the tool, but as a skill the user develops over time.

This cautious engagement is rooted in a situational trust in the technology. Liberty described a practical workflow that perfectly illustrates this balance. While she doesn't "trust it 100%," she confidently uses GenAI for creative tasks like generating story problems. She then applies her own expertise, explaining that "if it doesn't give me exactly what I'm looking for, I can use what it gave me. I switch it up and do what I'm looking for." This sentiment was shared by Jade, another senior, who trusts GenAI to explain a concept but has "trust issues with it" when asking it to solve a specific math problem. These examples show PSTs are already developing a nuanced TPACK, learning to discern which tasks are appropriate for AI and which require their own critical evaluation and expert verification.

Theme 3: Managing risks of inaccuracy and dependency

A significant concern, raised by all five interviewees and dominating the workshop discussion on drawbacks of Khanmigo (29 responses), was the inherent risk associated with GenAI. This theme combines perceived risk of GenAI technology with skepticism around its usefulness, highlighting the ethical and pedagogical dilemmas PSTs foresee.

The most frequently cited risk, mentioned in 22 of the 29 workshop responses and by all five interviewees, was the potential for student over-reliance leading to reduced cognitive engagement. PSTs expressed concerns that when students repeatedly turn to AI for instant answers instead of struggling with problems independently, they fail to engage in the deeper cognitive processing necessary for true understanding. Workshop participants voiced a fear that students would learn to manipulate the AI (11 responses), noting they might "coax out an answer [from AI] without them trying the problem" or use it for "just giving the answer instead of giving an explanation as to how they can solve a specific problem." This superficial approach, as Serenity, a workshop participant, stated, leads to students "getting the answer without showing interest in learning the process." Compounding this issue was the risk of students learning from inaccurate AI-generated responses. Caleb, during his interview, elaborated on this with a powerful cognitive example, warning that if a student learns a concept incorrectly from an AI that confidently gives a wrong answer, "it's going to be very hard to get rid of it," underscoring the high stakes of misinformation in foundational learning.

Beyond these pedagogical concerns, all interviewed PSTs identified concerns around data protection and student privacy. Amanda articulated this particularly well, worrying about the unseen data implications of using these tools with students. She explained, "You have to be careful what you ask them to do on their school computers. You don't know what pulls information. With FERPA and the fact that they're minors, that's always like a concern because, me as an adult, it's that fine line where I still need to protect their data." This demonstrates a sophisticated awareness of professional responsibilities and the potential ramifications of uncritical GenAI adoption.

Theme 4: Navigating an ambiguous professional landscape

This theme, a major point of frustration for all five interviewees, encompasses the elements of influence PSTs receive from important others and their perception of available resources and support. It highlights how PSTs are navigating a simultaneously encouraging and unsupportive professional landscape, receiving conflicting advice and lacking clear institutional guidance on how to proceed with GenAI.

PSTs are receiving explicit advocacy from within their teacher education programs. They acknowledged that some courses have made efforts to introduce GenAI through class activities like a "Stump the AI" exercise, where AI chatbots are challenged with questions they are likely to get wrong. Two PSTs shared experiences of assignments that required them to use GenAI to create lesson plans and then critique the AI-generated outputs. However, four out of the five interviewees described this exposure as superficial. Logan, a senior, expressed a desire for more structured and practical guidance: "They told us that it exists, but they should have been teaching us how to use it to create more innovative lesson plans… so that it's not something that we have to figure out by ourselves later down the road when we're swamped with lesson planning."

