Education and Information Technologies (2025) 30:20913–20942
https://doi.org/10.1007/s10639-025-13591-9

Extending the TAM framework: Exploring learning motivation and agility in educational adoption of generative AI

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Received: 23 January 2025 / Accepted: 21 April 2025 / Published online: 7 May 2025

Abstract
Generative AI technologies are rapidly transforming educational practices, creating both opportunities and challenges for teacher-preparation programs. As these advanced tools become increasingly prevalent in classrooms, understanding the factors that influence pre-service teachers' acceptance and adoption of such technologies has become critically important for effective educational policies and practices. This study aims to extend the Technology Acceptance Model (TAM) to examine the factors influencing pre-service teachers' adoption of generative AI tools. The research is based on data collected from 748 pre-service teachers from 12 universities in Turkey. The model includes the core constructs of TAM as well as exogenous variables such as Metacognitive Self-regulation (MSR), Subjective Norm (SN), Learning Motivation (LM) and Learning Agility (LA). The results of Structural Equation Modeling showed that the model explained 54% of the variance in Attitude and 51% of the variance in Behavioral Intention. MSR and LM had significant effects on Perceived Usefulness and Perceived Ease of Use, while LA and SN were found to be effective only on Perceived Ease of Use. These findings highlight that intrinsic cognitive and motivational factors are more influential than external social factors in determining how pre-service teachers evaluate the usefulness of generative AI tools. Additionally, our study reveals that learning agility significantly contributes to perceived ease of use, suggesting that adaptability is a key factor in technological adoption among educators. These results suggest that training programs for generative AI in teacher education should prioritize hands-on activities that strengthen self-regulation skills and intrinsic motivation, rather than focusing solely on technical features. Curriculum designers and teacher educators should create learning environments that nurture adaptability and metacognitive skills to facilitate successful integration of AI technologies in future educational practices.

Keywords Technology acceptance model · Generative artificial ıntelligence · Agility · Learning motivation · Structural equation modeling

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1 Introduction

The Technology Acceptance Model (TAM) is one of the models that have come to the forefront with technological developments. The model was developed by Davis (1989) to explain the behaviors of accepting and using new technologies. Adapted from Ajzen and Fishbein's Theory of Reasoned Action (Aljarrah et al., 2016), the model draws attention to ease of use and perceived benefit factors. Perceived usefulness is the belief that a technology will improve an individual's job performance, while perceived ease of use is the individual's belief about how easy or free access to the technology is (Davis, 1989). These two basic factors can affect an individual's attitude towards the technology in question.

The application of TAM in educational contexts has gained significant attention as digital technologies increasingly transform teaching and learning practices. In education, TAM provides a robust framework for understanding how teachers evaluate and adopt new technologies, which is critical for successful implementation of educational innovations (Kong et al., 2024). Research by Scherer et al. (2019) has demonstrated that TAM constructs explain over 40% of variance in educators'technology adoption behaviors, highlighting the model's relevance in educational settings. As educational technologies evolve from basic digital tools to complex technologies, the TAM framework needs adaptation to capture the unique factors influencing the acceptance of these advanced technologies. One of the most important technologies of recent times is generative artificial intelligence. These technologies offer convenience in designing the teaching process (Choi et al., 2024). With its widespread use in the field of education, pre-service teachers'acceptance of these technologies has become important. In this regard, TAM provides a strong theoretical framework to explain preservice teachers'acceptance of technology. For example, Belda-Medina and Kokošková (2024) examined the critical skills and perceptions of 58 pre-service teachers about using ChatGPT in language learning. They found that there were positive perceptions about perceived usefulness and behavioral intention, but concerns were expressed about accuracy and reliability. Şahin et al. (2024) examined the factors affecting the intention to use assistive technologies through the extended Technology Acceptance Model (TAM) with 311 pre-service teachers trained in special and inclusive education. They provided a theoretical basis for the role of individual and institutional factors affecting pre-service teachers'intention to use assistive technologies. Wulyani et al. (2024), in a study with 208 pre-service teachers, investigated the knowledge and use of AI tools in completing tasks, the frequency and sincerity levels of AI use, the reasons for using AI tools, the ease of using AI tools, and the desire to use AI tools according to the TAM framework. According to them, there are strong relationships between perceived ease of use and perceived usefulness and between perceived ease of use and technology acceptance.

In this research, it is suggested to add different exogenous variables to the model to increase the adequacy of TAM in explaining the acceptance of productive AI technologies. In this respect, the role of variables such as cognitive self-regulation and subjective norm in technology acceptance has been extensively examined in the literature. However, the role of factors such as learning agility and lifelong learning motivation in the acceptance of generative AI technologies has not yet been sufficiently investigated. This study aims to examine the factors affecting pre-service teachers'acceptance of generative AI within the TAM framework and to propose new extrinsic variables to increase the explanatory power of the model. Specifically, the research has four primary objectives: (1) to investigate how traditional TAM exogenous variables (Metacognitive Self-Regulation and Subjective Norm) influence pre-service teachers'acceptance of generative AI tools; (2) to examine the role of newly proposed variables (Learning Agility and Learning Motivation) in technology acceptance, addressing a gap in the existing literature; (3) to analyze the direct and indirect effects of these variables on Perceived Usefulness and Perceived Ease of Use; and (4) to evaluate the extended model's capacity to explain and predict pre-service teachers'attitudes and behavioral intentions toward generative AI adoption in educational settings. By addressing these objectives, this research contributes to both theoretical understanding of technology acceptance and practical implementation of AI tools in teacher education programs.

2 The relationship between TAM and Metacognitive self-regulation and subjective norm as extrinsic variables

Metacognitive self-regulation is an individual's ability to plan, monitor, and evaluate learning processes actively (Zimmerman & Moylan, 2009). Pintrich (2000) defined this concept as the learner's ability to set goals, monitor progress, and manage motivational and cognitive resources. For the purpose of this study, a pre-service teacher with strong metacognitive self-regulation can first explore its core features, test its applications in lesson planning, and approach a new technology by thinking about how to use it according to different student needs. Another important concept is the subjective norm, which is an individual's perception of the pressure of people or groups that he/she considers important about whether or not to perform the behavior (Fishbein & Ajzen, 1977). For the purpose of this study, subjective norms can be explained as pre-service teachers'beliefs about the approval of their social environment for technology use. These social influences can significantly shape technology acceptance in schools where teaching processes are usually carried out collaboratively. In the Technology Acceptance Model literature, the role of metacognitive self-regulation (An et al., 2024; Chen & Hwang, 2019; Navarro et al., 2023) and subjective norm (Teo, 2010; Tran et al., 2023) variables in technology acceptance has been extensively examined. Self-regulation skills are effective in making students active, which is one of the main goals of teaching processes. Metacognitive processes are high-level skills used to regulate cognitive, emotional and motivational strategies (Veenman et al., 2006). The combination of self-regulation skills with metacognitive skills initiates cognitive, motivational and emotional processes, making students masters of learning processes (Zimmerman, 2002). The relationship between technology acceptance and metacognitive self-regulation skills has been revealed by studies. Kemp et al (2024) investigated students' attitudes and intentions towards using virtual classrooms for learning purposes in the last half of 2021 and the first half of 2022 at two Australian universities and found that cognitive engagement positively affected perceived usefulness. Subjective norm refers to an individual's motivation to perceive and comply with the expectations of important people around him/her regarding the use of technology (Teo & Zhou, 2017). Venkatesh and Morris (2000) examined gender differences in individual acceptance and sustained use of technology. According to them, subjective norm has a strong influence in the early stages of technology use and this influence decreased as experience with technology increased. Venkatesh and Davis (2000) examined the role of subjective norm in technology acceptance in the TAM model and found that when a person's colleagues perceive a system to be useful, that person tends to share the same view.

