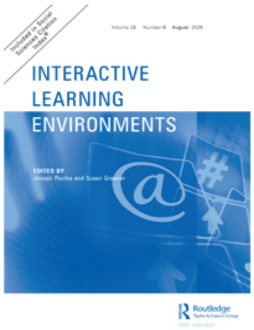

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Proposing a conceptual model for the adoption of artificial intelligence by teachers in STEM education

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ABSTRACT

This study explores the adoption of Artificial Intelligence (AI) in STEM education by proposing a new conceptual model that integrates UTAUT 2 and GETAMEL frameworks. Data collected from 582 science teachers in Turkey were analyzed using Structural Equation Modeling. The results demonstrated that the proposed model outperformed the original GETAMEL and UTAUT 2 models in predicting teachers' intentions to adopt AI in STEM education. Key factors influencing adoption included subjective norm, experience, perceived enjoyment, anxiety, and self-efficacy, which significantly impacted perceived usefulness and perceived ease of use. These factors, in turn, positively influenced attitudes and intentions toward using AI-powered tools. Additionally, price value, facilitating conditions, and habit were identified as significant predictors of intention. The mediating roles of perceived ease of use, perceived usefulness, and attitude were confirmed in explaining adoption intentions. This model offers valuable insights for promoting effective AI integration in STEM education, aiding policymakers, educators, and researchers in understanding the factors driving technology adoption. It highlights actionable strategies for enhancing the acceptance and utilization of AI-powered tools in educational settings.

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Artificial intelligence; STEM education; UTAUT 2; GETAMEL; teacher adoption

1. Introduction

STEM (Science, Technology, Engineering, and Mathematics) education is a crucial component in preparing students for the future workforce, especially in the fields of science and technology (Huderson & Huderson, 2019; Kennedy & Sundberg, 2020). However, traditional approaches to teaching STEM have not always yielded the desired outcomes. As such, educators are constantly searching for innovative solutions that can enhance the learning experience and improve student engagement with these subjects (Scherer & Teo, 2019; Sungur-Gül & Ateş, 2023). The integration of artificial intelligence (AI) into STEM education is one such solution that has the potential to provide personalized support, adaptive learning paths, and real-time feedback to students, all tailored to their individual needs and progress (Alabdulhadi & Faisal, 2021; Ateş, 2024; Lin et al., 2021; Xu & Ouyang, 2022). The benefits of AI in STEM education are clear, especially for students who may be struggling with these subjects (Krasovskiy, 2020). With personalized support, AI can help address the challenges that many students face in the classroom, such as keeping up with the pace of the lessons, maintaining motivation, and comprehending complex scientific concepts (Alabdulhadi & Faisal, 2021; Chen et al., 2020; Xu & Ouyang, 2022). Moreover, the use of AI in STEM education can foster interactive and engaging

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learning environments that can capture students' interest and imagination (Hwang et al., 2020; McLaren et al., 2010).

Despite these potential benefits, the adoption of AI in STEM education among teachers has been slow (Xia et al., 2022). This reluctance stems from several challenges, including concerns over teacher autonomy, anxiety about using new technologies, and a lack of experience with AI tools (Ateş, 2024). Such challenges highlight the need for a structured approach to understand the factors that shape teachers' intentions to adopt AI in their classrooms. Developing a conceptual model that captures these factors can provide valuable insights into the adoption process, helping to address teachers' concerns and guiding the design of effective strategies for AI integration in education.

This study adopts a conceptual framework by integrating two widely recognized models: the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Venkatesh et al., 2012) and the General Extended Technology Acceptance Model for E-Learning (GETAMEL) (Abdullah & Ward, 2016). These models were selected due to their proven effectiveness in examining technology adoption in educational settings and their complementary nature, as they address individual, institutional, and contextual factors relevant to technology adoption. UTAUT2 is particularly relevant for this study as it elucidates the individual-level behavioral intentions that influence technology use, focusing on variables such as performance expectancy, effort expectancy, social influence, facilitating conditions, price value, hedonic motivation, and habit (Venkatesh et al., 2012). These constructs are directly aligned with teachers' concerns regarding AI adoption, as they encapsulate educators' expectations of the technology's impact on student performance, the perceived effort required to integrate AI tools into their teaching practices, and the significant role of peer support in fostering a positive environment for technology adoption (Cukurova et al., 2023; Du & Gao, 2022; Wang et al., 2021).

The model has been successfully utilized in various educational contexts to understand technology acceptance, confirming its relevance and efficacy in capturing the nuances of teachers' motivations and apprehensions (Chávez Herting et al., 2023; Humida et al., 2022). GETAMEL, on the other hand, emphasizes the broader institutional and contextual factors that are vital for successful technology adoption, making it particularly significant for the education field (Abdullah & Ward, 2016). This model highlights aspects such as school leadership support, resource availability, organizational culture, and the alignment of technology with educational goals. In the context of AI adoption, GETAMEL helps identify how institutional readiness and a supportive infrastructure can facilitate or hinder teachers' willingness to adopt AI tools. For instance, strong leadership support can empower teachers to experiment with AI technologies, while a lack of resources may deter them from doing so. Furthermore, GETAMEL's focus on cultural attitudes towards technology underscores the importance of fostering an environment that values innovation and encourages risk-taking, both of which are essential for the successful integration of AI in STEM education.

The integration of the UTAUT2 model and the GETAMEL framework creates a comprehensive and nuanced framework for understanding the factors that influence the adoption of AI in educational settings. This merged approach recognizes the complexity of technology integration, emphasizing that it is not solely reliant on individual teachers' readiness to adopt AI. Instead, it highlights the significant role of the organizational context in shaping and facilitating this adoption process. By investigating the interplay between personal motivations – such as perceived ease of use, perceived usefulness, and individual attitudes toward technology – and the broader institutional dynamics – such as administrative support, organizational culture, and resource availability – this study aims to illuminate the pathways through which individual intentions to adopt AI can be effectively nurtured and enhanced. The findings are expected to provide valuable insights into how educational institutions can create an environment that not only encourages but also sustains AI adoption among educators. This holistic framework allows for a dual analysis: it examines how teachers' intrinsic and extrinsic motivations align with the organizational supports available to them. Ultimately, the study seeks to demonstrate that a conducive organizational environment can significantly amplify individual intentions, leading to more successful and sustained integration of AI technologies in education. By bridging micro-level individual factors with macro-level organizational influences, this research aims to contribute to the development of targeted strategies that facilitate effective AI adoption, thereby enhancing educational practices and outcomes.

While previous research has made significant strides in exploring technology acceptance through either the UTAUT2 model or the GETAMEL framework, a notable gap exists in the literature regarding the combined application of these models to investigate the adoption of AI in STEM education. Recent studies (Ateş & Gündüzalp, 2024; Ku et al., 2022; Ong, 2022; Sungur-Gül & Ateş, 2023; Wijaya et al., 2022) have offered valuable insights into teachers' intentions concerning technology use within STEM contexts, revealing important individual motivations and barriers to technology integration. However, none of these studies have successfully synthesized UTAUT2 and GETAMEL into a cohesive framework that specifically addresses the unique nuances of AI adoption in educational settings. This lack of integration highlights the need for a more comprehensive approach that encompasses both individual-level factors – such as teachers' attitudes, perceived ease of use, and perceived usefulness – and institutional factors, including organizational support, culture, and infrastructure. By merging these two models, this research seeks to fill the existing gap and provide a more robust understanding of the complexities surrounding technology acceptance among educators. This integrated framework will not only clarify how personal motivations and perceptions influence the adoption of AI but also elucidate how supportive organizational structures can facilitate or hinder this process. Ultimately, this approach aims to offer actionable insights for policymakers and educational leaders, enabling them to create environments that effectively support teachers in their adoption of AI technologies, thereby enhancing the overall quality of STEM education.

To address this critical gap, this study proposes a novel conceptual model, illustrated in Figure 1, which aims to predict teachers' behavioral intentions to adopt AI in STEM education by combining the strengths of both UTAUT2 and GETAMEL frameworks. The proposed model seeks to achieve four primary objectives: (1) Develop a comprehensive model that identifies the key factors influencing teachers' intentions to utilize AI in STEM education, providing a holistic view of both personal

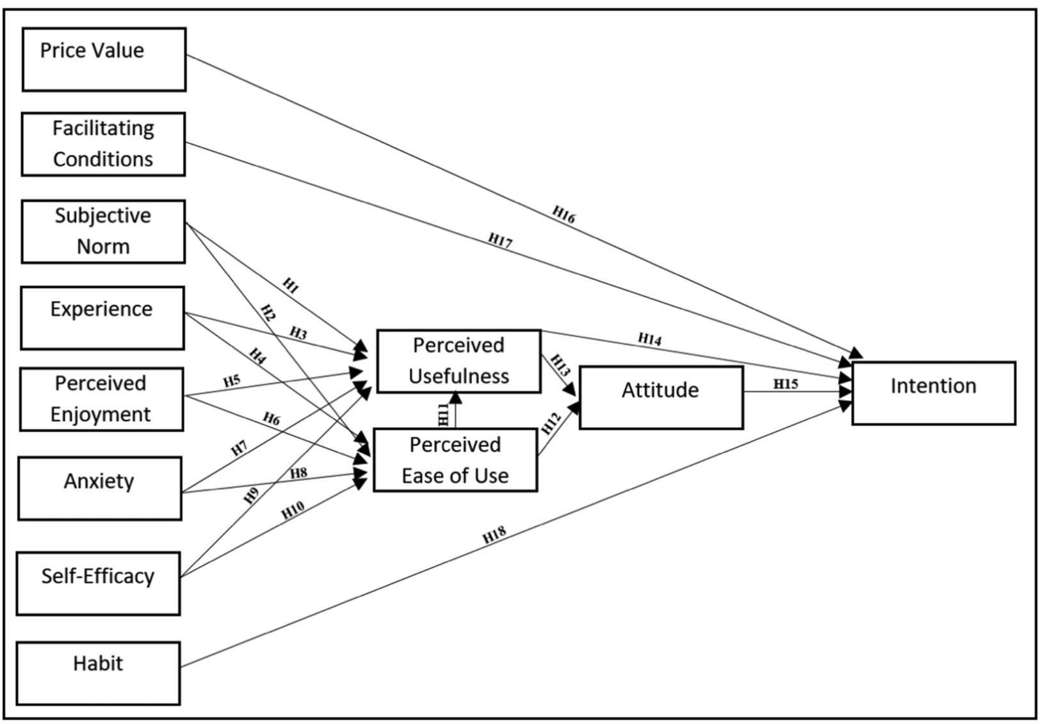

Figure 1. Proposed model combining UTAUT 2 and GETAMEL.