This gap in practical training is compounded by a confusing lack of consensus from the wider academic and professional communities. Amanda, a PST co-majoring in Psychology, vividly described this institutional inconsistency, noting how her professors' views were starkly divided by department. She explained that the Psychology department wants to "pretend like it is not even a thing," while the Education department is "trying to figure out how to use it." This creates a confusing environment where PSTs are simultaneously encouraged and discouraged from using the same technology. This ambiguity extends to the K-12 environment they are preparing to enter. Jade stated, "I don't wanna be the only one who's using it [GenAI] or not using it and then finding out everyone else uses it or doesn't use it. Because it's something that a lot of people are very strong for, and then some don't want you using it at all. And just making sure I find that common level of what is expected of me from higher up people and districts." This highlights that a major barrier to adoption isn't just personal skill or belief, but the absence of a consistent professional framework for AI integration.

Theme 5: A commitment to proactive and pragmatic integration

The final theme reflects the PSTs' ultimate stance, combining their pre-existing GenAI use experiences, developing TPACK, and intentions to use the technology. Voiced by all five interviewees, this theme shows how PSTs are not waiting passively for guidance but are instead proactively cultivating their own professional approach to using GenAI. PSTs are already integrating GenAI into their workflows as a strategic and pragmatic tool. Liberty provided an excellent example, explaining that she uses Magic School AI to "quickly create presentations, lesson plans, and write professional emails." This proactive use is coupled with a self-aware development of their TPACK. PSTs were consciously building the skills to use these tools effectively while recognizing their limitations. Jade expressed this evolving confidence: "Not fully confident right now, especially because I don't know of all the AI websites that are out there…I may have to just redo a whole bunch of things, such as learning what is fully reliable."

During the interview, Logan recounted his experience using GenAI the previous summer, when he co-taught a summer school program at an urban middle school as part of his university's outreach initiative. He stated, "One of the lessons I taught this summer was a statistics unit, and I used ChatGPT and Copilot to design simple experiments for my students. I can see myself using these tools more for similar tasks in the future." This illustrates that PSTs are committed to developing their strategies for integrating GenAI.

Discussion

This study explored the factors and experiences that incluences PSTs' adoption of GenAI in mathematics classrooms. The quantitative results indicate that TPACK-based workshop supported statistically significant improvements for PSTs' technology acceptance of GenAI technology in instruction. This aligns with prior research indicating that TPACK-based PD can enhance technology acceptance (Daher et al., 2021).

The significant increase in performance expectancy score suggests that the workshop illustrated GenAI's practical benefits to the PSTs, a finding consistent with other PD studies (Daher et al., 2021; Özbek et al., 2023). This was reflected in the qualitative data, where PSTs framed GenAI as a "collaborative partner" for enhancing efficiency and creativity. These perceptions align with findings from Yang and Appleget (2024), where PSTs recognized GenAI as a useful teaching tool. However, this optimism did not come without criticism. PSTs remained skeptical about GenAI's utility for complex mathematical reasoning and problem solving, corroborating research highlighting its computational limitations (Matzakos et al., 2023). This enhanced sense of utility and a significant increase in self-reported TPACK created a strong foundation for adoption. The pre-workshop survey yielded a mean TPACK score of 5.29, indicating that many participants already felt confident in integrating GenAI with pedagogy and content before the workshop. The statistically significant increase in post-workshop scores suggests that the intervention expanded PSTs' knowledge, boosting their confidence. Direct engagement with GenAI tools and structured pedagogical discussions likely facilitated this growth, allowing PSTs to explore AI's potential in their teaching contexts. These results align with prior research indicating that TPACK-based PD enhances teachers' perceived ability to integrate technology into instruction (Dalal et al., 2017; Meletiou-Mavrotheris & Paparistodemou, 2024). However, qualitative insights also revealed that some participants felt uncertain about implementing GenAI tools in real classrooms and expressed a need for more practical experience. This highlights the importance of continued exposure and structured practice to solidify PSTs' skills and confidence in leveraging GenAI, as Bae et al. (2024) suggested. The significant increase in effort expectancy suggests that the workshop lowered barriers to entry for using the technology. The live demonstrations and hands-on tasks could have improved the PSTs' perceived ease of use. During the interviews, PSTs shared that moving beyond basic use of GenAI requires skills and practice to leverage the technology's full potential. One of the skills noted was prompt engineering, validating calls to formally teach prompting strategies in higher education (Lee & Palmer, 2025).

