Informatics in Education, 2025, Vol. 24, No. 4, 653–679

DOI: 10.15388/infedu.2025.22

Investigating Preservice STEM Teachers' AI Literacy and Self-Efficacy Beliefs: Are They Ready for AI?

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Received: February 2025

Abstract. As artificial intelligence (AI) becomes increasingly integrated into education, preservice science, technology, engineering and mathematics (STEM) teachers must develop both AI literacy and self-efficacy to effectively incorporate AI tools into instruction. This study examined the cognitive and affective orientations of 180 Turkish preservice STEM teachers toward AI, specifically AI literacy, self-efficacy, interest, and attitudes, and identified predictors of AI self-efficacy. Using a performance-based AI literacy test and validated scales, data was analyzed through Rasch modeling and hierarchical regression analysis. While participants demonstrated moderate AI literacy and self-efficacy, the regression results revealed that AI use frequency, interest in AI, and attitudes toward AI significantly predicted AI self-efficacy, whereas demographic, academic, and cognitive factors did not. The findings emphasize the importance of fostering interest and positive attitudes, alongside hands-on experiences with AI tools, in enhancing preservice teachers' confidence to use AI. The study underscores the need for teacher education programs to integrate both conceptual knowledge and experiential learning opportunities about AI by providing preservice teachers with practical and meaningful activities to explore AI-based tools and applications within their required coursework.

Keywords: preservice teachers, STEM, artificial intelligence, AI literacy, AI self-efficacy.

1. Introduction

The developments in computer science and the recent advancements in machine learning technologies have paved the way for the proliferation of artificial intelligence (AI) tools in many areas of life today, including education. AI is a highly interdisciplinary field of science that rests on several domains, such as computer science, mathematics,

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neuroscience, biology, psychology, and others (Kusters *et al.*, 2020). AI is commonly regarded as one of the most revolutionary and disruptive technologies developed to date (Russell, 2021), which is expected to cause radical transformations in nearly every industry and usher in a new era of human-machine collaboration. AI also has great potential to drive innovation and bring transformative changes to teaching and learning (Bergdahl & Sjöberg, 2025; Kasneci *et al.*, 2023). In fact, the use of various generative AI (GenAI) tools such as ChatGPT from OpenAI and Co-pilot from Microsoft has become increasingly common among learners in many countries (Lo, 2023; Puryear & Sprint, 2022), prompting educators to reconsider their traditional teaching practices like assigning homework and making assessments (Gleason, 2022). AI can be employed in educational settings to provide students with personalized learning experiences based on their prior knowledge and specific academic needs, to design intelligent computer-based learning environments, and to automate formative and summative assessment practices through intensive data-driven techniques. This can enable teachers to better manage the learning process and give individual meaningful feedback to students (Guo & Lan, 2023; Liang *et al.*, 2023).

Because of the growing importance of AI in education, UNESCO published several extensive policy documents, such as AI competency frameworks for students (Miao & Shiohira, 2024) and teachers (Miao & Cukurova, 2024) and evidence-based recommendations for using AI in education and research (Miao & Holmes, 2023). UNESCO recommended comprehensive policy changes for governments to support educators in building professional competence to utilize AI properly and effectively in teaching and learning settings (Miao & Holmes, 2023). Similarly, the European Union has recently formulated a policy initiative called the 'Digital Education Action Plan (2021–2027)' to foster its member states' adaptation to the new technology-centric information age, and one of the actions suggested in the plan was the use of AI ethically for teachers in teaching and learning (European Union, 2023). As such, today's educators need to develop AI literacy and have high self-efficacy in AI to effectively use AI tools and integrate them meaningfully into their instruction (Ding *et al.*, 2024). To navigate the opportunities and challenges of AI, individuals need to build a basic understanding of AI and the skills to use and assess AI systems (Hornberger *et al.*, 2023). In addition, given its importance, AI literacy is recognized as one of the core competencies for the workforce of the future (Chiu *et al.*, 2024; Xia *et al.*, 2022). As the future workforce, higher education students need to be equipped with the ability to adapt to technological advancements. Rawas (2024) suggests that higher education should develop lifelong learners who can thrive in an era mainly dominated by contemporary information and communication technologies, such as generative AI. While there is a growing number of studies on AI literacy, the majority relied on self-reported instruments in terms of assessing AI literacy (Lintner, 2024). So, this study aimed to contribute to the literature by employing a performance-based AI literacy instrument to investigate a sample of Turkish STEM preservice teachers' AI literacy levels. In addition, this study explored several factors, such as AI literacy, interest in AI, and attitudes toward AI, in predicting AI self-efficacy beliefs among preservice teachers, which was not studied much in the literature.