and organizational dimensions; (2) Compare the explanatory power of the proposed model with that of UTAUT2 and GETAMEL individually, thereby determining its effectiveness in predicting adoption rates more accurately; (3) Test the relative importance of the variables within the proposed model, facilitating an understanding of which factors are most significant in influencing teachers' adoption behaviors; and (4) Explore the mediating roles of perceived ease of use, perceived usefulness, and attitude, examining how these constructs influence teachers' intentions to engage with AI technologies in STEM education.

2. Literature review and hypothesis development

2.1. Artificial intelligence in STEM education

Artificial Intelligence (AI) has become an increasingly popular tool in education, with the potential to enhance teaching and learning in a variety of ways (Chen et al., 2022; Lin et al., 2021; Sadiku et al., 2022; Sing et al., 2022). In the context of STEM education, AI can provide students with personalized and adaptive learning experiences (Alabdulhadi & Faisal, 2021), help them to understand complex concepts (Krasovskiy, 2020; Xu & Ouyang, 2022) , and provide feedback on their progress in real time (Dolenc et al., 2015; Hillmayr et al., 2020; Shin, 2020). The use of AI in STEM education can also help to engage students with these subjects, by providing interactive and immersive learning experiences (Hooshyar et al., 2018; Saito & Watanobe, 2020) that capture their interest and imagination.

One of the key advantages of AI in STEM education is its ability to provide personalized learning experiences (Alabdulhadi & Faisal, 2021). AI can adapt to the needs and progress of individual students, providing them with targeted support and feedback (Chen et al., 2020; Hooshyar et al., 2015). For example, AI-powered tools can analyze a student's performance and provide them with tailored learning materials, such as interactive simulations or multimedia resources, that are designed to address their specific learning needs (Dai & Ke, 2022; Harmon et al., 2021). This can be particularly helpful for students who are struggling with STEM subjects, as it can help to build their confidence and keep them motivated (Balakrishnan, 2018). By providing students with a visual representation of these concepts, AI can help to deepen their understanding and enhance their engagement with STEM subjects (Jho, 2020; Rau et al., 2015; Shin, 2020). The use of AI in STEM education can also help to provide real-time feedback on students' progress and can monitor students' performance and provide feedback on their strengths and weaknesses (Dolenc et al., 2015; Hillmayr et al., 2020; Shin, 2020). This can be particularly useful for formative assessment, as it can help teachers to identify areas where students may be struggling and provide targeted support.

2.2. The research model and hypotheses

The objective of this proposed study is to develop a comprehensive conceptual model that can accurately predict teachers' intentions to adopt AI in STEM education. To achieve this, we plan to combine two well-established frameworks, the UTAUT 2 and GETAMEL approaches. However, it is important to note that some of the constructs in both frameworks measure similar characteristics. Therefore, in our proposed model, we will only include one variable to represent each of these characteristics, namely: performance expectancy/perceived usefulness, effort expectancy/perceived ease of use, social influence/subjective norm, and hedonic motivation/perceived enjoyment. As a result, our study's hypotheses were adjusted accordingly to reflect the specific constructs included in our model. Through this approach, we aim to provide a more accurate and streamlined understanding of the factors that influence teachers' intentions to adopt AI in STEM education.

2.2.1. General extended technology acceptance model for E-learning

The General Extended Technology Acceptance Model for E-Learning (GETAMEL) is a comprehensive expansion of the Technology Acceptance Model (TAM) that focuses on predicting the acceptance and utilization of technology in educational settings (Abdullah & Ward, 2016; Jiang et al., 2021). GETAMEL seeks to enhance the precision of predicting technology adoption in educational settings by introducing supplementary factors and introduces a series of elements that impact an individual's motivation to use technology in educational contexts (Abdullah & Ward, 2016).

One of these constructs is experience, which refers to the extent to which an individual has used a technology in the past meaning that the more experience an individual has with a technology, the more likely they are to use it in the future (Abdullah et al., 2016; Fussell & Truong, 2022). In the context of STEM education and the adoption of AI, experience can be particularly relevant for teachers who may have varying levels of exposure to technology in their teaching practices. For instance, teachers who have previously used AI in the classroom may have a better understanding of its potential benefits and may be more likely to integrate it into their future teaching practices. Subjective norm is another construct, which reflects the perceived social pressure that individuals feel to use a technology (Sungur-Gül & Ateş, 2021; Venkatesh et al., 2003). This pressure can come from peers, instructors, or other social influences (Ateş & Garzón, 2022; Venkatesh et al., 2012). In the context of STEM education and the adoption of AI, subjective norm can be particularly important as teachers may be influenced by the expectations and norms of their colleagues or superiors. Enjoyment is another important construct, which refers to the extent to which individuals find a technology enjoyable to use (Holdack et al., 2022; Venkatesh et al., 2012; Zhou et al., 2022). If individuals find a technology enjoyable, they are more likely to continue using it. Anxiety is another construct that is often considered in technology acceptance models, reflecting the perceived feelings of nervousness or apprehension that individuals may have towards using a technology (Arpaci & Basol, 2020; Chong et al., 2022). Anxiety is an important factor to consider because many teachers may feel apprehensive about using AI, particularly if they lack experience with the technology or if they feel that their skills may not be adequate to work with AI tools. This anxiety can also stem from concerns about the impact of AI on their role as teachers, and whether it may undermine their professional autonomy. Experience is also a key factor to consider because it can influence teachers' perception of the value of AI in STEM education. Teachers who have more experience with AI are likely to be more willing to use it in their teaching. Conversely, those who lack experience with AI may be less likely to see its potential benefits and may feel more hesitant about integrating it into their teaching. Finally, self-efficacy is an important factor to consider because it reflects teachers' confidence in their ability to use technology effectively in their teaching (Luo & Du, 2022; Songkram & Osuwan, 2022). Thus, we propose that teachers who have high levels of self-efficacy are likely to be more willing to use AI in STEM education. Conversely, those who lack confidence in their ability to use AI may be less willing to use it and may be less effective in their implementation.

2.2.1.1. Subjective norm. Subjective norm is one of the key constructs that plays a crucial role in the GETAMEL approach (Abdullah et al., 2016). Subjective norm refers to the perceived social pressure that individuals feel to use technology, based on the beliefs of those around them (Ajzen, 1991; Venkatesh et al., 2012). This can include the influence of peers, colleagues, and superiors, as well as the expectations and norms of the broader social and cultural context in which the individual operates (Fishbein & Ajzen, 1975; Taufique & Vaithianathan, 2018). The role of subjective norm is to capture the extent to which individuals perceive that others expect them to use technology, and how this perception influences their own attitudes and intentions towards technology adoption (Ateş & Garzón, 2022, 2023). In the context of e-learning, subjective norm can be particularly important, as the adoption of new technologies often requires changes in behavior and can be influenced by social factors such as peer pressure or the expectations of supervisors (Songkram & Osuwan, 2022). In the context of STEM education and the adoption of AI, subjective norm can play an important role in understanding the factors that influence teachers' intention to use this technology. Teachers' decisions regarding the adoption of AI in STEM education can be influenced by the perceived expectations of others, such as colleagues, students, parents, and administrators. Subjective norm helps to capture these perceived expectations and social pressures, and can therefore provide valuable insights into the factors that influence teachers' behavior (Sungur-Gül & Ateş, 2021). Taking into account the framework of GETAMAL, previous studies have demonstrated that the subjective norm significantly impacts individuals' perceptions regarding the ease of use and usefulness of the technology in education settings (Abdullah et al., 2016; Humida et al., 2022; Ibili et al., 2023). Therefore, we propose that it is important to consider the role of subjective norm in the context of STEM education and the adoption of AI, as it can help to provide insight into the social factors that may influence teachers' perceptions regarding the ease of use and usefulness of the technology. Given previous research, we can propose two hypotheses to test.

H1: The more teachers perceive social pressure to adopt AI in STEM education, the higher their perceived usefulness of AI in STEM education will be.

H2: The more teachers perceive social pressure to adopt AI in STEM education, the higher their perceived ease of use of AI in STEM education will be.

2.2.1.2. Experience. Experience refers to the level of prior experience that individuals have with the technology in question, which can shape their perceptions of its usefulness and ease of use (Abdullah & Ward, 2016). Earlier research has shown that individuals with more experience using a particular technology in education are more likely to perceive it as useful and easy to use (Abdullah et al., 2016; Ibili et al., 2023). In the context of STEM education and the adoption of AI, experience could potentially play a crucial role in shaping teachers' perceptions regarding the ease of use and usefulness of this technology in the classroom. Those with more experience using AI may be more likely to perceive it as useful and easy to use, and may have a greater sense of confidence in its implementation. Therefore, experience could be an important factor to consider when designing strategies to promote the adoption of AI in STEM education. The existing literature provides support for two potential hypotheses.