One of the most insightful findings of this study is the dynamic between trust and risk. While PSTs' trust in GenAI for educational tasks significantly increased, their perception of its risks did not significantly decrease. This outcome can likely be attributed to the workshop's design, which facilitated a discussion of GenAI's risks without providing explicit strategies for their mitigation. By making potential threats more salient and concrete, the workshop did not alleviate fear but rather transformed it into a more informed, critical awareness. This is reflected in the modest post-workshop trust score ($M = 5.40$) and the qualitative theme of "cautious engagement," which indicates that PSTs trust GenAI for specific tasks (e.g., creative brainstorming) while remaining wary of its limitations (e.g., for high-stakes mathematical problem-solving). The interviewed PSTs emphasized the need for human oversight, a concept extensively advocated in the literature (Deng & Joshi, 2024; Razmerita, 2024). Ultimately, the PSTs' persistent risk perception reflects a sophisticated professional understanding of GenAI's potential for misinformation and student dependency, a well-documented concern (Hsu et al., 2024; Rahman & Watanobe, 2023). This understanding is a more desirable outcome for teacher education than uncritical acceptance.

Additionally, the findings highlight the critical role of the institutional context. The significant increases in social infleunce and facilitating conditions indicate that the workshop, which was delivered as a part of the PSTs' teacher education courses, was perceived as a form of institutional endorsement. However, the modest post-workshop mean SI score of 5.05 is explained by the qualitative theme where PSTs reported receiving conflicting messages from different university departments, lacking meaningful hands-on practice in their teacher education program, and a lack of clear AI policies in K-12 settings. This underscores the need for cohesive messaging among educators, especially through the implementation of clear and transparent policy in higher education and K-12 school districts (Cacho, 2024; Song, 2024). Similarly, while the workshop acted as a supportive resource for the PSTs, all interviewees called for more comprehensive and practical GenAI training to be embedded within their curriculum and practicum, aligning with recommendations from prior research on PSTs' perceptions of GenAI (Thararattanasuwan & Prachagool, 2024; Wang et al., 2024).

One of the most significant changes was observed in behavioral intention, which implies that the workshop successfully strengthened PSTs' motivation to incorporate GenAI tools into their teaching and learning practices. This significant shift is consistent with previous studies on technology acceptance, which indicate that educators are more inclined to adopt digital tools when they receive targeted training on how to use them pedagogically (Daher et al., 2021). The high average post-workshop score (5.67 out of 7) signifies a strong overall inclination to utilize these tools. This enthusiasm was echoed by interview subjects, with all PSTs expressing their intent to leverage GenAI tools to enhance both their efficiency and teaching methods. However, despite the promising rise in BI, it does not ensure actual adoption, as factors like institutional policies and the availability of resources for GenAI may still affect the implementation process (Zhang & Hou, 2024). This implies that future initiatives should focus not only on fostering intention but also on offering ongoing support and strategies to address potential barriers to successful, sustained implementation.

The PSTs showed considerable engagement with GenAI tools for educational use even prior to the workshop, as indicated by a high average UB score of 5.92 out of 7 in the pre-workshop survey. This is consistent with qualitative feedback from participants, who noted using GenAI for various educational purposes. This suggests that the participants' perceptions of the educational use of GenAI tools were already influenced by prior experiences. The tool demonstrations, pedagogical discussions, and hands-on activities during the workshop provided an opportunity to enhance or refine their understanding of the pedagogical benefits and use strategies which might have supported the growth of positive perceptions among the PSTs to adopt GenAI tools.