Metacognitive self-regulation and subjective norm appear to be important factors in pre-service teachers' technology acceptance. Dahri et al. (2024) conducted a ChatGPT-based scenario learning activity with 300 pre-service teachers. The study concluded that metacognitive self-regulation learning can be improved and made more effective by using AI technologies such as ChatGPT. Regarding subjective norm, Teo and van Schaik (2009) used the Technology Acceptance Model as a framework to determine computer use intention in their study with 250 pre-service teachers. Teo and van Schaik (2009), who added subjective norm to the model as a variable, found that this variable did not have a significant effect on ease of use. In contrast to this study, Wong (2015) found that subjective norms had an indirect effect on usage and adoption in his study with 234 pre-service teachers. Sanusi et al. (2024) concluded that subjective norm is one of the two most important determinants of pre-service teachers' intentions to learn AI.

3 The relationship between TAM and learning agility and motivational lifelong learning as external variables

In the digital age, knowledge of technology has become increasingly important. It has even become an important variable in the acquisition of new skills. Learning agility is one of the prominent concepts in the acquisition of new skills. Learning agility is the ability to experiment, self-reflect, capitalize on individual strengths, continuous improvement, awareness, and mentally associated experiences gained in one situation with different challenges in another (De Meuse, 2017). Learning agility is an element that provides individuals with competence in using technological tools (Azhar et al., 2024). This concept, which has recently gained popularity and provides information about individuals' potential performance in new situations and their long-term success in the professional world (Gravett & Caldwell, 2016), is the ability of individuals to quickly learn new and challenging learning experiences and adapt these experiences to different situations (DeRue et al., 2012). Individuals with learning agility can make and implement challenging decisions, confront poor performance and behaviors, create change, develop trusting relationships, and develop ideas and collaboration (Gravett & Caldwell, 2016). The educational relevance of learning agility has increased exponentially with the acceleration of technological changes in classrooms (Kim et al., 2018). While previous generations of teachers may have mastered a stable set of educational technologies throughout their careers, today's educators are immersed in rapidly evolving new technologies, such as artificial intelligence. Relevant to the purpose of this study, pre-service teachers' learning agility can play an important role in adapting to the rapidly changing educational technology environment. A pre-service teacher who is agile in the learning processes can quickly master the use of new technologies, transfer skills between similar tools, adapt to software updates, and develop pedagogical practices beyond standard use cases. Research by Kaya (2023) shows that improving teachers'learning agility levels and lifelong learning dispositions are fundamental to both their development and students'success. One of the important concepts in this era is the tendency towards lifelong learning based on motivation. It is also a concept related to Ryan & Deci's (2000) Self-Determination Theory. According to this theory, motivation for lifelong learning is closely related to three basic psychological needs: being able to control one's own learning process, being effective in the learning process, and being able to connect with others in the learning process. Motivational lifelong learning disposition can also be defined as individuals'intrinsic motivation and commitment towards learning activities. The relationship between learning agility and motivational lifelong learning is considered two important components in the context of technology adoption. These constructs are conceptually related, but distinct. While learning agility drives adaptation to new technologies (Azhar et al., 2024), lifelong motivational learning drives the desire to engage (Ryan & Deci, 2000). In the context of generative AI adoption, this engagement is particularly important, because these complex tools require both the ability to learn quickly (agility) and a constant desire to master them (motivation). This is because generative AI technologies differ from other educational technologies in several respects. First, these tools are constantly and rapidly updated to gain new features and capabilities (Xu et al., 2021). Even tools such as the ChatGPT can undergo significant changes within a few months. Second, because generative AI is related to broad subject areas such as pattern processing, content analysis, content generation, cognitive inference and planning, data privacy, and security (Gupta et al., 2024), the user needs to develop new skills to use the tool effectively. Third, as the use of these tools in educational contexts is still emerging, educators need to explore them (Lee et al., 2024a, 2024b). Each of these characteristics can be said to be closely related to learning agility and motivational lifelong learning. Unlike traditional educational technologies, generative AI tools are thought to require a'continuous relearn and adapt'approach rather than a'learn and use'approach. Preservice teachers with both high learning agility and strong motivational disposition are likely to approach AI tools with confidence, overcome initial difficulties, and integrate these technologies more deeply into their teaching repertoire. Understanding this relationship may provide a more nuanced perspective on the psychological factors that drive technology acceptance beyond the traditional TAM constructs.

In terms of TAM, there are not many studies directly related to education on the effect of learning agility on both perceived ease of use and perceived benefit. Aljawarneh (2024) examined the relationship between user satisfaction, cloud-based learning applications and university educational agility in his study with 213 participants. He concluded that there is a positive relationship between cloud-based learning applications and university educational agility in terms of user satisfaction. Malanga et al. (2022) examined the intention and acceptance of using Learning Management Systems for university education in Brazil by integrating the extended technology acceptance model, the unified theory of technology acceptance and use, and the quality construct adapted from the Service Quality Assessment Model in a large sample of 1237 university students in Brazil. Contrary to Aljawarneh's (2024) positive perspective, the result of the study revealed that the intention to use Learning Management Systems was not affected by learning agility. In the related study, the factors that affect the intention to use are facilitating conditions that are easy to use, operable, user-friendly, social influence such as attention-grabbing, usage preference and relevance, habit, routine, fun and enjoyable, reliability, tangibility, responsiveness and assurance. The study is oriented towards a traumatic period such as the COVID-19 process. The factors directly related to intention to use reflect the needs of this period. Therefore, the direct effect of learning agility among so many variables may not have been revealed. The role of lifelong learning motivation in TAM has become more important with constantly updated and developing technologies. Agudo-Peregrina et al. (2014) proposed a TAM3 (Technology Acceptance Model) based model in which two additional variables were included to examine the factors affecting the acceptance of e-learning systems. Two different settings were analyzed for the proposed research model: The first setting was based on a sample of higher education students from different public universities in the Madrid region; the second setting was based on a sample of applicants to the lifelong learning program at the Polytechnic University of Madrid (UPM). This study supported TAM relationships, but apart from the intention-behavior link, it revealed the bidirectional nature of perceived benefit, linking one component to efficiency and performance and the other to flexibility. Tang et al. (2023) also examined the online learning characteristics of lifelong learners within the TAM framework in a study conducted with 514 participants in an open education university. As a result of the study, a positive relationship was found between learning satisfaction and lifelong learning intention.

Research has revealed the relationship between learning agility and lifelong learning and technology acceptance. Today, with the developing features of productive artificial intelligence technologies, the role of learning agility and lifelong learning motivation in technology acceptance has become more important. In relation to this research, pre-service teachers, who will be the practitioners of education in the future, should be open to learning and renew themselves in order to associate the constantly developing artificial intelligence technologies with educational processes. In this context, a lifelong learning disposition based on learning agility and motivation can enable pre-service teachers to quickly grasp updates in AI tools and adapt them to their teaching processes. It is predicted that pre-service teachers with high learning agility and motivational lifelong learning disposition will have higher levels of acceptance of generative AI. Based on the explanations, adding learning agility and motivation-based lifelong learning disposition as exogenous variables to TAM can help to better understand the acceptance of continuously developing technologies such as generative AI. Associating these variables with the model can increase the explanatory power of TAM in terms of theoretical aspects and provide information for the development of teacher education programs in terms of practice.

4 Research model and hypotheses

In this study, TAM is taken as a basis to examine the factors affecting pre-service teachers'technology acceptance towards generative AI. In the literature, the effect of MSR and SN as exogenous variables of TAM has been addressed in many studies. In this study, learning agility (LA) and motivation-based lifelong learning (MLL) tendency were also added to the model as exogenous variables based on the continuously developing and learning nature of generative AI.