2. Literature Review

2.1. *AI in Education*

AI-related technologies have the potential to improve learning and teaching experiences in educational settings, and AI-based tools have been affecting teachers' practices in education, as it transforms the way one learns and teaches, by making education more individualized and more engaging (Bowen & Watson, 2024). Given the growing variety of AI-powered educational tools available today, it is essential for researchers and practitioners to understand the role of AI in education and the opportunities it presents along with the challenges it poses. To enable teachers to benefit from AI technologies, teachers should be made aware of what AI-based tools are available to use and how to use them in their teaching processes; thus, evidence-based professional development programs are needed for both preservice and in-teachers in this context (Lee *et al.*, 2022). There are various benefits of AI in education that have been discussed in recent literature (Adeshola & Adepoju, 2024; Wu & Zhang, 2025; Xia *et al.*, 2024; Zhai *et al.*, 2021). For example, AI-based tools can be used to create personalized learning environments and intelligent tutoring systems (ITS), monitor students' understanding levels, provide learners with feedback on their learning, and diagnose learning difficulties students experience (Zhai *et al.*, 2021). AI can also improve assessment and evaluation methods by analyzing big data collected from students' learning processes, by grading students' work, and by providing teachers with valuable information in real-time in classroom settings (Cooper & Klymkowsky, 2024; Zhai *et al.*, 2022). In their study with secondary students, Wu and Zhang (2025) found that applications and tools powered by generative AI technologies had a positive effect on students' digital literacy and innovation capability (e.g., critical thinking). There are also concerns about the role of AI in education, such as cheating in examinations, engaging in academic dishonesty and plagiarism in out-of-school assignments, problems of privacy, cost, accessibility, and the potential bias in AI-generated content (Adeshola & Adepoju, 2024; Gašević *et al.*, 2023; Michel-Villarreal *et al.*, 2023).

2.2. *AI Literacy and Self-Efficacy among Preservice Teachers*

According to Hornberger *et al.* (2023), AI literacy refers to the skills and knowledge needed to understand artificial intelligence. AI literacy encompasses several competencies that allow individuals for critically assessing AI technologies, interacting and collaborating with AI systems effectively, and utilizing AI tools in online settings, at home, and at work (Long & Makerko, 2020). Because of the proliferation of AI-based tools and technologies in today's educational landscape, researchers started focusing more on preservice and in-service teachers' AI literacy (Ayanwale *et al.*, 2024; Ding *et al.*, 2024; Du *et al.*, 2024; Sanusi *et al.*, 2024). Developing AI literacy is important for educators in order for them to effectively utilize and integrate this emerging technology into their teaching processes and navigate properly in tomorrow's technology-driven educational landscape (Ayanwale *et al.*, 2024; Rütti-Joy *et al.*, 2023). According to previous studies, preservice and in-service teachers do not sufficiently know about the functioning of AI and thus they face challenges in integrating AI tools into their classroom practices (Du *et al.*, 2024; Younis, 2024).