Overall, the findings suggest that the integration of GenAI in mathematics education goes beyond individual acceptance. As noted by participants like Jade and Logan, the proliferation of GenAI necessitates a systemic reevaluation of curriculum design (Segal & Klemer, 2025; Segal et al., 2025) and institutional AI policies (Zhang & Hou, 2024). Ultimately, fostering technology acceptance is merely the foundational step. It enables educators to move beyond superficial tool adoption and engage in more urgent, broader discussions regarding how GenAI can be structured to support, rather than undermine, the development of deep mathematical thinking and problem-solving competencies.

Implications

This study offers important theoretical and practical implications. Theoretically, it presents an extended UTAUT model that incorporates trust, perceived risk, and TPACK as critical factors in educators' adoption of GenAI, offering a more nuanced framework for future research in this area. Practically, the findings provide a clear directive for MTEs and teacher preparation programs to prepare the next generation of teachers. MTEs must proactively design learning experiences that equip PSTs with the critical competencies to use these tools effectively and ethically in mathematics classrooms. This study's findings suggest that MTEs should model a pedagogy of inquiry with GenAI. This involves moving beyond showcasing GenAI as a tool for generating problems or lesson plans and instead teaching PSTs a process of critical co-creation. For mathematics, this means explicitly engaging PSTs in activities where they test GenAI's computational accuracy, critique its pedagogical approaches, and learn to refine its outputs to align with specific mathematical learning goals and standards. Furthermore, this study implies that MTEs should cultivate a professionally and ethically responsible disposition toward GenAI. MTEs should highlight GenAI's limitations and potential for error in mathematical contexts. By doing so, they prepare PSTs to act as expert critics and validators of AI-generated content. This includes fostering a deep understanding of ethical issues, such as how student dependency on AI for answers can undermine the development of mathematical reasoning and problem-solving skills, and how using these tools intersects with professional and ethical responsibilities like protecting student data. Beyond isolated training, teacher education programs should integrate AI literacy as a formal curricular component. This ensures that emerging AI technologies, their ethical considerations, and pedagogical applications are not treated as peripheral topics but are embedded into the core of mathematics teacher preparation.

Finally, this research implies that MTEs must assume a leadership role in resolving the ambiguous professional landscape their students are navigating, extending MTEs' responsibility beyond their classrooms. MTEs are uniquely positioned to collaborate with higher education administrations and local K-12 school districts to help shape emerging AI policies, ensuring they are pedagogically sound and supportive of innovative teaching. Parallel to policy efforts, MTEs can collaborate with stakeholders to redefine curriculum standards, shifting the focus from procedural computation toward higher-order tasks and assessment strategies where AI serves as a partner in exploring complex mathematical concepts and real-life problems. This shift in curriculum design ensures that AI is integrated into the fabric of mathematics instruction in ways that enhance teacher agency and student learning. Thus, as advocates and connectors, MTEs can help build the supportive and consistent institutional ecosystem that PSTs require to utilize GenAI for meaningful classroom practice, thereby shaping the future of mathematics education in the age of AI.

Limitations and recommendations

The findings of this study should be interpreted in light of several limitations. First, while significant positive shifts were observed across most acceptance constructs, the lack of a control group prevents the attribution of these changes solely to the workshop. So, these findings should be viewed as the possible influence of the workshop rather than a definitive claim of causal impact. Second, the small sample of 25 PSTs from a single university, primarily focused on mathematics education, limits the generalizability of the results. While the statistically significant improvements are promising, they show evidence of the workshop's potential in a specific setting rather than a universally applicable outcome. Future research should replicate this study with larger, more diverse samples across multiple institutions and disciplines to test the broader applicability of this TPACK-based PD and explore how different contexts shape GenAI adoption. Moreover, the study's design constrains the scope of the conclusions. The single-session, pre-post design captures only immediate perceptual shifts. Thus, the shifts in intentions to adopt GenAI should be understood as a measure of immediate motivation, not a predictor of long-term classroom practice. To address this, future longitudinal studies should be conducted to track how these initial positive perceptions translate into sustained teaching behaviors as PSTs enter their own classrooms. Furthermore, the study relied on self-reported data, meaning the significant increase in self-reported TPACK reflects a growth in PSTs' confidence rather than an objective measure of their competence. Future work should bridge this gap by offering extended hands-on practicum experiences to teach AI-augmented math lessons and incorporating performance-based assessments, such as the expert evaluation of AI-generated lesson plans or observational data from classroom simulations, to triangulate self-reported gains with demonstrated skill. Finally, the data were collected from participants in three separate workshop sessions, introducing a potential clustering effect that could violate the assumption of independence in our statistical tests. Future research should use statistical methods that account for such group-level variations.