In the proposed model, the effects of the exogenous variables MSR, SN, LA and MLL on perceived utility (PU) and perceived ease of use (PEOU) are examined. In accordance with the basic assumptions of TAM, the effects of PU and PEOU on attitude (Att) and their relationships with behavioral intention (BI) are also included in the model. The following hypotheses were developed in line with these relationships:

Hypotheses related to Metacognitive Self-Regulation:

H1: Metacognitive Self-Regulation positively affects the perceived utility of generative AI

Individuals with high metacognitive self-regulation skills are better able to determine how technologies fit their learning goals and instructional objectives. These skills include the ability to plan, monitor, and evaluate one's own learning process (Zimmerman & Moylan, 2009). In this way, individuals can more consciously analyze how a technology or method can contribute to their own learning and teaching processes. This can be a significant advantage, especially for pre-service teachers. Preservice teachers who have developed metacognitive self-regulation skills can systematically evaluate the potential benefits of generative AI in their teaching processes. For example, they can analyze the contributions of AI in providing feedback to students, personalizing instructional materials, or making learning processes more efficient. This process of deliberate evaluation enables pre-service teachers to use generative AI more effectively, leading to higher perceptions of its usefulness (Dahri et al., 2024; Kemp et al., 2024; Navarro et al., 2023). Therefore, strengthening metacognitive self-regulation skills can increase the efficiency of the teaching process by enabling pre-service teachers to use educational technology more effectively and consciously.

H2: Metacognitive Self-Regulation positively influences the perceived ease of use of generative AI

Self-regulated learners can make the process more effective by adopting strategic approaches when learning about new technologies. These individuals facilitate the learning process by breaking down complex tools into smaller and more manageable components (Pintrich, 2000). For example, they could analyze the feedback provided by an AI tool and reorganize their teaching strategies based on this feedback. This flexible and strategic approach can reduce perceived difficulties when using generative AI tools. Reduced perceived difficulties may contribute to easier and more effective use of these tools. As a result, the strategic skills of self-regulated learners positively affect the perception of the ease of use of generative AI tools (Chen & Hwang, 2019; Dahri et al., 2024; Lai, 2024). Therefore, developing self-regulation skills can increase the efficiency of the teaching process by enabling pre-service teachers to more effectively and consciously use generative AI tools.

Hypotheses related to subjective norm:

H3: Subjective norm positively influences the perceived usefulness of generative AI

When influential individuals in pre-service teachers'professional and social circles support the value of productive AI, it can provide social validation of the benefits of AI. This validation is the most important determinant of pre-service teachers'intention to learn AI (Sanusi et al. 2024). Positive feedback from influential people in the teaching process can help pre-service teachers embrace the benefits of AI and use this technology more effectively. This social support facilitates pre-service teachers' perceptions of generative AI as a more useful tool (Wong, 2015). Therefore, social validation in a professional environment can strengthen pre-service teachers'positive attitudes towards AI and their propensity to use it.

H4: Subjective norm positively influences the perceived ease of use of generative AI

Social influence can shape perceptions of access to technology by encouraging individuals, providing examples of effective use, and creating supportive learning environments. For pre-service teachers, the successful integration of AI by significant others increases their confidence in their own abilities (Sanusi et al., 2024). Observing others'successful experiences reinforces preservice teachers'confidence that they can use technology more easily and effectively (Tran et al., 2023; Wong, 2015). Therefore, support and positive examples from the social environment can positively affect pre-service teachers'perceptions and attitudes towards the use of artificial intelligence.

Hypotheses related to Motivational Lifelong Learning:

H5: Motivational Lifelong Learning positively influences the perceived usefulness of generative AI

Learning motivation is an important variable that supports individuals in the continuity of educational processes (Davidovitch & Dorot, 2023). By investigating how artificial intelligence can be used in the teaching process, highly motivated pre-service teachers can gain a deeper understanding of the benefits offered by this technology. For example, they could explore the contributions of AI in providing student-specific feedback, personalizing instructional materials, and making the learning process more effective. Exploring digital interactions in combination with the motivation to learn sheds more light on how they deal with problems in learning environments (Mädamürk et al., 2021). Therefore, a high motivation to learn may enable pre-service teachers to consciously assess and effectively utilize the potential of generative AI.

H6: Motivational Lifelong Learning positively influences the perceived ease of use of generative AI

To make the best use of technology, teachers need to be highly motivated to accept and use it in their teaching activities (Sharma & Srivastava, 2020). As teachers have a positive attitude towards the learning process, they may be more resilient to the initial challenges they face when learning generative AI tools. For example, they may patiently seek solutions to overcome the technical problems or comprehension difficulties that arise during the initial process of using an AI tool. Resilience and perseverance reduce perceived difficulties in technology use and make the learning experience easier and more productive (Agudo-Peregrina et al., 2014). Therefore, a high motivation to learn may contribute to pre-service teachers'more effective and comfortable use of generative AI tools.

Hypotheses related to learning agility:

H7: Learning agility positively influences the perceived usefulness of generative AI

Learning agility provides individuals with the ability to use technological tools (Azhar et al., 2024). Individuals with this skill can quickly recognize the connections between new technologies and existing teaching practices. By quickly experimenting with and applying generative AI in different educational scenarios, they can recognize the practical benefits offered by this technology from a broader perspective. For example, they can integrate AI into various teaching processes such as providing student-specific feedback, adapting course materials, or increasing classroom interaction. Exploring the potential of technology in different contexts allows them to understand its uses better and perceive its usefulness more highly (DeRue et al., 2012). Therefore, individuals with high learning agility can enrich their teaching processes more effectively by adopting generative AI.

H8: Learning agility positively affects the perceived ease of use of generative AI

Individuals with high learning agility can adapt to new interfaces and functionalities more quickly. This adaptability may allow preservice teachers to use generative AI systems with less cognitive effort. For example, a pre-service teacher who learns to work with an AI-based language model may adapt more quickly when faced with a similar model. They can also find more flexible and creative solutions to technical problems. This flexibility and adaptation process reduces perceived difficulties in using productive AI tools and increases the perception of ease of use (Aljawarneh, 2024; Azhar et al., 2024). Therefore, pre-service teachers with high learning agility can more effectively and comfortably use generative AI tools.

Hypotheses related to the key components of TAM:

H9: Perceived ease of use positively influences perceived utility

When technologies are perceived as simple and straightforward to use, users can focus on exploring their functional capacities rather than struggling with the interfaces (Durodolu, 2016). This reduced cognitive load may enable pre-service teachers to engage more deeply with pedagogical applications of generative AI. For example, as pre-service teachers explore how AI can be integrated into teaching strategies, they can utilize these functionalities without wasting time with the challenges of using technology. Consequently, their perception of the potential value of generative AI in education has become stronger (Kim et al., 2025). Therefore, the ease of use can support pre-service teachers in using AI tools more effectively and efficiently.

H10: Perceived usefulness positively affects attitude

Professional development opportunities targeting AI literacy can play an important role in addressing these uncertainties and increasing pre-service teachers' familiarity with GenAI technologies (Bae et al., 2024). For example, when pre-service teachers discover the functions of AI, such as assessing student performance, personalizing instructional materials, or increasing classroom interaction, they can focus directly on the beneficial aspects of using this technology without wasting time on its challenges. Consequently, pre-service teachers'perceptions of the potential value of generative AI in education may become stronger (Belda-Medina & Kokošková, 2024; Wulyani et al., 2024). Therefore, recognizing the practical benefits of generative AI can help pre-service teachers use this technology more effectively.

H11: Perceived ease of use positively affects attitude

When pre-service teachers spend minimal effort learning generative AI, they can more easily overcome the difficulties they face in using these tools. If technologies are perceived as intuitive and accessible, pre-service teachers are more inclined to use them (Arochman & Fortinasari, 2024). For example, pre-service teachers can quickly understand the functions of artificial intelligence and integrate it into their teaching processes. This enables pre-service teachers to use generative AI more efficiently and increases the perceived ease of use of the tools (Hsu et al., 2024). Therefore, making technologies easily learnable and accessible can help pre-service teachers to use generative AI tools more effectively.