Bewersdorff *et al.* (2025) defined AI-self efficacy of learners as "the confidence in their capabilities to effectively interact with, understand, learn about, and use (when desired) AI technologies and applications" (p.1). Technology self-efficacy is described as an essential component for understanding all innovative technologies (Hong, 2022). According to Hong (2022), AI self-efficacy research should be distinguished from common technology self-efficacy research, because the acceptance of AI technologies is peculiar. While individual's intentions to purchase and use common technologies are about their acceptance and self-efficacy of those technologies, when it comes to AI acceptance and self-efficacy, their emotional or cognitive reactions to the tool significantly matter. Ding *et al.* (2024) suggested developing extended PD programs for supporting teachers' AI literacy development and their integration of AI into their classroom practices. However, as PD program development also needs a significant amount of time and effort, to keep up with the rapid advancements in the field of AI presents an additional challenge. This shows the need for adaptive and flexible PD strategies, which could evolve in parallel with the rapid developments and innovations in AI technologies. According to Hoya *et al.* (2024), highlighting AI's utility would contribute to preservice teachers to develop positive attitudes and intentions to use AI tools. The researchers stated that "since self-efficacy beliefs plays a critical role, teacher training should focus not only on these topics, but also on fostering preservice teachers' confidence in using AI tools" (p. 15). In order to make this possible, hands-on experiences, practicing sessions, and opportunities for experimenting with AI tools in a classroom environment should be offered to preservice teachers, which can enhance their AI self-efficacy. Hoya *et al.* (2024) also suggested developing curricula in teacher education programs to foster the integration of AI technologies into teaching.

2.3. *Factors Influencing AI Self-Efficacy*

According to Bećirović *et al.* (2025), the rapid developments and innovations in AI technologies cause an issue in terms of teachers' perceived self-efficacy; as new developments are achieved and offered, teachers face pressure to cope with, and they could get stressed in adopting those developments and negative perceptions could emerge. Teachers' self-efficacy, therefore, is an essential subject to focus on in order to help AI-technologies integrate the real educational settings. Teachers should be aware of and well-prepared for the rapid developments in AI technologies. Bewersdorff *et al.* (2025) investigated through a path analysis how affective (i.e., attitudes towards AI and AI interest), cognitive (i.e., AI literacy), and behavioral variables (i.e., the use of AI) interacted and predicted AI self-efficacy among university students from the U.S., the U.K., and Germany. The findings indicated that positive attitudes toward AI and the use of AI contributed significantly to interest in AI, which, along with AI literacy, positively influenced AI self-efficacy. As such, the researchers emphasized the importance of educational strategies that not only improve AI literacy but also enhance students' AI attitudes, interests, and usage to strengthen their AI self-efficacy effectively. In another study, Sun *et al.* (2024) explored the variables that potentially shape teachers' willingness to integrate AI, with an emphasis on preservice STEM teachers' attitudes toward incorporating AI into teaching. The study examined the effects and interrelations of technological pedagogical content knowledge (TPACK), perceived ease of use, perceived usefulness, and self-efficacy in shaping preservice STEM teachers' willingness to integrate AI. The results showed that these variables directly influenced preservice teachers' willingness to integrate AI. Additionally, the findings indicated that most participants lacked confidence in their capacity to integrate AI technologies into education. In another study conducted with 318 in-service teachers from China, Du *et al.* (2024) found that teachers' AI literacy could directly influence their self-efficacy to learn AI, and that was one of the immediate precursors of behavioral intentions to learn AI. Also, Bećirović *et al.* (2025) suggested that having a strong understanding of AI significantly enhances teachers' self-efficacy in using AI tools in their teaching. Thus, teachers' AI literacy should be enhanced in order to improve their AI self-efficacy. By doing so, teachers would be better equipped to use AI tools effectively in their teaching practices and they also will be able to foster their students' understanding of AI.