H3: Teachers' experience with using AI in the classroom positively affects their perceived usefulness of AI in STEM education.

H4: Teachers' experience with using AI in the classroom positively affects their perceived ease of use of AI in STEM education.

2.2.1.3. Perceived enjoyment. Perceived enjoyment is another construct included in the GETAMEL model, which refers to the extent to which individuals perceive that using technology in e-learning is enjoyable and engaging (Abdullah & Ward, 2016). This construct is important because it can influence individuals' perceptions regarding the ease of use and usefulness of the technology, particularly in the context of e-learning where engagement and motivation are crucial for effective learning outcomes (Ateş & Garzón, 2023). Previous research has shown that perceived enjoyment has a significant positive effect on individuals' perceived usefulness and perceived ease of use towards technology adoption in e-learning (Humida et al., 2022). In the context of AI in STEM education, perceived enjoyment can be a critical factor in promoting the adoption of this technology among teachers. By providing personalized support, adaptive learning paths, and real-time feedback based on students' individual needs and progress, AI has the potential to enhance the learning experience and increase students' engagement with STEM subjects. Thus, we propose that if teachers perceive the use of AI as enjoyable and engaging, they may be more likely to think this technology is easy to use and useful and encourage their students to engage with it as well. This could ultimately lead to improved learning outcomes and better preparation for the workforce of the future. Therefore, we hypothesize that:

H5: Perceived enjoyment has a significant positive effect on perceived usefulness in the adoption of AI in STEM education.

H6: Perceived enjoyment has a significant positive effect on perceived ease of use in the adoption of AI in STEM education.

2.2.1.4. Anxiety. Anxiety refers to "fear of impending interaction with a computer that is disproportionate to the actual threat presented by the computer" (Howard, 1986, p. 18). It can also be defined as the feeling of discomfort or nervousness that individuals may experience when using new technologies, particularly if they perceive the technology as complex or difficult to use settings (Abdullah & Ward, 2016). It is a construct that can have a significant negative impact on individuals' intentions to adopt new technologies (Arpaci & Basol, 2020). To alleviate anxiety and promote the adoption of AI in STEM education, it is important to understand the effect of anxiety on technology readiness. Therefore, in the proposed model, we believe that anxiety is considered as a potential barrier to the adoption of AI in STEM education, and its relationship with other constructs such as perceived usefulness and perceived ease of use will be investigated to better understand its impact on individuals' intentions to adopt AI in the classroom. Previous research has shown that anxiety can have a significant effect on individuals' perceived usefulness and perceived ease of use towards technology adoption, which in turn can influence their attitudes and intentions to use technology (Abdullah et al., 2016; Alwabel et al., 2020; Ibili et al., 2023). Based on prior studies, we can propose two hypotheses.

H7: Anxiety negatively affects perceived usefulness of AI in STEM education.

H8: Anxiety negatively affects perceived ease of use of AI in STEM education.

2.2.1.5. Self-efficacy. Self-efficacy is a construct that refers to "beliefs in one's capabilities to mobilize the motivation, cognitive resources, and courses of action needed to meet given situational demands" (Wood & Bandura, 1989, p. 408). In the context of STEM education and the adoption of AI, self-efficacy may be particularly relevant for individuals who may not have a strong background in technology or who may be less confident in their ability to use new technologies effectively. Previous studies have revealed that self-efficacy plays a significant role in shaping individuals' attitudes and intentions to adopt technology by positively impacting their perceived usefulness and perceived ease of use (Ibili et al., 2023; Rosli & Saleh, 2023). These findings suggest that individuals who believe in their ability to use a particular technology are more likely to perceive it as useful and easy to use, which in turn may increase their attitude and intention to use the technology (Venkatesh et al., 2003). Thus, the current study highlight the need to address self-efficacy as a key factor in promoting the adoption of AI in STEM education among teachers. Therefore, the following hypotheses are proposed:

H9: Higher levels of self-efficacy will be associated with higher levels of perceived usefulness of AI in STEM education.

H10: Higher levels of self-efficacy will be associated with higher levels of perceived ease of use of AI in STEM education.

2.2.1.6. Perceived ease of use. Perceived ease of use is a critical construct in understanding individuals' perception of the effort required to use technology (Davis, 1989). Perceived ease of use may play a crucial role in the adoption of AI in STEM education, as it can affect individuals' perceived usefulness and attitudes towards using technology. Previous studies have established a significant positive relationship between perceived ease of use and individuals' attitudes towards technology adoption, as well as their perceived usefulness of the technology (Ateş & Garzón, 2022, 2023). These findings suggest that when individuals perceive a technology as easy to use, they are more likely to have a positive attitude towards its adoption and perceive it as useful (Sungur-Gül & Ateş, 2023). Therefore, it is crucial to consider the perceived ease of use of AI in STEM education among teachers, as it may significantly impact their intention to adopt and effectively use the technology. Two hypotheses can be proposed based on previous research:

H11: Perceived Ease of Use positively affects perceived usefulness of AI in STEM education.

H12: Perceived Ease of Use positively affects attitude towards using AI in STEM education.

2.2.1.7. Perceived usefulness. Perceived usefulness is a construct that refers to the degree to which individuals perceive that using a technology will enhance their job performance or task completion (Davis, 1989). In the context of STEM education and the adoption of AI, perceived usefulness may be a critical construct to consider as it can significantly influence individuals' attitudes and intentions towards using this technology. Previous research has shown that perceived usefulness has a significant positive effect on individuals' attitudes towards technology adoption and their intentions to use technology in e-learning (Alismaiel et al., 2022; Papakostas et al., 2023; Zhou et al., 2022). Therefore, it is important to consider the perceived usefulness of AI in STEM education among teachers to increase their attitudes and intentions to adopt and use the technology effectively. Drawing on prior research, two hypotheses can be formulated:

H13: Perceived usefulness positively affects teachers' attitudes towards adopting AI in STEM education.

H14: Perceived usefulness positively affects teachers' intention to adopt and use AI in STEM education.

2.2.1.8. Attitude. Attitude is a construct that reflects an individual's overall evaluation of a technology, including their feelings, beliefs, and perceptions towards using it (Abdullah & Ward, 2016). In the context of STEM education and the adoption of AI, attitude may be an important construct to consider, as it can strongly influence individuals' intentions to use technology. Previous research has shown that individuals with more positive attitudes towards technology are more likely to use it in education (Liao et al., 2022; Papakostas et al., 2023; Wang et al., 2022). In the context of STEM education and the adoption of AI, we suppose that understanding individuals' attitudes towards the technology is crucial for promoting its adoption and effective use. Building on previous studies, we can put forward following hypothesis.

H15: Attitude towards AI in STEM education has a positive relationship with intention to use AI in STEM education among teachers.

2.2.2. Unified theory of acceptance and use of technology 2

The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. (2003) to explain the factors that influence the acceptance and use of technology proposing four main constructs that determine an individual's behavioral intention to use technology: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy refers to the degree to which an individual believes that using technology will help them to perform better, while effort expectancy refers to the degree to which an individual believes that using technology will be easy (Venkatesh et al., 2012). Social influence refers to the degree to which an individual perceives that others believe they should use technology (Ajzen, 1991; Venkatesh et al., 2003), and facilitating conditions refer to the degree to which an individual believes that the necessary resources and support are available to use technology (Venkatesh et al., 2003). The Unified Theory of Acceptance and Use of Technology 2 (UTAUT 2) was developed by Venkatesh et al. (2012) as a modification and extension of the original UTAUT model. UTAUT 2 includes all the constructs of UTAUT, as well as additional constructs including hedonic motivation, price value, and habit. UTAUT 2 is considered an improvement over the original UTAUT model, as it incorporates additional variables and provides a more comprehensive framework for understanding technology adoption (Tamilmani et al., 2018). In recent studies, UTAUT 2 has been extensively utilized to examine technology adoption in educational contexts (Bower et al., 2020; Chávez Herting et al., 2023; Hu et al., 2020; Osei et al., 2022; Terblanche et al., 2023).

In the context of STEM education and the adoption of AI, UTAUT 2 can provide a useful framework for understanding the factors that influence teachers' intention to use this technology. The model can help to identify the key factors that need to be addressed to promote the adoption of AI in STEM education, such as improving teachers' performance and effort expectancies, addressing concerns about social influence and facilitating conditions, and addressing hedonic motivation, price value, and habit.

2.2.2.1. Price value. Price value is a construct that reflects the extent to which individuals perceive that the cost of using a technology is justified by its benefits (Venkatesh et al., 2012). In the context of STEM education and the adoption of AI, price value can be particularly relevant for teachers who may need to justify the use of technology to school administrators or other stakeholders. Previous research has shown that price value can have a significant positive effect on individuals' intentions to use technology in education (Ateş & Garzón, 2023; Meet et al., 2022). The study conducted by Meet et al. (2022) uncovered the crucial role of price value in determining Generation Z's willingness to adopt MOOCs, highlighting its significance in shaping their behavioral intentions towards online learning. Thus, we propose that teachers who perceive that the benefits of using AI in STEM education outweigh the costs are more likely to have positive attitudes and intentions towards technology adoption. Therefore, it is important to consider price value when designing strategies to promote the adoption of AI in STEM education among teachers, in order to ensure that individuals perceive the technology as beneficial and worth the investment. Previous research provides the foundation for following hypothesis to be proposed.

H16: Price value positively affects teachers' intention to use AI in STEM education.