H12: Attitude positively affects behavioral intention

Positive attitudes set the stage for action by creating psychological preparation for technology adoption. When pre-service teachers positively evaluate generative AI, they may be more willing to incorporate these tools into their instructional planning and classroom activities (Mnguni et al., 2024). For example, pre-service teachers may more readily accept the benefits of AI contributions to lesson preparation, student interaction, or personalized learning processes. This may enable pre-service teachers to more effectively use generative AI (Acquah et al., 2024). Therefore, positive attitudes may increase pre-service teachers'willingness to integrate generative AI into their teaching process.

H13: Perceived usefulness positively affects behavioral intention

Beyond attitudes, the direct realization of the practical value of a technology can motivate adoption intention (Songkram et al., 2023). When pre-service teachers clearly recognize how generative AI tools can improve teaching outcomes, they develop a stronger commitment to implementing these technologies regardless of their emotional response. For example, when pre-service teachers see the practical contributions of AI such as assessing student performance or personalizing instructional materials, they may be more committed to using these tools. This increases their willingness to adopt productive AI (Hoya et al., 2024). Therefore, recognizing the practical benefits of technology can reinforce pre-service teachers'determination to integrate these technologies into their teaching processes.

The proposed model addresses the factors affecting the acceptance of generative AI by pre-service teachers from a holistic perspective. Testing the model will increase the explanatory power of TAM in terms of theoretical aspects and provide implications for the development of teacher education programs in terms of practice.

5 Method

5.1 Participants

We surveyed 748 pre-service teachers from 12 Turkish universities, focusing on Language and Preschool Education programs. The study investigated the extended Technology Acceptance Model (TAM), with hypotheses tested using Structural Equation Modeling (SEM). In addition to testing the research model, the survey items summarized participants' AI engagement, usage purposes, and experiences. Invitations were sent via institutional email lists in collaboration with university coordinators. Participants voluntarily accessed the anonymous survey link, which included an embedded informed consent form. Only those who agreed to the terms proceeded to the questionnaire.

The participant group reflected the general demographic trends in teacher education programs, with 79.8% females and 20.2% males. The sample included pre-service teachers from all grade levels: 21.5% were first-year students, 34.4% were second-year students, 21.7% were third-year students, and 22.5% were in their final year. The distribution between programs was balanced, with 50.5% from Language Education and 49.5% from Preschool Education. The survey items captured a wide range of participant experiences, focusing on their familiarity with AI tools, usage frequency, and primary purposes for use.

The findings highlighted the diversity of participants' AI-related experiences. A majority (56.0%) identified as beginners, while 21.1% had no prior experience, and 11.2% reported advanced expertise. The primary purposes for using AI tools included preparing homework or projects (38.5%) and obtaining information during study sessions (27.8%). Other uses, such as content production (7.75%) and problem solving (4.95%), were less common. In terms of frequency, 31.4% used AI tools a few times a month, 28.9% a few times a week, and 11.2% daily, while 5.21% reported never using them. These results provided an overview of pre-service teachers' engagement with AI tools, complementing the hypothesis testing conducted within the SEM framework.

5.2 Measures

This study explores pre-service teachers' acceptance and use of generative AI tools in teaching by employing an extended version of the Technology Acceptance Model (TAM). The framework integrates both traditional TAM constructs—Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Attitude (Att), and Behavioral Intention (BI)—and extended variables, including Metacognitive Self-Regulation (MSR), Subjective Norm (SN), Learning Motivation (LM), and Learning Agility (LA). The survey items measured cognitive, emotional, personal, and social factors influencing pre-service teachers' acceptance of generative AI tools. These constructs were measured to capture personal and social factors influencing AI tool acceptance, as well as cognitive and affective dimensions underpinning behavioral intentions. The survey consisted of 34 items (Appendix 1) adapted from established scales, ensuring each construct was tailored to the educational context of generative AI integration. The survey took approximately 15 min to complete.

5.2.1 Extended variables

Metacognitive Self-Regulation (MSR), defined as the ability to plan, monitor, and regulate learning processes (Pintrich et al., 1991), was evaluated using five items adapted from the *Motivated Strategies for Learning Questionnaire* (MSLQ; Pintrich et al., 1991) and revised for technology-integrated learning (Lim & Newby, 2020). Example items included *"When studying on my own, I try to find the best way to learn it"* and *"I adjust my study methods when using AI tools."* Total scores ranged from 5 to 25, with strong reliability (α = 0.92; CR = 0.93) and validity (AVE = 0.70; RMSEA = 0.07).

Subjective Norm (SN), reflecting perceived social pressure to adopt AI tools (Ajzen, 2006), was measured with three items adapted from Ajzen's *Theory of Planned Behavior* (Ajzen, 2006) and contextualized using Şimşek and Ateş's (2022) TAM extensions. Example items included *"People who are important to me support my use of generative AI tools in teaching."* Scores ranged from 3 to 15, demonstrating adequate reliability (α = 0.85; CR = 0.86) and validity (AVE = 0.67).

Learning Motivation (LM), capturing intrinsic and extrinsic motivation for skill development (Chukwuedo et al., 2021), was assessed using six items adapted from

Chukwuedo et al.'s (2021) scale. Example items included *"Learning new things is a passion for me"* and *"Mastering AI skills excites me."* Total scores ranged from 6 to 30, with high reliability (α = 0.93; CR = 0.94) and strong factor loadings (0.76–0.87).

Learning Agility (LA), denoting adaptability to new experiences (Kim et al., 2018), was measured with five items adapted from Kim et al.'s (2018) scale. Example items included *"New experiences are learning opportunities for me"* and *"I adapt quickly to AI tools."* Scores ranged from 5 to 25, with excellent reliability (α = 0.93; CR = 0.95) and model fit (RMSEA = 0.06).

5.2.2 TAM constructs

Perceived Ease of Use (PEOU), defined as the belief that using AI tools requires minimal effort (Davis, 1989), was assessed using four items adapted from Davis's (1989) model. Example items included *"Learning generative AI tools in teaching will be easy."* Scores ranged from 4 to 20, with strong reliability (α = 0.94; CR = 0.94) and validity (AVE = 0.78).

Perceived Usefulness (PU), the belief that AI tools enhance teaching performance (Davis, 1989), was measured with four items, such as *"Using generative AI tools will improve my teaching performance."* Scores ranged from 4 to 20, demonstrating high reliability (α = 0.95; CR = 0.95) and validity (AVE = 0.83).

Attitude (Att) toward AI tools, reflecting positive/negative evaluations (Ajzen, 2006), was evaluated with three items, including *"Generative AI tools make learning more interesting."* Scores ranged from 3 to 15, with strong reliability (α = 0.91; CR = 0.91) and validity (AVE = 0.77).

Behavioral Intention (BI), capturing commitment to adopt AI tools (Davis, 1989), was measured using four items, such as *"I plan to use generative AI tools often in my teaching in the future."* Scores ranged from 4 to 20, with high reliability (α = 0.94; CR = 0.94) and validity (AVE = 0.80).

5.3 Data analysis

We used structural equation modeling (SEM) in R (lavaan package version 0.6–15; Rosseel, 2012) to test relationships between latent and observed variables. SEM was employed to test hypothesized relationships among latent and observed variables. A two-step approach was used (Schumacker & Lomax, 2004). First, the measurement model was evaluated through Confirmatory Factor Analysis (CFA) to validate the constructs'reliability and validity. Second, the structural model was tested to examine direct and indirect relationships among constructs, including Metacognitive Self-Regulation (MSR), Subjective Norm (SN), Learning Motivation (LM), Learning Agility (LA), Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude (Att), and Behavioral Intention (BI).