Appendix

Extended UTAUT Pre- and Post-survey Instrument.

Constructs	Item Name	Item [Strongly Disagree (1) to Strongly Agree (7)]	Sources
Performance Expectancy (6)	PE1	I find generative AI tools useful in educational settings.	(Xiong et al., 2023; Yildiz & Arpaci, 2024; Yilmaz et al., 2023)
	PE2	Using generative AI tools increases my chances of achieving my academic and professional goals.	
	PE3	Generative AI tools help me learn faster.	
	PE4	Generative AI tools will help me teach faster.	
	PE5	The use of generative AI tools makes my life easier.	
	PE6	The use of generative AI tools increases my chances of resolving challenges related to teaching and learning.	

Constructs	Item Name	Item [Strongly Disagree (1) to Strongly Agree (7)]	Sources
Effort Expectancy (4)	EE1	Learning how to use generative AI tools to teach is easy for me.	(Xiong et al., 2023; Yildiz & Arpaci, 2024; Yilmaz et al., 2023)
	EE2	It is easy to leverage generative AI tools for teaching.	
	EE3	I can easily become skilled in using generative AI tools in my future classrooms.	
	EE4	My interaction with generative AI tools is straightforward.	
Facilitating Conditions (3)	FC1	Generative AI tools are compatible with or similar to other technologies I use.	(Xiong et al., 2023; Yildiz & Arpaci, 2024; Yilmaz et al., 2023)
	FC2	I can get help from others when I struggle to use generative AI tools for educational purposes.	
	FC3	If I experience any problems while using generative AI tools, I can access the necessary information to find a solution.	
Social Influence (3)	SI1	People who are important to me think I should use generative AI tools to teach and learn.	(Xiong et al., 2023; Yildiz & Arpaci, 2024; Yilmaz et al., 2023)
	SI2	People who influence my behavior think that I should use generative AI tools to teach and learn.	
	SI3	People whose opinions I value encourage using generative AI tools for teaching and learning.	
Trust (3)	TR1	Generative AI tools perform tasks according to my expectations for educational purposes.	(Xiong et al., 2023)
	TR2	Generative AI tools are reliable and can be confidently used for teaching and learning.	
	TR3	Overall, I trust generative AI tools to help me teach and learn.	
Perceived Risk (3)	PR1	I am concerned about the mistakes and failures of generative AI tools for teaching and learning.	(Xiong et al., 2023)
	PR2	I am concerned that generative AI tools will disclose my private information.	
	PR3	Overall, I perceive using generative AI tools as risky.	
TPACK (3)	TP1	I can choose generative AI tools that enhance the teaching approaches for a lesson.	(Ning et al., 2024; Yildiz & Arpaci, 2024)
	TP2	I can choose generative AI technologies that enhance students' learning for a lesson.	
	TP3	I can adapt the use of generative AI tools to different teaching activities.	
Behavioral Intention (3)	BI1	I intend to use generative AI tools to teach in my future classrooms.	(Xiong et al., 2023; Yildiz & Arpaci, 2024)
	BI2	I will always try to integrate GenAI technology in my future classrooms.	
	BI3	I plan to continue using GenAI tools frequently to learn.	
Use Behavior (1)	UB1	I use generative AI tools for educational purposes.	N/A

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