2.2.2.2. Facilitating conditions. Facilitating conditions is a construct that refers to the degree to which individuals perceive that they have the necessary resources and support to use a technology effectively (Venkatesh et al., 2003). In the context of STEM education and the adoption of AI, facilitating conditions may be particularly relevant because the successful integration of technology into teaching practices may require access to resources such as hardware, software, and training programs, as well as support from colleagues and administrators. Research conducted previously has demonstrated that facilitating conditions have a noteworthy positive impact on individuals' intentions to use e-learning (Malanga et al., 2022). In a recent study, Terblanche et al. (2023) found that facilitating conditions had a significant influence on students' behavioral intention to use e-learning applications based on accounting students from four South African universities. Similarly, according to the study conducted by Al-Adwan et al. (2022), the presence of a technological and organizational infrastructure was identified as a crucial factor that significantly influences students' intentions to continue using e-learning systems. Therefore, it is important to consider facilitating conditions when designing strategies to promote the adoption of AI in STEM education among teachers, in order to ensure that individuals have the necessary resources and support to effectively integrate technology into their teaching practices. With reference to prior studies, we can hypothesize that:

H17: Facilitating conditions will have a positive effect on teachers' intentions to adopt AI in STEM education.

2.2.2.3. Habit. Habit refers to the degree to which individuals' use of technology is automatic and routine, and can be influenced by factors such as past experience and frequency of use (Venkatesh et al., 2012). In the context of STEM education, the development of habits related to the use of AI can be important for sustaining long-term adoption and integration of the technology in teaching practices. Studies have revealed that individuals' habits play a crucial role in predicting their intentions to adopt technology in educational settings. For example, according to Zacharis and Nikolopoulou's (2022) study on factors predicting university students' behavioral intention to use eLearning platforms in the post-pandemic normal, the habit construct was found to have a significant influence on students' intentions to use eLearning platforms. In different context, Yu et al. (2021) revealed that habit was found to be a key predictor of patients' behavioral intentions to use a mobile health education website. This suggests that individuals who have a habit of using mobile devices and related technologies may have a greater tendency to use mobile health education resources. In this study context, by developing habits related to the use of AI, teachers may be more likely to continue to use the technology. Therefore, it is important to consider the role of habit when designing strategies to promote the adoption of AI in STEM education among teachers. From the literature, we can derive following possible hypothesis.

H18: Habit positively affects the intention of pre-service and in-service teachers to use AI in STEM education.

3. Method

3.1. Data collection process

The aim of this study was to investigate the adoption of specific AI-powered tools by science teachers in middle schools, concentrating on commonly used applications within the realm of STEM education. This targeted approach allows for a more nuanced understanding of how teachers perceive, utilize, and integrate these technologies into their instructional practices.

To achieve this, the study focused on several specific AI tools that have been increasingly adopted in STEM classrooms. These tools include intelligent tutoring systems (ITS), which provide personalized instruction and feedback to students based on their individual learning needs; adaptive learning platforms, which adjust the content and pace of learning activities in real time to cater to each student's abilities; and AI-powered educational games that engage students through interactive and immersive experiences while teaching essential STEM concepts (Ateş, 2024). Teachers were informed about these tools and their functionalities prior to participation in the study, ensuring that they had a clear understanding of the technologies being examined. By investigating these particular technologies, we aim to uncover insights into the unique challenges and opportunities presented by each tool, as well as the varying degrees of experience teachers may have with them.

Participants were recruited using convenience sampling methods, with invitations sent via e-mail and social media platforms. The survey emphasized the most relevant AI tools commonly utilized in STEM settings, ensuring that the study captures a wide range of experiences and perceptions regarding specific AI applications rather than generalizing about AI technology as a whole.

Data were collected through a structured survey that was distributed to science teachers who have demonstrated experience in using technology in their teaching practices and expressed a keen interest in exploring the potential applications of these specific AI tools in STEM education. The survey included targeted questions regarding each AI tool's usability, perceived effectiveness, and the extent to which teachers have integrated these technologies into their lessons.

Ethical considerations were prioritized throughout the study. Informed consent was obtained from all participants, ensuring they were aware of the study's purpose, procedures, and their rights. The confidentiality and anonymity of participants were maintained by removing identifiers during data analysis. The survey questions concentrated on professional experiences and avoided invasive queries, allowing participants to share their insights comfortably. To further ensure participant well-being, data were securely stored in encrypted formats, and personal information was deleted after analysis.

The questionnaire included introductory explanations of the selected AI concepts and tools, aiding participants – especially those with limited exposure to AI – in understanding the context of the study. This clarity enabled participants to reflect on their potential adoption of the specified AI tools based on their comprehension of their capabilities and benefits. Additionally, the questionnaire featured scenarios and case studies illustrating practical applications of these AI tools in educational settings, assisting teachers in envisioning how these technologies could be effectively integrated into their teaching practices.

Through this detailed investigation of specific AI tools and their adoption by science teachers, the study seeks to illuminate the factors that facilitate or hinder the integration of AI technologies into STEM education. By focusing on the practical applications and implications of these tools, the research aims to contribute to the development of effective strategies for enhancing technology adoption in educational practices, ultimately benefiting both educators and students.

3.2. Sample

The study involved a total of 623 science teachers from various metropolitan areas in Turkey, who participated between January and April 2023. However, 41 participants were excluded from the analysis due to incomplete surveys or failure to meet eligibility criteria, resulting in a final sample of 582 science teachers.

The demographic characteristics of the sample indicated that 56% of participants were female and 44% were male. Age distribution showed that 40% of participants were between 31 and 40 years old, followed by 30% aged 41–50, 20% under 30, and 10% over 50. In terms of educational background, 75% held a bachelor's degree, 23% had a master's degree, and only 2% possessed a doctoral degree. Regarding teaching experience, 62% of participants had more than 10 years of teaching experience, 23% had 5–10 years, and the remaining 15% had less than 5 years.

In terms of technology usage, 89% of participants reported using technology regularly in their teaching practices, while 11% used it occasionally or not at all. The most commonly used technologies included computers (95%), projectors (81%), and interactive whiteboards (64%). Notably, only 13% reported incorporating AI tools in their teaching practices. To gauge familiarity with AI tools, the study examined participants' exposure to specific AI technologies. The findings revealed that the most recognized AI tools among participants were automated grading systems (used by 8%), AI-driven educational games (5%), and data analytics for student performance (3%). However, a significant portion (87%) reported limited or no prior hands-on experience with AI tools.

3.3. Data collection tools

The study employed a proposed conceptual model that comprises 12 constructs derived from the GETAMEL and UTAUT 2 models, using previously tested items with established validity and reliability. The scale items were first pre-tested with 198 science teachers, followed by the use of the blind translation-back-translation method (Bracken & Barona, 1991) to ensure consistency and accuracy as the original version of the items and constructs were in English and the scales in the current study were prepared in Turkish. To improve the quality of the translated scales, academicians with proficiency in both Turkish and English and experts in the field of STEM education and e-learning were consulted for review.

The GETAMEL model contributed nine constructs, including subjective norm, experience, perceived enjoyment, anxiety, and self-efficacy. These constructs reflect normative, affective, and cognitive processes involved in the adoption of technology in education. Meanwhile, the UTAUT 2 model contributed three constructs, which include price value, facilitating conditions, and habit. These constructs reflect the external and internal factors that affect technology adoption in education. However, as four constructs in the models measure similar characteristics, the proposed conceptual model includes only one variable to represent each of these characteristics. For example, the constructs of performance expectancy and perceived usefulness both reflect the extent to which technology is perceived as beneficial to achieving goals. In the proposed model, only perceived usefulness is included to represent this characteristic. Similarly, the constructs of effort expectancy and perceived ease of use both reflect the perceived ease of using technology, and the construct of social influence and subjective norm both reflect the influence of social factors on technology adoption. In the proposed model, only perceived ease of use and subjective norm are included to represent these characteristics.

Multiple items were employed in the study to assess its constructs. Among the constructs in the GETAMEL approach, to evaluate the constructs of perceived ease of use and attitude, the study utilized three measurement items each. For perceived ease of use, items such as "I find the use of AI in STEM education easy to integrate into my teaching." were used. Meanwhile, for attitude, items such as "I think using AI-powered tools for science teaching is a good idea." were employed in the evaluation process. To assess perceived usefulness and subjective norm constructs in the study, two items were utilized for each. For instance, perceived usefulness was evaluated by measuring agreement with the statement "The use of AI-powered tools in STEM teaching is useful for my study." while subjective norm was assessed by measuring agreement with the statement "People who are important to me believe that I should use AI-powered tools for STEM education." Experience was evaluated using three items. One example item is "I enjoy using AI-powered tools for STEM teaching." Three measurement items were used to assess the participants' perceived enjoyment of using AI-powered tools in STEM education (e.g. "Adapting AI-powered tools in STEM education enhances my enjoyment of teaching."), level of anxiety that participants may experience when using such tools in their teaching (e.g. "I feel apprehensive about using AI-powered tools for STEM teaching."), and self-efficacy in using AI-powered tools in STEM education (e.g. "I feel confident when utilizing AI-powered tools in STEM education even when no one is there for assistance."). Within the constructs of UTAUT 2, price value (e.g. "The price of AR technology in STEM education is reasonable.") and habit (e.g. "Using AI in STEM education would become a habit for me.") were evaluated with three items each. Further, facilitating conditions was measured with four items (e.g. "I have the resources necessary to use AI in STEM classes."). Lastly, intention to use AI-powered tools for teaching STEM in the future was measured with three items (e.g. "I will use AI-powered tools for teaching STEM in the future.").

The items were designed to be specific and focused, and respondents were asked to indicate their level of agreement or disagreement on a five scale ranging from "Strongly Disagree" to "Strongly Agree." Overall, the study utilized 35 different items to measure 12 constructs, which were all listed and sourced in Table 1 of the research report.