Prior to model estimation, data were assessed for multivariate normality using skewness and kurtosis metrics calculated with the moments package (version 0.14; Komsta & Novomestky, 2015). Outliers were identified and removed using

Mahalanobis distances, calculated with the MASS package (version 7.3–60; Venables & Ripley, 2002). Model fit was evaluated using recommended indices (Hu & Bentler, 1999): Root Mean Square Error of Approximation (RMSEA < 0.08), Standardized Root Mean Square Residual (SRMR < 0.08), Tucker-Lewis Index (TLI > 0.90), and Comparative Fit Index (CFI > 0.90). The reliability of the scales was confirmed with Cronbach's Alpha and McDonald's Omega using the psych package (version 2.3.3; Revelle, 2023). The analysis confirmed a good fit for both the measurement and structural models, providing robust evidence for the hypothesized relationships.

6 Results

6.1 Descriptive statistics

Table 1 shows the mean, standard deviation, skewness, and kurtosis values for the study variables. The mean scores for all variables were above the midpoint of the scales used, indicating generally positive responses from participants. Standard deviations ranged between 2.73 and 5.26, suggesting a moderate spread of responses across participants. The skewness and kurtosis values fell within the recommended range of −2 to +2 (Kline, 2015), confirming that the data distributions are appropriate for conducting structural equation modeling (SEM). These findings suggest that participants reported high levels of Learning Motivation (LM), Learning Agility (LA), and Metacognitive Self-Regulation (MSR), as well as positive perceptions of Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of generative AI tools in teaching. The data distribution indicates no significant deviations from normality, ensuring the reliability of subsequent analyses.

Table 2 presents the correlations among constructs. Strong correlations were observed between Learning Motivation and Learning Agility (r = 0.871), as well as between Perceived Ease of Use and Perceived Usefulness (r = 0.856). Attitude was highly correlated with Behavioral Intention (r = 0.880) and Perceived

Table 1 Descriptive statistics of the observed variables

Variable	Mean	Std. Dev	Skewness	Kurtosis
LM	22.54	5.26	−0.93	4.01
LA	18.88	4.45	−1.08	4.17
MSR	19.28	4.37	−1.11	4.47
SN	10.74	2.73	−0.65	3.29
PEOU	14.60	3.63	−0.61	3.22
PU	15.42	3.60	−0.90	3.87
Att	11.49	2.74	−0.83	3.59
BI	15.05	3.71	−0.75	3.36

LM Learning Motivation, *LA* Learning Agility, *MSR* Metacognitive Self-Regulation, *SN* Subjective Norm, *PEOU* Perceived Ease of Use, *PU* Perceived Usefulness, *Att* Attitude, *BI* Behavioral Intention

Table 2 Correlations amongst constructs

Construct	LM	LA	MSR	SN	PEOU	PU	Att	BI
LM	**0.834**							
LA	0.871***	**0.851**						
MSR	0.742***	0.742***	**0.835**					
SN	0.597***	0.576***	0.672***	**0.816**				
PEOU	0.627***	0.627***	0.662***	0.671***	**0.885**			
PU	0.658***	0.644***	0.677***	0.642***	0.856***	**0.913**		
Att	0.645***	0.625***	0.657***	0.653***	0.847***	0.893***	**0.878**	
BI	0.620***	0.600***	0.636***	0.659***	0.832***	0.867***	0.880***	**0.896**

Note: Values in the diagonal (set in boldface) are the square root of AVE of the constructs. Values below the diagonal are the correlations amongst the constructs.*p < .05, **p < .01,*** p < .001

Table 3 Measurement model results

Item	Factor Loading	R^2	Item	Factor Loading	R^2
LM01	**0.86*****	0.74	PEOU01	**0.87*****	0.76
LM02	**0.83*****	0.68	PEOU02	**0.94*****	0.88
LM03	**0.87*****	0.75	PEOU03	**0.87*****	0.76
LM04	**0.85*****	0.72	PEOU04	**0.86*****	0.74
LM05	**0.84*****	0.71	PU01	**0.91*****	0.82
LM06	**0.76*****	0.57	PU02	**0.92*****	0.85
LA01	**0.85*****	0.73	PU03	**0.94*****	0.88
LA02	**0.71*****	0.51	PU04	**0.89*****	0.79
LA03	**0.90*****	0.80	Att01	**0.90*****	0.81
LA04	**0.91*****	0.82	Att02	**0.91*****	0.83
LA05	**0.87*****	0.76	Att03	**0.82*****	0.67
MSR01	**0.81*****	0.66	BI01	**0.89*****	0.80
MSR02	**0.86*****	0.75	BI02	**0.90*****	0.81
MSR03	**0.85*****	0.72	BI03	**0.89*****	0.79
MSR04	**0.86*****	0.74	BI04	**0.90*****	0.81
MSR05	**0.79*****	0.62			
SN01	**0.81*****	0.66			
SN02	**0.88*****	0.77			
SN03	**0.76*****	0.57			

LM: Learning Motivation, LA: Learning Agility, MSR: Metacognitive Self-Regulation, SN: Subjective Norm, PEOU: Perceived Ease of Use, PU: Perceived Usefulness, Att: Attitude, BI: Behavioral Intention*p < .05, **p < .01,*** p < .001

Usefulness (r = 0.893). The square root of the AVE for each construct exceeded its correlations with other constructs, supporting the discriminant validity of the measures. These results provide a detailed view of the relationships among the study constructs (Table 2).

6.2 Measurement model

Table 3 presents the factor loadings, R^2 values, and internal consistency measures for the study constructs. All factor loadings exceeded the recommended threshold of 0.70, with R^2 values ranging from 0.51 to 0.88, indicating that the items reliably measured their respective constructs (Kline, 2015). Composite reliability (CR) and Average Variance Extracted (AVE) for each construct were also above the critical values of 0.70 and 0.50, respectively, confirming convergent validity (Fornell & Larcker, 1981; Hair et al., 2019). The results of the measurement model are summarized in Table 3.

Table 4 summarizes the results of the convergent validity and internal consistency reliability of the study constructs. All constructs demonstrated an Average Variance Extracted (AVE) exceeding the critical threshold of 0.50, indicating adequate convergent validity. Composite Reliability (CR) values were above 0.70 for all constructs, confirming strong internal consistency. Cronbach's alpha and McDonald's omega values further reinforced the reliability of the scales, both exceeding 0.85 across all constructs.

6.3 Structural model

The structural model was assessed using maximum likelihood estimation, and the fit indices indicated a good overall fit to the data. The Comparative Fit Index (CFI) was 0.985, and the Tucker-Lewis Index (TLI) was 0.963, both exceeding the recommended threshold of 0.90. The Root Mean Square Error of Approximation

Table 4 Convergent validity and internal consistency reliability

Scale	Number of Items	AVE[a]	CR[b]	Cronbach's Alpha	McDonald's Omega
LM	6	0.70	0.93	0.93	0.93
LA	5	0.72	0.93	0.93	0.93
MSR	5	0.70	0.92	0.92	0.92
SN	3	0.67	0.86	0.85	0.86
PEOU	4	0.78	0.94	0.94	0.94
PU	4	0.83	0.95	0.95	0.95
Att	3	0.77	0.91	0.91	0.91
BI	4	0.80	0.94	0.94	0.94

LM Learning Motivation, LA Learning Agility, MSR Metacognitive Self-Regulation, SN Subjective Norm, PEOU Perceived Ease of Use, PU Perceived Usefulness, Att Attitude, BI Behavioral Intention
a AVE = $(\sum\lambda^2)/((\sum\lambda^2) + \sum(1-\lambda^2))$ b CR = $(\sum\lambda)^2/((\sum\lambda)^2 + \sum(1-\lambda^2))$