3. Theoretical Framework

According to Bandura (1994), self-efficacy beliefs refer to people's beliefs in their capacity and capability to carry out tasks successfully and accomplish goals in a specific area. Individuals with high self-efficacy beliefs about a given task tend to believe in their ability to achieve that task (Bandura, 1991). Similarly, people with lower self-efficacy are more likely to perceive their competence as inadequate and the required task as more difficult compared to people with higher levels of self-efficacy. It is important to emphasize that individuals' self-efficacy beliefs may not necessarily represent their actual ability and competence. Instead, self-efficacy beliefs of individuals reflect their subjective judgments of their true capability. For instance, it is plausible that some individuals having greater ability levels may demonstrate low self-efficacy beliefs while others with lower levels of actual competence may perceive themselves as highly capable of accomplishing a specific task (Bandura, 2012). Individuals' self-efficacy beliefs in the context of using technology for personal or professional reasons were frequently studied in the related literature (Aesaert & van Braak, 2014; Afari *et al.*, 2023; Holden & Rada, 2011). The findings of the extant studies indicated that individuals demonstrating higher technology self-efficacy beliefs in general tended to be more likely to use and adopt technology and be more confident in using technology. Wang and Chuang (2024) conceptualized AI self-efficacy as a person's overall confidence in their ability to use and interact with AI-based tools and the related technologies. Today, AI technologies play a growing and critical role in education, especially within STEM fields

(Sun *et al.*, 2024). AI-based tools such as ChatGPT are transforming how educators and students engage with and comprehend STEM concepts (Chng *et al.*, 2023). Among a variety of psychological factors influencing AI integration, self-efficacy is important in affecting teachers' inclination to integrate AI into their lesson planning and instruction (Al Darayseh, 2023). A lack of self-efficacy in using AI-based tools among teachers may, in turn, negatively impact their effectiveness and perceived capability in integrating AI into their instructional activities (Çelik, 2023). Strengthening teachers' beliefs in their confidence in using AI has the potential to foster their AI adoption in today's technology-driven teaching landscape, which can empower student engagement in the classroom.

4. Significance of the Study

Since AI is becoming more and more ubiquitous in many aspects of today's modern societies, STEM teachers must know about AI itself (i.e., gaining AI literacy) and have high levels of self-efficacy in AI so that they can take advantage of AI tools and integrate them into their teaching practices to foster student learning. As such, the goal of this study was twofold. First, it aimed to comprehensively investigate preservice STEM teachers' cognitive and affective orientations toward AI, including AI literacy, AI self-efficacy, interest in AI, and attitudes toward AI. Secondly, this study explored how demographic, academic, cognitive, affective, and behavioral variables predicted preservice STEM teachers' AI self-efficacy. This study is significant because, to the best of the authors' knowledge, currently, no studies exist in the literature that examined AI literacy, self-efficacy beliefs, interests, and attitudes towards AI among preservice STEM teachers in the Turkish context. As many aspects of today's society rapidly transition into an AI-driven landscape, future educators must be both proficient in AI and confident in their ability to integrate it into their teaching practices. Accordingly, this research aimed to contribute to the growing literature on preservice teachers' AI literacy and self-efficacy. Moreover, while previous studies have predominantly relied on self-reported instruments on AI literacy, which often suffered from questionable validity and reliability considerations (Lintner, 2024), the present study employed a performance-based AI literacy instrument, which was rigorously validated using modern psychometric techniques based on the Item Response Theory (IRT) with a large sample of university students (Hornberger *et al.*, 2025), which enabled a more robust and objective assessment of AI literacy. Specifically, the present study aimed at addressing the following research questions:

RQ-1. What are the levels of AI literacy and self-efficacy among Turkish preservice STEM teachers?

RQ-2. What are the levels of interest in and attitudes toward AI among Turkish preservice STEM teachers?

RQ-3. To what extent do cognitive, affective, behavioral, academic, and demographic factors predict AI self-efficacy among Turkish preservice STEM teachers?