3.4. Data analysis

To analyze the data collected in this study, several tools were employed, including SPSS and AMOS. Confirmatory factor analysis (CFA) was utilized to evaluate the measurement model and the quality of the measures taken. This allowed us to confirm that the constructs being measured were accurately represented by the collected data. Structural equation modeling (SEM) was then applied to assess the proposed theoretical framework, evaluate the hypothesized relationships between research constructs, and conduct modeling comparisons. This provided us with an understanding of the complex relationships between the various constructs and allowed us to test the proposed theoretical model. To further investigate the relationships between the constructs, the bootstrapping method was utilized. This method allowed us to examine the mediating role of study variables within our research framework, providing us with insights into the mechanisms by which these variables impact the overall model. Through these data analytic procedures, the research objectives were successfully attained, and the results provided a comprehensive understanding of the factors that influence the adoption of AI-powered tools in STEM education. Overall, the rigorous data analysis procedures used in this study ensure the reliability and validity of the findings and provide a solid foundation for future research in this area.

The first step in analyzing the data was to evaluate the measurement model using CFA with maximum likelihood estimation. The results indicated that the model fit the data well, with a satisfactory χ^2 value (1434.24), χ^2/df ratio (2.88), RMSEA (0.049) value with 90% confidence intervals, and

Table 1. Measurement items, factor loadings, and sources.

Constructs and statements	FL	α	AVE	CR	Source
Perceived ease of use		0.85	0.69	0.87	Davis (1989); Nikou and Economides (2017)
I find the use of AI in STEM education easy to integrate into my teaching.	0.82				
It is easy for me to become skillful at using AI in STEM education.	0.83				
My interaction with AI in STEM education during teaching is clear and understandable.	0.85				
Perceived usefulness		0.81	0.76	0.86	Davis (1989); Nikou and Economides (2017)
The use of AI-powered tools in STEM teaching is useful for my study.	0.88				
AI-powered tools in STEM teaching enhance my effectiveness.	0.86				
Perceived enjoyment		0.79	0.67	0.86	Lu et al. (2009); Moon and Kim (2001)
Adapting AI-powered tools in STEM education enhances my enjoyment of teaching.	0.84				
AI-powered tools in STEM education are fun to use during my teaching.	0.79				
Incorporating AI-powered tools in STEM education brings me joy and satisfaction in teaching.	0.83				
Anxiety		0.79	0.71	0.88	Kuek and Hakkennes (2020)
I feel apprehensive about using AI-powered tools for STEM teaching.	0.78				
It scares me to think that I could make mistakes I cannot correct when using AI-powered tools for STEM teaching.	0.85				
Using AI-powered tools for STEM teaching is somewhat intimidating to me.	0.89				
Experience		0.79	0.67	0.86	Abdullah et al. (2016)
I enjoy using AI-powered tools for STEM teaching.	0.80				
I am comfortable using AI-powered tools for STEM teaching.	0.88				
I can use AI-powered tools for STEM teaching.	0.77				
Self-Efficacy					Salloum et al. (2019)
I feel confident when utilizing AI-powered tools in STEM education even when no one is there for assistance.	0.78	0.79	0.66	0.85	
I have sufficient skills to use AI-powered tools in STEM education.	0.82				
I feel confident when using AI-powered tools in STEM education.	0.84				
Attitude					Lu et al. (2009); Taylor and Todd (1995)
I think using AI-powered tools for science teaching is a good idea.	0.89	0.76	0.72	0.89	
I enjoy using AI-powered tools for science teaching.	0.88				
Using AI-powered tools for science teaching is a pleasant experience.	0.78				
Subjective Norm					Ajzen (2006); Lu et al. (2009); Taylor and Todd (1995)
People who are important to me believe that I should use AI-powered tools for STEM education.	0.79	0.74	0.65	0.79	
People who have a significant influence on my behavior believe that I should use AI-powered tools for STEM education.	0.82				
Price Value					Ateş & Garzón, 2023; Venkatesh et al. (2012)
The price of AR technology in STEM education is reasonable.	0.88	0.79	0.73	0.89	
AR technology provides good value for the money in STEM education.	0.83				
At the current price, AR technology offers a good value in STEM education.	0.86				
Facilitating Conditions					Ateş & Garzón, 2023; Venkatesh et al. (2012)
I have the resources necessary to use AI in STEM classes.	0.87	0.86	0.70	0.90	
I have the knowledge necessary to use AI in STEM classes.	0.77				
AI is compatible with other technology I use.	0.84				
I can get help from STEM teachers when I am having difficulties using AI.	0.86				
Habit					Ateş & Garzón, 2023; Venkatesh et al. (2012)
Using AI in STEM education would become a habit for me.	0.84	0.85	0.66	0.85	
I would become addicted to using AI in STEM education.	0.76				
I feel compelled to use AI in STEM education.	0.83				

(*Continued*)

Table 1. Continued.

Constructs and statements	FL	α	AVE	CR	Source
Intention					Ajzen (2006); Davis (1989); Nikou and Economides (2017)
I will use AI-powered tools for teaching STEM in the future.	0.75	0.79	0.64	0.84	
I plan to use AI-powered tools for teaching STEM in the future.	0.84				
I will try to use AI-powered tools for teaching STEM in the future.	0.81				

Note. FL: Factor Loading, AVE: Average Variance Extracted, CR: Composite Reliability.

various indices such as CFI (0.96), IFI (0.92), and TLI (0.95). The items in the measurement model were found to be significantly loaded to their associated latent variable, indicating good construct validity. To ensure the reliability of the data, internal consistency was evaluated using Cronbach's alpha (α) and composite reliability. The results showed that all variables had α values higher than the recommended value of 0.70 (Bagozzi & Yi, 2012) and composite reliability values ranging from 0.79 to 0.90, which exceeded the recommended threshold of 0.60 (Bagozzi & Yi, 2012). In order to establish the construct validity of the study, both convergent validity and discriminant validity were tested, as recommended by Hair et al. (2017) and Kline (2015). AVE values for study variables, ranging from 0.64 to 0.76 which were higher than 0.5, showed good convergent validity (Hair et al., 2018). Discriminant validity of the measures was also supported as the squared correlations were all smaller than the AVE values (Hair et al., 2018). These findings indicate that the measures used in the study are reliable and valid, and the proposed theoretical framework is appropriate for evaluating the relationships among research constructs (see Table 2).

4. Findings

4.1. Model fit indices and explanatory power of the proposed conceptual model

The structural model was evaluated using SEM, and the results showed that the model had a good fit to the data ($\chi^2 = 997.69$, df = 348, $\chi^2/df = 2.87$, $p < 0.001$, SRMR = 0.050, RMSEA = 0.051, TLI = 0.94, IFI = 0.92, CFI = 0.94, GFI = 0.91). The chi-square test revealed that the proposed merged model ($\chi^2/df = 2.87$) was a better fit compared to the original GETAMEL ($\chi^2 = 587.47$, df = 201, $\chi^2/df = 2.92$, $p < 0.001$, SRMR = 0.043, RMSEA = 0.044, CFI = 0.93, IFI = 0.93, TLI = 0.92, GFI = 0.90) and UTAUT 2 ($\chi^2 = 842.79$, df = 273, $\chi^2/df = 3.09$, $p < 0.001$, SRMR = 0.051, RMSEA = 0.052, CFI = 0.94, IFI = 0.90, TLI = 0.92, GFI = 0.90) models. Moreover, the proposed model had a higher prediction ability ($R^2 = 0.54$) compared to GETAMEL ($R^2 = 0.48$) and UTAUT 2 ($R^2 = 0.44$). These results are presented in Table 3. It is important to

Table 2. Results of the measurement model evaluation.

Constructs	1	2	3	4	5	6	7	8	9	10	11	12
1. *PEOU*	–											
2. *PU*	0.71	–										
3. *ATT*	0.61	0.67	–									
4. *SN*	0.53	0.48	0.51	–								
5. EXP	0.44	0.46	0.39	0.33	–							
6. PE	0.48	0.50	0.35	0.29	0.29	–						
7. *ANX*	0.36	0.34	0.40	0.39	0.37		–					
8. *SE*	0.33	0.39	0.33	0.34	0.33	0.31	0.27	–				
9. *PV*	0.37	0.33	0.31	0.33	0.33	0.32	0.29	0.27	–			
10. FC	0.31	0.29	0.35	0.39	0.38	0.30	0.33	0.33	2.30	–		
11. HBT	0.33	0.31	0.37	0.31	0.25	0.29	0.37	0.29	0.29	0.25	–	
12. *INT*	0.49	0.51	0.48	0.44	0.41	0.48	0.39	0.37	0.36	0.35	0.41	–
$\sqrt{AVE}$	0.83	0.87	0.85	0.81	0.82	0.82	0.84	0.81	0.85	0.84	0.81	0.80
Mean	5.07	4.89	5.01	4.79	4.71	4.76	3.99	4.12	4.71	4.52	4.39	5.02
SD	1.28	1.33	1.22	1.27	1.38	0.99	1.38	1.38	1.39	1.42	1.09	1.01

Note. PEOU: Perceived Ease of Use, PU: Perceived Usefulness, ATT: Attitude, SN: Subjective Norm, EXP: Experience, PE: Perceived Enjoyment, ANX: Anxiety, SE: Self-Efficacy, PV: Price Value, FC: Facilitating Conditions, HBT: Habit, INT: Intention.

note that the proposed model provided a better fit and prediction ability than the two original models, indicating the effectiveness of the proposed integrated model in understanding and predicting AI adoption in STEM education.