Table 5 Results of hypothesis testing

Hypotheses	Path	Coefficients (β)	Results
H_1	MSR → PU	**0.10*** **	✓ **Supported**
H_2	MSR → PEOU	**0.21*** **	✓ **Supported**
H_3	SN → PU	0.04	✗ Not supported
H_4	SN → PEOU	**0.37*** **	✓ **Supported**
H_5	LM → PU	**0.12*** **	✓ **Supported**
H_6	LM → PEOU	**0.11*** **	✓ **Supported**
H_7	LA → PU	0.02	✗ Not supported
H_8	LA → PEOU	**0.16*** **	✓ **Supported**
H_9	PEOU → PU	**0.68*** **	✓ **Supported**
H_{10}	PU → Att	**0.63*** **	✓ **Supported**
H_{11}	PEOU → Att	**0.31*** **	✓ **Supported**
H_{12}	Att → BI	**0.53*** **	✓ **Supported**
H_{13}	PU → BI	**0.40*** **	✓ **Supported**

β = Standardized regression coefficient

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$

(RMSEA) was 0.098, with a 90% confidence interval of [0.077, 0.120], and the Standardized Root Mean Square Residual (SRMR) was 0.022, indicating a satisfactory fit. The chi-square statistic was significant ($\chi 2 = 70.934$ $p < 0.001$), but this is common in large sample sizes. These results suggest that the structural model adequately represents the hypothesized relationships (Hu & Bentler, 1999). The model explained a substantial proportion of variance in the endogenous variables. The results of hypothesis testing are summarized in Table 5, which includes the standardized path coefficients (β) for all hypothesized relationships. Significant paths are shown in black in Fig. 1, while non-significant paths are highlighted in red.

The results of hypothesis testing demonstrate strong support for the hypothesized relationships within the TAM framework in explaining pre-service teachers' adoption of generative AI tools in teaching. Specifically, Perceived Ease of Use (PEOU) significantly influenced Perceived Usefulness (PU, H_9: $\beta = 0.68$, $p < 0.001$) and Attitude (Att, H_{10}: $\beta = 0.31$, $p < 0.001$), while PU strongly predicted both Att (H_{10}: $\beta = 0.63$, $p < 0.001$) and Behavioral Intention (BI, H_{13}: $\beta = 0.40$, $p < 0.001$). Attitude emerged as a significant determinant of BI (H_{12}: $\beta = 0.53$, $p < 0.001$). These findings highlight the central role of PU and Att in fostering behavioral intention, which underscores the relevance of TAM constructs in understanding the adoption of generative AI tools among pre-service teachers.

The external variables—Metacognitive Self-Regulation (MSR), Subjective Norm (SN), Learning Motivation (LM), and Learning Agility (LA)—also played a critical role in shaping PU and PEOU, although their effects varied. MSR had a significant positive effect on both PU (H_1: $\beta = 0.10$, $p < 0.001$) and PEOU (H_2: $\beta = 0.21$, $p < 0.001$). This suggests that teachers who actively plan, monitor, and adjust their learning strategies (e.g., setting goals, reflecting on progress) are better positioned to recognize AI's practical benefits and usability. SN strongly influenced PEOU (H_4: $\beta = 0.37$, $p < 0.001$), indicating that institutional policies (e.g., school-level AI guidelines) and peer encouragement reduce technical hesitations. Its nonsignificant

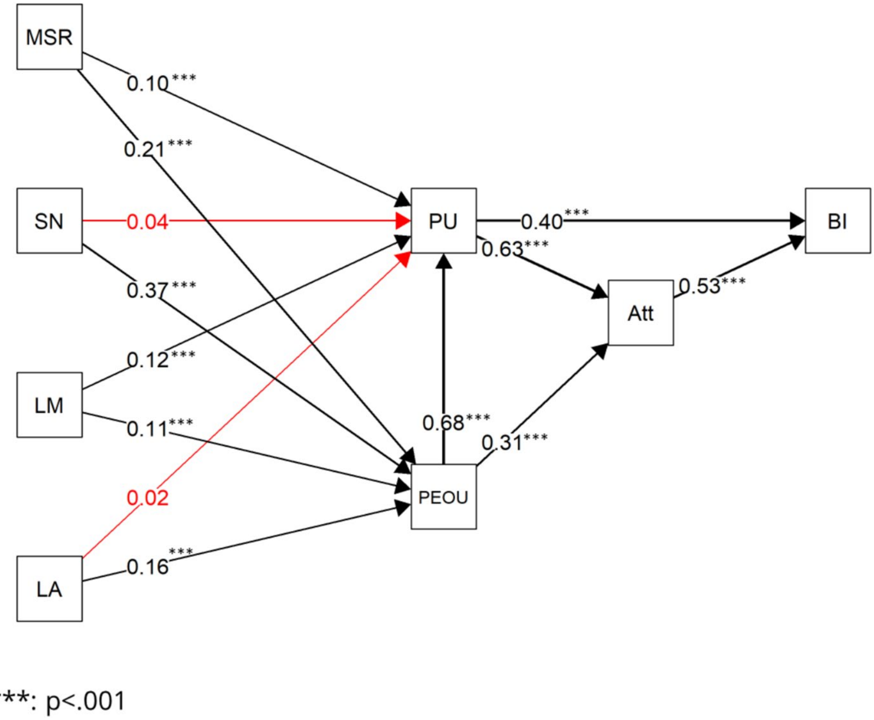

Fig. 1 Results for the Model of Pre-Service Teachers' Intention to Use Generative AI Tools in Teaching. LM: Learning Motivation, LA: Learning Agility, MSR: Metacognitive Self-Regulation, SN: Subjective Norm, PEOU: Perceived Ease of Use, PU: Perceived Usefulness, Att: Attitude, BI: Behavioral Intention. Note: Black paths represent statistically significant coefficients ($p < 0.05$) and red paths represent non-significant coefficients ($p > 0.05$)

effect on PU (H_3: $\beta = 0.04$, $p > 0.05$) implies social approval alone does not enhance perceived utility. LM positively impacted PU (H_5: $\beta = 0.12$, $p < 0.001$) and PEOU (H_6: $\beta = 0.11$, $p < 0.001$). Teachers driven by a passion for learning (e.g., valuing skill development) are more likely to explore AI's functional and operational potential. LA improved PEOU (H_8: $\beta = 0.16$, $p < 0.001$), as adaptability to new experiences helps teachers navigate technical challenges. However, its nonsignificant effect on PU (H_7: $\beta = 0.02$, $p > 0.05$) highlights that technical agility requires alignment with teaching goals to enhance perceived usefulness.

Overall, the findings revealed that most of the external variables had significant effects on TAM constructs, except for SN → PU and LA → PU, which were not supported. The supported relationships indicate that MSR, SN, LM, and LA collectively account for substantial variance in PEOU (39%) and PU (42%). These results suggest that pre-service teachers' perceptions of generative AI tools as useful and easy to use are driven primarily by their cognitive and motivational attributes, as well as social pressures, with the exception of subjective norm and learning agility directly influencing usefulness. The structural model explained significant proportions of variance in the dependent variables (Table 6).

Table 6 Variance explained (R^2) and key predictors of TAM constructs

Dependent Variable	Variance Explained (R^2)	Key Predictors
Attitude (Att)	54%	PU (63%), PEOU (31%)
Behavioral Intention (BI)	51%	Att (53%), PU (40%)
Perceived Usefulness (PU)	42%	MSR (10%), LM (12%), PEOU (68%)
Perceived Ease of Use (PEOU)	39%	MSR (21%), SN (37%), LM (11%), LA (16%)

R^2 Values: The total variance explained by the model for each dependent variable

Key Predictors: The contribution of each variable with standardized regression coefficients (β)

Specifically, the TAM framework accounted for 54% of the variance in Attitude (Att) and 51% in Behavioral Intention (BI). Key predictors included Perceived Usefulness (β = 0.63) and Perceived Ease of Use (β = 0.31) for Attitude, and Attitude itself (β = 0.53) for Behavioral Intention. External variables collectively contributed to 39% of the variance in PEOU and 42% in PU (see Table 6).