4.2. Path analysis results for proposed models

The study used SEM to test the proposed model, which consisted of three main steps. Firstly, the study evaluated the relationship between the constructs of GETAMEL approach. Secondly, path analysis was conducted to examine the UTAUT 2 model. Finally, the path and mediating analysis results were integrated into the proposed model.

4.2.1. GETAMEL approach: insights from structural equation modeling

Based on the analysis of the GETAMEL approach, conducted at a p-value of 0.01, the results showed that subjective norm, experience, perceived enjoyment, anxiety, and self-efficacy had a significant positive impact on both perceived usefulness ($\beta SN = 0.35$, $\beta EXP = 0.37$, $\beta PE = 0.34$, $\beta ANX = 0.40$, and $\beta SE = 0.34$) and perceived ease of use ($\beta SN = 0.39$, $\beta EXP = 0.36$, $\beta PE = 0.37$, $\beta ANX = 0.38$, and $\beta SE = 0.32$). Furthermore, perceived ease of use had a positive effect on perceived usefulness ($\beta = 0.48$) and attitude ($\beta = 0.46$). Perceived usefulness had positively affected attitude ($\beta = 0.47$) and both perceived usefulness ($\beta = 0.47$) and attitude ($\beta = 0.49$) had a positive impact on intention to use AI-powered tools in STEM education. This indicates that teachers who have a stronger subjective norm, more experience, find more enjoyment, have less anxiety, and higher self-efficacy are more likely to perceive the use of AI-powered tools in STEM education as useful and easy to use. It can be inferred from the results that perceived ease of use had a positive impact on both perceived usefulness and attitude. Finally, the results indicated that perceived ease of use and perceived usefulness had positively affected attitude and perceived usefulness and attitude had positive association with intention. The results are presented in Figure 2.

4.2.2. Uncovering the impact of UTAUT 2 approach: results of structural equation modeling

As illustrated in Figure 3, the analysis of the UTAUT 2 constructs revealed that social influence ($\beta = 0.38$, $p < 0.01$), performance expectancy ($\beta = 0.49$, $p < 0.01$), effort expectancy ($\beta = 0.45$, $p < 0.01$), and facilitating conditions ($\beta = 0.37$, $p < 0.01$) had a significant positive impact on the intention to use AI in STEM education. In addition, the extended constructs of hedonic motivation ($\beta = 0.45$, $p < 0.01$), price value ($\beta = 0.41$, $p < 0.01$), and habit ($\beta = 0.31$, $p < 0.01$) were also found to be significant predictors of intention to use AI-powered tools in STEM education. These findings suggest that constructs in this model play a crucial role in shaping teachers' willingness to use AI-powered tools in STEM education.

4.2.3. Unveiling the impact of a combined conceptual model through structural equation modeling

The study assessed the proposed relationships within the structural model and presented in Figure 4. The first set of hypotheses (H1–H10) examined the impact of on perceived usefulness and perceived ease of use. The analysis results confirmed the hypothesized positive effect of subjective norm ($\beta = 0.31$, $p < 0.01$), experience ($\beta = 0.34$, $p < 0.01$), perceived enjoyment ($\beta = 0.29$, $p < 0.01$), anxiety ($\beta = 0.36$, $p < 0.01$), and self-efficacy ($\beta = 0.28$, $p < 0.01$) on perceived usefulness. In other words, teachers

Table 3. Evaluation of model fit and predictive performance.

Models	χ^2	df	χ^2/df	GFI	IFI	TLI	CFI	RMSEA	SRMR	R^2
Proposed model	997.69	348	2.87	0.91	0.92	0.94	0.94	0.05	0.05	0.54
GETAMEL	587.47	201	2.92	0.90	0.93	0.92	0.93	0.04	0.04	0.48
UTAUT 2	842.79	273	3.09	0.90	0.90	0.92	0.94	0.05	0.05	0.44

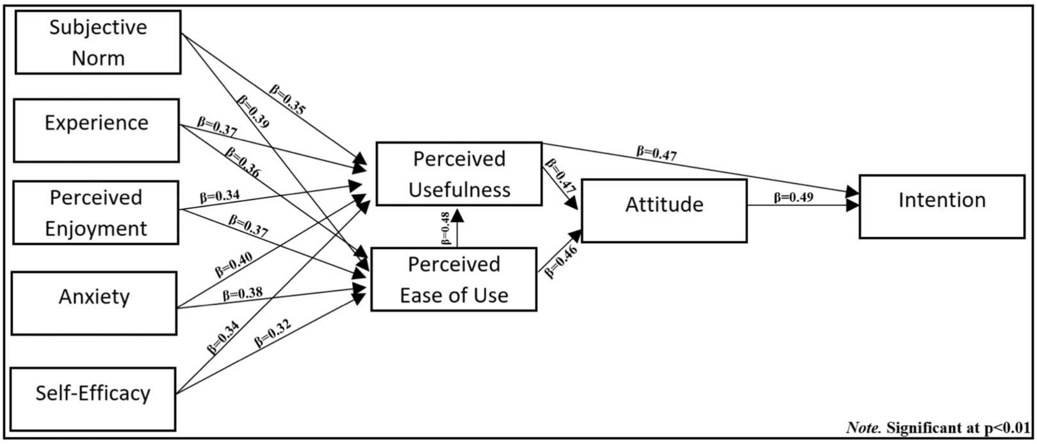

Figure 2. Modeling the impact of GETAMEL approach.

who had a stronger subjective norm, more experience, found more enjoyment, had less anxiety, and higher self-efficacy were more likely to perceive the use of AI-powered tools in STEM education as useful. Similarly, subjective norm ($\beta = 0.36$, $p < 0.01$), experience ($\beta = 0.32$, $p < 0.01$), perceived enjoyment ($\beta = 0.35$, $p < 0.01$), anxiety ($\beta = 0.35$, $p < 0.01$), and self-efficacy ($\beta = 0.22$, $p < 0.01$) had a significant and positive influence on perceived ease of use, supporting H1–H10. The findings suggest that teachers who had a higher level of subjective norm, more experience, found more enjoyment, experienced less anxiety, and had higher self-efficacy were more likely to perceive the use of AI-powered tools in STEM education as easy to use. This suggests that these factors may play an important role in promoting the adoption and effective use of these tools in the classroom.

The results also revealed that perceived ease of use had a significant impact on perceived usefulness ($\beta = 0.44$, $p < 0.01$) and attitude ($\beta = 0.42$, $p < 0.01$), while perceived usefulness had a significant

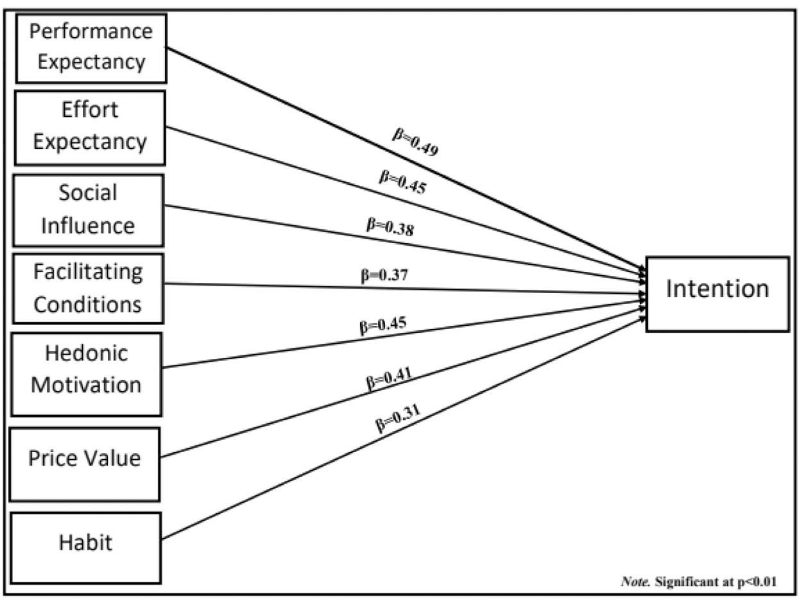

Figure 3. Path analysis results predicting intention to use AI in STEM education using UTAUT 2.

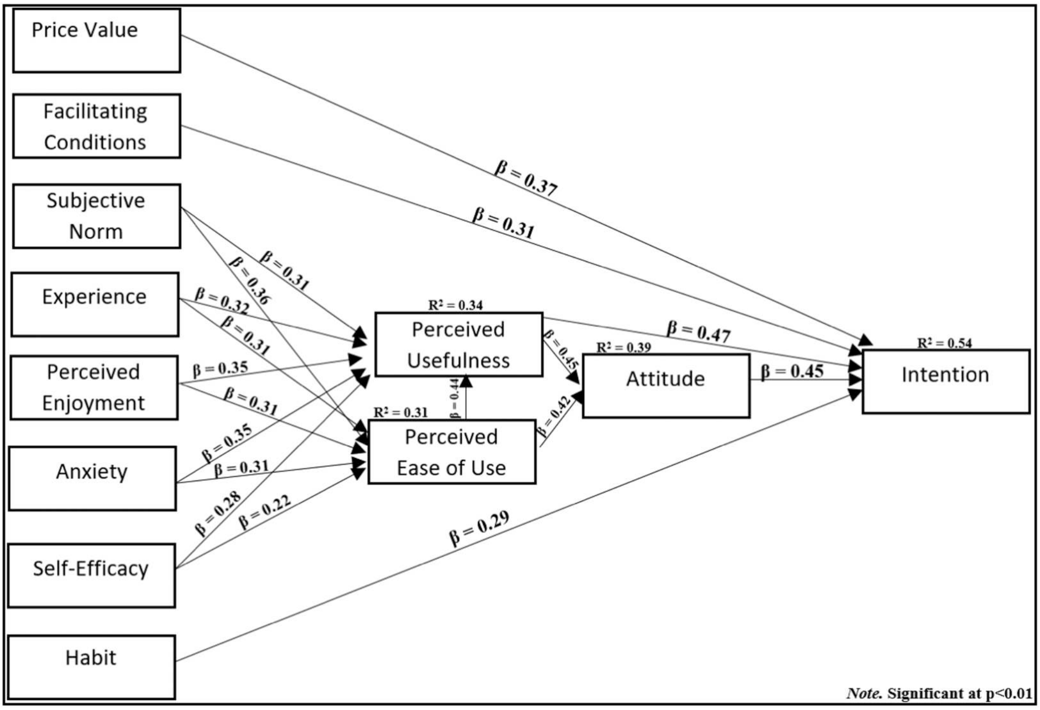

Figure 4. Path analysis results of the proposed combined conceptual framework for predicting intention to use AI in STEM education.

impact on attitude ($\beta = 0.45$, $p < 0.01$) and intention ($\beta = 0.47$, $p < 0.01$), and attitude had a significant impact on intention ($\beta = 0.45$, $p < 0.01$), thus supporting H11–H15. These results imply that when teachers perceive AI-powered tools in STEM education as easy to use, they are more likely to see the tools as useful and develop a positive attitude towards using them. This positive attitude, in turn, increases the likelihood of intention to use the tools. Therefore, it is important for the perceived ease of use to be considered in the design and implementation of AI-powered tools in STEM education to promote their usefulness and acceptance among teachers.

Additionally, the study found that price value ($\beta = 0.37$, $p < 0.01$), facilitating conditions ($\beta = 0.31$, $p < 0.01$), and habit ($\beta = 0.29$, $p < 0.01$) had a significant and positive impact on intention, supporting H16, H17, and H18, respectively. This means that factors such as the perceived value of the price, the ease of access to the technology, and the habit of using it can all influence teachers' intention to use AI-powered tools in STEM education. To summarize, the proposed model in the study was able to explain 54% of the variance in teachers' intention to use AI-powered tools in STEM education. In addition, the antecedents of attitude, perceived usefulness, and perceived ease of use accounted for 39%, 34%, and 31% of their respective total variances, respectively. These findings suggest that the proposed model has significant explanatory power and can be useful for understanding teachers' adoption of AI in STEM education.

4.2.4. Analyzing the mediating effect in the proposed conceptual model

The bootstrapping analysis, conducted at a *p*-value of 0.01, revealed that subjective norm, experience, perceived enjoyment, anxiety, and self-efficacy had significant indirect effects on perceived usefulness ($\beta SN = 0.24$, $\beta EXP = 0.21$, $\beta PE = 0.19$, $\beta ANX = 0.18$, and $\beta SE = 0.20$), attitude ($\beta SN = 0.21$, $\beta EXP = 0.18$, $\beta PE = 0.17$, $\beta ANX = 0.21$, and $\beta SE = 0.24$), and intention ($\beta SN = 0.17$, $\beta EXP = 0.15$, $\beta PE = 0.16$, $\beta ANX = 0.17$, and $\beta SE = 0.19$), highlighting the important role of these factors in shaping teachers' attitudes and intentions towards using AI-powered tools in STEM education. Furthermore, perceived ease of use was found to have a significant indirect effect on attitude ($\beta = 0.21$) and intention ($\beta = 0.19$), suggesting that teachers' perceptions of the ease of use of these tools can positively influence their attitudes and intentions. Finally, perceived usefulness was found to have a significant indirect effect on intention ($\beta = 0.24$), further highlighting the importance of teachers' perceptions of the usefulness of AI-powered tools in influencing their intentions to use them in STEM education.

5. Discussion

In this study, a novel conceptual model was developed to predict teachers' behavioral intentions to adopt AI in STEM education by combining the UTAUT 2 and GETAMEL approaches. The study results indicated that the proposed model outperformed the original UTAUT 2 and GETAMEL models in predicting the adoption of AI-powered tools in STEM education. All constructs in the model were found to be positively related to the intention to adopt AI in STEM education, highlighting the importance of considering multiple factors when designing and implementing such tools in education. Additionally, the study found that perceived ease of use, perceived usefulness, and attitude played significant mediating roles in the relationship between the predictors and the intention to adopt AI in STEM education. The study's results contribute to the literature on the adoption of AI-powered tools in STEM education by providing insights into the individual and social factors that influence teachers' intentions to adopt and use these tools. The findings can be utilized to develop educational strategies to promote the adoption and effective use of AI-powered tools in STEM education while overcoming potential barriers to their adoption and use.

5.2. Practical implications

The practical implications derived from our study are expansive and encompass the roles of policymakers, educators, AI tool developers, and their collaborative efforts in ensuring the effective adoption and use of AI-powered tools in STEM education among middle school teachers in Turkey.

For policymakers, our study underscores the necessity of creating an educational environment that is conducive to the adoption of AI tools. This entails formulating policies that integrate AI tools into STEM curricula in alignment with educational standards and learning outcomes. There is a critical need for prioritizing funding for technological infrastructure and AI tools, coupled with facilitating professional development programs for educators. These programs should extend beyond mere AI tool usage to include integration into pedagogical practices, ensuring that educators are equipped to effectively employ these tools in their teaching. Additionally, fostering partnerships between educational institutions and AI tool developers is pivotal in developing technologies that are relevant and effective for educational purposes.

Educators, on their part, are encouraged to actively engage in professional development opportunities, enhancing their skills and understanding of AI tools. The study highlights the importance of educators' attitudes and the perceived usefulness of AI tools, underscoring the need for proactive learning in integrating these tools into teaching practices. Participation in collaborative learning communities is also vital, as it allows educators to exchange experiences and explore innovative methods of using AI in STEM education. Moreover, educators should aim to adapt their curriculum to incorporate AI tools in ways that bolster student engagement and learning outcomes.

AI tool developers should prioritize creating tools that are user-friendly and align with the actual needs of teachers and students. This includes focusing on intuitive design and adaptability to various teaching styles and learning environments. Collaboration with educators is essential in understanding their needs and the educational context, thereby informing the development of more effective AI tools. Furthermore, providing comprehensive support and resources, including guides, tutorials, and customer support, is crucial in aiding educators to use these tools effectively.

Additionally, it's crucial to consider cultural sensitivity in AI tool implementation. Both educators and policymakers should be mindful of the cultural context in which AI tools are introduced, tailoring training and professional development to integrate these cultural nuances. AI tools should be selected and utilized in ways that align with and enhance existing pedagogical approaches, rather than conflicting with them. Policymakers should also consider socio-cultural and pedagogical factors when formulating policies related to AI in education, supporting diverse teaching practices and cultural considerations.

In summary, the effective integration of AI tools into STEM education is a multidimensional effort requiring the collaboration of various stakeholders. By addressing the specific needs and challenges identified in our study, and through the combined efforts of policymakers, educators, and AI tool developers, it is feasible to enrich the educational experience and outcomes for students in Turkey's middle school STEM programs. This comprehensive approach ensures not only the successful adoption of AI tools but also their sustainable integration into educational practices, ultimately fostering a more enriched and inclusive learning environment.

5.1. Theoretical implications

This study offers significant theoretical implications by providing a comprehensive understanding of the factors influencing teachers' decision-making regarding the adoption and use of AI-powered tools in STEM education. By integrating the UTAUT2 and GETAMEL models, our research presents an effective framework for predicting teacher intentions to utilize AI technologies in their instructional practices. This integrated approach enriches the existing theoretical landscape by addressing both individual-level motivations and organizational-level influences, which are essential for understanding technology adoption (Ateş et al., 2024). Previous studies have primarily applied the UTAUT2 and GETAMEL models independently to investigate factors influencing technology adoption in educational contexts (e.g. Chang et al., 2017; Liu et al., 2021; Osei et al., 2022; Sprenger & Schwaninger, 2023; Terblanche et al., 2023). However, these investigations often overlooked the potential benefits of synthesizing these models to create a more robust framework for predicting teachers' intentions to adopt AI tools in STEM education. Our findings suggest that the integration of these models provides a nuanced perspective that captures the complexities of teacher attitudes and institutional dynamics, thereby enhancing our understanding of AI adoption. Moreover, while some existing research has examined individual and social factors influencing technology adoption in AI adoption (Venkatesh, 2022), there is a notable gap in the literature specifically addressing the context of AI adoption among middle school teachers in Turkey. This study fills this gap by focusing on an underexplored area, offering unique insights into the specific challenges and opportunities faced by educators in this context. By contextualizing our findings within the existing literature, we extend previous research (e.g. Jain et al., 2022; Venkatesh, 2022; Wang et al., 2021) that emphasizes the significance of local factors, such as educational policies, cultural attitudes toward technology, and resource availability, in shaping teachers' intentions to integrate AI into their classrooms.