7 Discussion

This study examined pre-service teachers' adoption of generative AI tools through an extended TAM framework. The findings confirm the model's robustness, with Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) emerging as pivotal predictors of Behavioral Intention (BI). Notably, PU's strong influence on Attitude (β = 0.63) and BI (β = 0.40) highlights educators' prioritization of pedagogical utility, while PEOU's dual impact on PU (β = 0.68) and Attitude (β = 0.31) underscores the foundational role of usability. External variables further enriched the model: Metacognitive Self-Regulation (MSR) and Learning Motivation (LM) enhanced both PU and PEOU, reflecting the interplay between cognitive strategies and intrinsic engagement. In contrast, Subjective Norm (SN) and Learning Agility (LA) shaped only PEOU, suggesting social encouragement and adaptability ease technical adoption but do not directly translate to perceived utility. The model's high explanatory power (R^2 = 51–54% for BI and Attitude) validates its applicability to AI integration in education. The findings provide valuable insights into the roles of core TAM constructs and external variables in influencing technology acceptance, contributing to both theoretical and practical understandings of AI integration in education.

7.1 Technology acceptance and behavioral intention

The results demonstrated that technology acceptance significantly influences pre-service teachers' behavioral intention to adopt generative AI tools. Perceived Usefulness (PU) emerged as a central predictor, consistent with the foundational TAM framework. Teachers who perceived generative AI tools as beneficial for enhancing teaching effectiveness expressed stronger intentions to integrate them into their practices. This finding aligns with the research by Davis (1989), which establishes PU as a critical determinant in shaping behavioral intention. Furthermore, studies by Şimşek and Ateş (2022) and Wulyani et al. (2024) corroborate the role of PU in fostering positive attitudes toward educational technologies. The influence of Perceived Ease of Use (PEOU) on PU further highlights how usability perceptions shape evaluations of utility, subsequently affecting attitudes and intentions. These findings are consistent with research demonstrating that usability significantly impacts the perceived value of technology in educational settings (An et al., 2022; Sulasmi & Dalle, 2022).

Behavioral intention was also strongly associated with PU, emphasizing the importance of explicitly communicating the practical advantages of generative AI tools. Tools designed to align with teacher expectations and pedagogical objectives are more likely to be adopted, as evidenced by An et al. (2024). Additionally, Dahri et al. (2024) emphasized that addressing teachers' cognitive and practical needs enhances their willingness to adopt technology. Hsu and Lin (2021) further demonstrated that intrinsic motivational factors mediated the relationship between usability and behavioral intention, underscoring the role of clear functionality and user-centric design in facilitating adoption.

7.2 Role of external variables

External variables played a crucial role in shaping perceptions of generative AI tools, both in this study and in broader research contexts. Metacognitive Self-Regulation (MSR) significantly influenced both PU and PEOU. Teachers with strong self-regulatory skills are more adept at planning, monitoring, and evaluating their learning processes, enabling them to effectively navigate complex technological environments. This aligns with the broader literature, where Deci and Ryan (2008) highlight self-regulation as fundamental to adaptive learning behaviors in educational contexts. Similarly, Chukwuedo et al. (2021) identified self-regulation as enhancing engagement with emerging technologies, while Haviz et al. (2024) specifically linked self-regulatory strategies to improved perceptions of ease of use. These findings emphasize that MSR is not only critical for technology adoption in this study but also a consistently validated factor across various educational technology contexts.

Learning Motivation (LM), particularly intrinsic motivation, positively influenced PU and PEOU. Intrinsic motivation fosters engagement with technology driven by genuine interest and enjoyment rather than external pressures. This intrinsic engagement enables users to better understand the utility and usability of technology, thereby enhancing acceptance. The current findings align with self-determination theory, which underscores the role of intrinsic drivers in sustaining engagement and persistence in learning (Teo, 2010; Tran et al., 2023). Sulistiyo et al. (2022) further demonstrated that intrinsic motivation shapes positive attitudes toward ICT tools, emphasizing its relevance in fostering exploration and adoption of generative AI tools. The consistent emphasis on intrinsic motivation across studies highlights its foundational role in the TAM framework, particularly for technologies requiring sustained engagement.

Subjective Norm (SN) significantly influenced PEOU but had no notable influence on PU. This suggests that while social encouragement enhances usability perceptions by building confidence and familiarity, it does not necessarily translate into utility evaluations. Azhar et al. (2024) noted that SN is particularly impactful during the initial stages of technology adoption, helping users navigate early challenges (e.g., institutional policies promoting AI use or peer modeling of basic tool applications). This aligns with the notion that social validation is critical for early adopters but diminishes as users gain firsthand experience and develop independent judgments about utility. Aljawarneh (2024) found that while SN bolsters ease of use, its impact on utility often diminishes as personal experience becomes a more dominant factor. Similarly, Malanga et al. (2022) and Lin and Wang (2022) demonstrated that utility perceptions are more closely tied to personal and contextual factors rather than external social pressures. Thus, SN acts as a scaffold for initial experimentation but recedes as educators transition to utility-driven adoption.

Learning Agility (LA) significantly influenced PEOU, demonstrating that adaptability is essential for interacting with user-friendly technologies. Teachers with high learning agility can quickly adjust to new tools, reducing cognitive barriers and enhancing their usability perceptions. However, LA's indirect role in shaping PU may strengthen over time: as educators accumulate hands-on AI experience, their agility enables them to creatively align tools with pedagogical objectives (e.g., adapting AI outputs for differentiated instruction or troubleshooting system limitations), thereby uncovering latent utility. This aligns with findings by Hsu and Lin (2021), who identified adaptability as critical for promoting ease of use across diverse technological platforms. Lin and Wang (2022) further emphasized that fostering learning agility through structured training programs maximizes usability benefits. However, Xiao et al. (2024) noted that adaptability alone may not directly enhance utility perceptions without contextual alignment and functional integration. These dynamics suggest LA's value evolves from easing initial usability to enabling deeper, utility-focused integration as experience grows.

8 Conclusions, implications, and future directions

8.1 Theoretical and practical implications

This study extends the Technology Acceptance Model (TAM) by integrating external variables—Metacognitive Self-Regulation (MSR), Learning Motivation (LM), Subjective Norm (SN), and Learning Agility (LA)—to examine pre-service teachers' behavioral intention to adopt generative AI tools for educational purposes. The findings highlight that these external factors enrich TAM's explanatory power, particularly in understanding complex interactions between technology, user characteristics, and social influences. By demonstrating that intrinsic motivation and self-regulation significantly shape perceptions of usefulness (PU) and ease of use (PEOU), the study advances theoretical insights into the cognitive and affective dimensions of technology acceptance. Furthermore, the nuanced roles of SN and LA highlight the need for a more dynamic understanding of adaptability and social influences within the TAM framework. For instance, Zheng et al.

(2024) emphasize how motivation moderates technology acceptance, aligning with this study's findings that LM strongly influences PU and PEOU. Similarly, Shahzad et al. (2024) underscore the role of self-efficacy and creativity, which aligns with the contributions of MSR in fostering positive perceptions of generative AI tools. These contributions provide a robust foundation for future research exploring technology adoption in dynamic educational environments.