The results of this study provide significant insights into the adoption of AI-powered tools in STEM education (Ateş, 2024), particularly among middle school science teachers. Our findings reveal that subjective norm, experience, perceived enjoyment, anxiety, and self-efficacy significantly influenced teachers' perceived usefulness and perceived ease of use of these tools, explaining 34% and 31% of the variance, respectively. This supports hypotheses H1 to H10, indicating that teachers who perceive a stronger subjective norm toward using AI-powered tools, possess greater experience with such tools, find them enjoyable, experience less anxiety when using them, and exhibit higher self-efficacy are more likely to view these tools as both useful and easy to use in their instructional practices (Venkatesh, 2022). These findings underscore the importance of individual and social factors in promoting the adoption and effective utilization of AI-powered tools in STEM education. The significance of subjective norm aligns with the UTAUT2 model, which posits that social influence plays a critical role in technology acceptance. This relationship is supported by existing literature, which indicates that teachers' perceptions are significantly shaped by the opinions and behaviors of their peers and educational communities (Ateş et al., 2024; Venkatesh et al., 2012; Wang et al., 2021). Our study further corroborates these findings by highlighting how supportive peer environments can enhance educators' confidence and willingness to adopt new technologies. Additionally, the results support hypotheses H11 to H15, indicating that perceived ease of use positively impacts perceived usefulness and attitude, while perceived usefulness is significantly related to attitude and intention. This implies that when teachers perceive AI-powered tools as easy to use, they are more inclined to recognize their utility and develop a positive attitude toward them. Such positive attitudes subsequently enhance their intention to adopt these tools (Al-Adwan et al., 2024). This finding aligns with previous studies demonstrating the critical role of perceived ease of use in shaping technology adoption behaviors (Davis, 1989; Liu et al., 2021). For instance, Sprenger and Schwaninger (2023) employed the GETAMEL approach to examine whether minimal exposure to digital technology through video demonstrations could predict future technology use. Their findings revealed that perceived usefulness significantly predicted the intention to use technology, reinforcing the relevance of our results in the context of AI in STEM education. Moreover, Liu et al. (2021) utilized the GETAMEL framework to investigate the factors influencing mobile library application adoption among university students. Their study identified that subjective norms, enjoyment, computer-related experience, self-efficacy, perceived ease of use, and perceived usefulness are vital for the successful design and implementation of technology. The nuanced differences in perceived usefulness and ease of use across different user groups further highlight the importance of contextual factors in technology adoption, corroborating our findings that contextual and individual factors together shape teachers' adoption intentions (Lucas et al., 2021). In addition to the previously mentioned constructs, our findings also provide support for hypotheses H16 to H18, indicating that price value, facilitating conditions, and habit positively influence teachers' intention to use AI-powered tools in STEM education. These results suggest that teachers are more likely to adopt and utilize these tools if they perceive them as valuable relative to their cost, if there are adequate conditions for their use, and if they have developed a habit of incorporating technology into their teaching (Ateş & Garzón, 2023). This aligns with the conclusions of Jain et al. (2022), who demonstrated the significance of UTAUT constructs in predicting intentions to use AI-enabled tools. Their research established the viability of a robust social-psychological model for understanding technology acceptance in educational contexts, complementing the insights provided by our study. Shortly, this research extends the existing literature by integrating individual and contextual factors into a comprehensive model that predicts the adoption of AI-powered tools in STEM education.

The mediating effects observed in this study align with previous research that has investigated these constructs within educational contexts. For instance, studies by Girish et al. (2022), Humida et al. (2022), and Rahmi et al. (2018) have similarly found that perceived ease of use and perceived usefulness significantly mediate the relationship between various factors and the intention to adopt technology. Our findings support the notion that when teachers perceive AI-powered tools as easy to use, they are more likely to regard them as beneficial, thus fostering a positive attitude towards their integration into teaching practices. This integration is consistent with the UTAUT2 model, which emphasizes the interplay between these constructs in influencing behavioral intention. The mediating role of perceived ease of use is particularly critical in the context of AI adoption (Damerji & Salimi, 2021). This study underscores the importance of developing user-friendly, intuitive AI-powered tools that require minimal training for effective use. When teachers find these tools accessible, their confidence in employing them increases, leading to higher perceived usefulness. This reinforces the argument presented in existing literature that technology designed with the user in mind facilitates greater adoption rates among educators (Granić, 2022; Tseng et al., 2022). Conversely, the mediating role of perceived usefulness emphasizes the necessity of designing AI tools that are directly relevant to teachers' pedagogical goals. Tools that enhance teaching practices, improve student engagement, and foster better learning outcomes are more likely to be adopted. This supports the findings of previous studies that link perceived usefulness with technology acceptance, suggesting that practical relevance in the classroom significantly influences teachers' willingness to incorporate new technologies (Ateş & Gündüzalp, 2024). Moreover, the mediating role of attitude is pivotal in shaping teachers' intentions to adopt AI tools. Our findings suggest that promoting a positive perception of AI technologies is essential for increasing their acceptance among educators. This aligns with existing research that highlights the influence of teachers' attitudes on their technology adoption behaviors. Creating a supportive environment that encourages teachers to explore and experiment with AI tools can foster positive attitudes, further driving their willingness to adopt these innovations (Hopcan et al., 2024).

5.3. Limitation and suggestions for future research

This study provides valuable insights into the adoption of AI-powered tools in STEM education by science teachers; however, several limitations must be acknowledged.

Firstly, the sample of 582 science teachers, while substantial, is predominantly from Turkey. This geographical and cultural specificity may limit the generalizability of our findings to broader international contexts. The educational systems, cultural attitudes toward technology, and professional development opportunities in Turkey may differ significantly from those in other countries, which could influence the adoption and perception of AI tools in in STEM education.

Secondly, the study relies on teachers' self-assessments of their use and perception of AI tools in STEM education, which can introduce biases such as social desirability or personal beliefs about technology in education. Although measures were implemented to ensure the accuracy and reliability of the data, the subjective nature of self-reporting must be considered when interpreting the findings.

Furthermore, while this study provided an in-depth examination of the technical aspects of AI tool adoption in STEM education, it did not extensively explore the socio-cultural and pedagogical factors that significantly influence technology acceptance. Factors such as societal attitudes toward technology, cultural context, teaching philosophies, and methodologies can play a critical role in how technology is adopted and utilized. The absence of a thorough exploration of these factors may impact the interpretation of our results, as a teacher's cultural background or teaching style could significantly influence their perception of the usefulness and ease of use of AI tools in STEM education.

Lastly, another limitation is the lack of exploration into ethical considerations, privacy concerns, and perceived risks associated with AI adoption in STEM education. These factors are increasingly relevant in discussions about AI technologies and can greatly influence teachers' intentions and willingness to integrate AI tools into their classrooms. Understanding these elements could provide deeper insights into the barriers educators face when adopting AI in STEM education.

In light of these limitations, several directions for future research could significantly enhance our understanding of AI-powered tool adoption in STEM education.

Firstly, future studies should aim to extend research to a global scale by conducting comparative international studies that include science teachers from diverse geographical locations and cultural backgrounds. This approach would provide a more comprehensive perspective on global trends in AI tool adoption and help determine whether patterns observed in the Turkish context hold true in other international settings.

Secondly, future research should employ a more diverse sampling strategy that includes teachers from various educational levels, years of teaching experience, and socio-economic backgrounds. This diversity will ensure a richer, more representative understanding of the factors influencing AI adoption in STEM education, uncovering nuances across different educational settings and demographics.

Incorporating a mixed-methods approach would also be beneficial for future studies. While quantitative data offers a broad overview, qualitative methods – such as interviews, focus groups, or classroom observations – can provide deeper insights into teachers' experiences, challenges, and perceptions regarding AI tools in STEM education. This combination would allow for a more nuanced understanding of the dynamics involved in integrating AI into teaching practices.

Additionally, future research should consider incorporating objective measures of AI tool usage to validate self-reported data. Usage analytics could provide tangible measures of how frequently and in what contexts AI tools are utilized in the in STEM education. Classroom observations could further illustrate how these tools are integrated into teaching and learning processes.

Conducting longitudinal studies would be valuable for understanding the evolution of AI tool adoption over time. Such studies could track changes in attitudes, usage patterns, and the effectiveness of AI tools in STEM education, offering insights into the long-term impacts and sustainability of technology integration in educational settings.

Future research endeavors should adopt a comprehensive approach that integrates socio-cultural and pedagogical factors into the study of AI tool adoption. Investigating how cultural contexts influence teachers' attitudes and practices toward AI tools is essential. Additionally, examining how AI tools align with existing teaching methodologies and philosophies could provide valuable insights into their seamless integration into diverse pedagogical frameworks.

Finally, studies could explore teachers' perceptions of ethical issues surrounding AI technologies in STEM education, including concerns about fairness, transparency, and accountability. Additionally, research could assess how privacy concerns related to student data collection and usage impact teachers' trust in AI tools and their subsequent adoption behaviors. Incorporating qualitative methods, such as interviews or focus groups, could yield valuable insights into the specific ethical dilemmas and privacy issues educators encounter. Furthermore, quantitative studies could measure the relationship between perceived risks and teachers' intentions to use AI in STEM education, helping to identify barriers to adoption. By exploring these dimensions, future research will not only enhance our understanding of the challenges educators face when adopting AI but also inform the development of strategies and policies that address these concerns. This focus on ethical and privacy considerations will be essential for fostering a supportive environment that encourages the integration of AI technologies in in STEM education.

6. Conclusion

In this study, we aimed to investigate the factors that influence the adoption of AI in STEM education among middle school science teachers in Turkey. The findings of this study contribute to the existing literature on the adoption of technology in education, specifically the use of AI in STEM education. By integrating the GETAMEL and the UTAUT 2, this study developed a comprehensive theoretical framework for predicting teachers' behavioral intentions to adopt AI in STEM education. Our integrated model demonstrated that the constructs of the proposed model had a significant positive relationship with teacher adoption of AI in STEM education. The study results also revealed the mediating role of perceived ease of use, perceived usefulness, and attitude in the relationship between the constructs and the intention to adopt AI in STEM education. These results suggest that in order to promote the adoption of AI in STEM education among middle school science teachers, it is important to address not only the technical aspects of the technology, but also the social and psychological factors that influence individuals' attitudes and intentions towards its use. To sum up, this conceptual framework offers remarkable efficacy, comprehensiveness, and practicality, making it a valuable asset for educators, policymakers, educational institutions, and curriculum.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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