The findings have practical implications for educators, policymakers, and developers of generative AI tools. First, teacher training programs should emphasize developing self-regulation and intrinsic motivation skills through interactive workshops that simulate real-world scenarios, such as designing AI-generated lesson plans, creating adaptive quizzes, or automating feedback processes. For example, pre-service teachers could engage in role-playing activities where they use text-based AI tools (e.g., systems generating student-facing content), visual design platforms (e.g., tools producing custom illustrations), or adaptive learning systems (e.g., applications tailoring exercises to individual student needs) to address pedagogical challenges. Such workshops can enhance intrinsic motivation by showcasing AI's capacity to reduce administrative burdens and foster creativity, while self-regulation strategies can be strengthened through guided goal-setting and reflective practice. By fostering a mindset of lifelong learning and adaptability, pre-service teachers can better navigate the evolving technological landscape, as suggested by Bower et al. (2024), who emphasize aligning technology training with pedagogical goals to enhance motivation and performance expectancy. Second, curriculum developers should integrate AI literacy modules that demonstrate practical applications, such as using generative AI for personalized learning materials (e.g., differentiated reading passages), real-time feedback systems (e.g., automated essay scoring), or interactive content creation (e.g., simulations for science lessons), thereby bridging theoretical knowledge with classroom utility. Developers should prioritize user-centric designs aligned with educators' workflows—for instance, integrating AI tools that streamline lesson planning (e.g., template generators), enhance communication (e.g., multilingual translation assistants), or support inclusive practices (e.g., accessibility-focused content adaptors)—to enhance perceived usefulness. Al-Emran et al. (2024) reinforce this by highlighting how system and service quality directly influence user satisfaction, underscoring the need for intuitive and efficient AI tools. Third, while Learning Agility (LA) enhances PEOU, its limited impact on PU may stem from insufficient hands-on exposure to AI tools or a short-term focus during training. Institutions should address this by incorporating longitudinal training that highlights AI's long-term benefits, such as adaptive learning analytics or AI-assisted curriculum co-creation, enabling teachers to envision sustained utility beyond immediate tasks. Finally, educational institutions should cultivate supportive environments through peer mentoring, communities of practice, and professional development workshops that emphasize collaborative exploration of AI's potential. For example, schools might create initiatives where teachers experiment with AI-driven platforms (e.g., lesson idea generators, quiz builders, or interactive storytelling tools) to design inclusive activities, share successes, and troubleshoot challenges collectively. These efforts align with Lee et al. and's (2024a, 2024b) emphasis on fostering ethical and informed AI usage, ensuring technological advancements align with pedagogical goals. Together, these strategies empower educators as adaptive innovators, accelerating the ethical and effective integration of generative AI in education.

8.2 Limitations and future directions

This study has several limitations that provide opportunities for further exploration. First, the reliance on self-reported data may introduce response bias; future research should include objective measures such as classroom observations (e.g., tracking AI tool integration in lesson plans) or usage analytics (e.g., log data from AI platforms). For instance, Lee et al., (2024a, 2024b) combined self-reports with behavioral metrics to validate AI adoption patterns in STEM education, offering a methodological template for holistic analysis. Second, the sample was limited to pre-service teachers in Turkey, which may restrict the generalizability of findings. While the core constructs examined—such as intrinsic motivation and self-regulation—are grounded in universal theories like Self-Determination Theory (Ryan & Deci, 2000) and have demonstrated cross-cultural relevance in technology adoption (Teo, 2010), expanding the study to diverse cultural contexts (e.g., contrasting collectivist vs. individualist educational systems) or institutional settings (e.g., vocational vs. K-12 schools) would provide a broader perspective. For example, Lin et al. (2024) demonstrated the value of integrating generative AI in STEM education across diverse contexts, suggesting potential cross-disciplinary applications. Third, the study focused on a specific set of external variables; future research could investigate nuanced factors such as AI-specific self-efficacy (e.g., confidence in troubleshooting AI outputs), ethical concerns (e.g., addressing biases in generative content), or systemic barriers (e.g., lack of institutional training frameworks) to further refine the extended TAM framework. Longitudinal studies would also be valuable to examine how perceptions and behavioral intentions evolve over time, particularly across critical transition phases (e.g., from pre-service training to in-service practice, or during rapid AI tool updates).

9 Conclusions

This study provides critical insights into the factors influencing pre-service teachers' adoption of generative AI tools through an extended TAM framework. By integrating cognitive, motivational, and social variables, the research underscores the importance of addressing both individual and contextual factors in designing effective educational technologies. The extended model explained 54% of the variance in Attitude (Att) and 51% in Behavioral Intention (BI), highlighting the robustness of TAM in predicting technology adoption. Among the external variables, Metacognitive Self-Regulation (MSR) and Learning Motivation (LM) significantly contributed to perceptions of usefulness and ease of use, while Learning Agility (LA) and Subjective Norm (SN) played nuanced roles in shaping ease of use. The inclusion of LM and LA as external variables represents a novel contribution to the TAM framework, aligning with findings by Zheng et al. (2024) and Shahzad et al. (2024) that highlight the interplay between motivation, adaptability, and technology acceptance. These insights not only advance theoretical understandings of technology acceptance but also offer actionable guidance for promoting the effective integration of generative AI in education.

Appendix

Survey items

Metacognitive Self-Regulation (MSR):

1. When studying on my own, I try to find the best way to learn it.
2. When studying on my own, I analyze my learning style to find a more effective way to study.
3. While studying, I ask myself questions to ensure I understand the material.
4. While studying, I try to identify concepts or principles I do not understand well.
5. I set goals for myself to guide my activities in each study session.

Subjective Norm (SN):

1. People who are important to me support my use of generative AI tools in teaching.
2. My students will support my use of generative AI tools in teaching.
3. Schools support the use of generative AI tools in teaching.

Learning Motivation (LM):

1. I enjoy acquiring new knowledge and skills in various areas to improve myself.
2. I can easily learn anything if I think it will contribute to my personal development.
3. One of my main goals in life is to continuously acquire new knowledge and skills.
4. Even if I had sufficient financial resources, I would still strive to acquire new knowledge and skills.
5. Learning new things is a passion for me.
6. I am more eager than my friends to learn new knowledge and skills.

Learning Agility (LA):

1. New experiences are learning opportunities for me.
2. I can easily remember new information.
3. I am optimistic about my ability to learn new information.
4. I enjoy exploring new information.
5. I look for ways to use new information.

Perceived Ease of Use (PEOU):

1. Learning generative AI tools in teaching will be easy.
2. Using generative AI tools in teaching will be clear and straightforward.

3. Interacting with generative AI tools in teaching will be flexible.
4. It will be easy to become skilled in using generative AI tools in teaching.

Perceived Usefulness (PU):

1. Using generative AI tools will improve my teaching performance.
2. Using generative AI tools will enhance my teaching effectiveness.
3. Using generative AI tools will increase my teaching efficiency.
4. Generative AI tools will be beneficial for my teaching.

Attitude (Att):

1. Generative AI tools make learning more interesting.
2. Learning with generative AI tools is fun.
3. I enjoy using generative AI tools.

Behavioral Intention (BI):

1. I plan to use generative AI tools often in my teaching in the future.
2. I intend to use generative AI tools as much as possible in my teaching in the future.
3. I think I will discuss the positive aspects of generative AI tools in my class in the future.
4. I think I will recommend generative AI tools to my colleagues in the future.

Author contributions Authors contributed to this article equally.

Funding Open access funding provided by the Scientific and Technological Research Council of Türkiye (TÜBİTAK). This study is not funded.

Data availability Data will be made available on request.

Declarations

Ethics approval and consent to participate This study was conducted in accordance with ethical standards as approved by the Akdeniz University Social Sciences and Humanities Research and Publication Ethics Committee. The research was unanimously determined to comply with the ethical guidelines for scientific research and publication, with the approval granted under Meeting Decision Number 23/470.

Consent for publication All authors have contributed to and have approved the final manuscript.

Competing interests The authors declare no potential conflict of interest.

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