5. Methods

5.1. *Participants*

The non-probabilistic convenience sampling technique (Mills & Gay, 2019) was employed in recruiting the sample for this study. It is necessary to point out that this sampling technique may yield some bias and limitations such as decreasing representativeness of the broader population to be studied and restricting generalization of findings beyond the sample (Golzar *et al.*, 2022). The participants were undergraduate preservice STEM teachers enrolled at a public research university in Istanbul, Türkiye. The term "preservice STEM teachers" in this study refers to teacher candidates pursuing a bachelor's degree in education and specializing in one of the following STEM-related teaching areas: 'high school physics', 'high school chemistry', 'high school mathematics', 'middle school science', 'middle school mathematics', and 'computer and educational technologies' (CET). Since the university where the present study was conducted did not offer a secondary biology education program, the sample did not include any teacher candidates specializing in biology education. A total of 180 preservice teachers majoring in STEM fields volunteered to participate in the research. 31% of the participants were male ($n = 55$) and 69% were female ($n = 125$). The age of the participants varied between 19 and 26, with an average of 22.6 ($SD = 1.4$). In addition, participants' grade point averages (GPAs), which indicate overall academic achievement, ranged from 0.50 to 3.55 on a 4-point scale ($M = 2.51$, $SD = 0.47$). Senior level students constituted the majority (43%) in the sample and 85% of the participants reported their socio-economic status (SES) as moderate. Table 1 provides detailed information regarding the demographic and academic characteristics of the participants in this study.

Table 1
Demographic and academic characteristics of the participants

Characteristic	Category	Frequency	Percentage
Gender	Male	55	31%
	Female	125	69%
Faculty	High School Physics	12	7%
	High School Chemistry	24	13%
	High School Mathematics	26	14%
	Middle School Science	31	17%
	Middle School Mathematics	57	32%
	Computer and Educational Technologies	30	17%
Class Standing	Freshman	12	7%
	Sophomore	49	27%
	Junior	41	23%
	Senior	78	43%
Socio-Economic Status	Low	19	11%
	Moderate	154	85%
	High	7	4%

5.2. *Instruments*

The data collection tool for this study consisted of two main parts: (1) a set of questions prepared by the researchers about the participants' demographic and academic characteristics, and (2) four separate validated instruments adopted from previous studies to assess participants' AI literacy, AI self-efficacy, interest in AI, and attitudes toward AI. The demographic questions included gender, age, and socio-economic status (low, moderate, high), while the questions about academic characteristics covered GPA, major (e.g., physics education), and year in the undergraduate program (e.g., sophomore). The first part of the survey also included two questions related to personal experience with the use of AI: (1) "Have you ever used an AI tool (such as ChatGPT)?" (response options: Yes, No), and (2) "On a scale from 0 (not at all) to 5 (very often), how often do you use AI tools (such as ChatGPT) in general?" (0 = Not at all, 1 = Rarely, 2 = Occasionally, 3 = Sometimes, 4 = Often, 5 = Very often). Since ChatGPT is one of the most well-known and widely used AI tools among students (Adeshola & Adepoju, 2024), it was chosen as the example of an AI tool in the survey items.

5.2.1. *AI Literacy Test*

The AI Literacy Test, developed by Hornberger *et al.* (2025), was employed in this study to assess preservice STEM teachers' AI literacy levels. Hornberger *et al.* (2023) initially developed this instrument in German with a large group of university students (N = 1286) in Germany and later Hornberger *et al.* (2025) translated it into English and then further revised and validated both the English and German versions of the test in a multinational study with university students (N = 1465) from the U.K., the U.S., and Germany. The final version of the AI Literacy Test consists of a total of 28 questions, with 27 of them being multiple-choice and one is a sorting-type item. The researchers categorized the questions into 14 categories such as 'Machine Learning Steps' and 'Human Role in AI', which were based on the AI competency framework developed by Long and Magerko (2020). We specifically employed Hornberger *et al.*'s (2025) AI Literacy Test in this study because it aimed to evaluate respondents' genuine understanding of the fundamental AI concepts, unlike most other instruments in the literature that mainly rely on self-reported knowledge measured through agreement statements on Likert scale items (Lintner, 2024). Fig. 1 shows a sample question from the AI Literacy Test.

What is a key criterion for the quality of a model in machine learning?

A) It can predict the output values of the test data as well as possible.
B) It contains as few variables as possible.
C) It is as well adapted as possible to the training data.
D) The predictions are as unambiguous as possible.

Fig. 1. A sample question from the AI Literacy Test (Hornberger *et al.*, 2025).

Hornberger *et al.* (2025) conducted a comprehensive validation process by employing a three-parameter (3-PL) Item Response Theory (IRT) model. According to the results of the IRT analyses, the researchers found that the initial set of 30 items in the AI Literacy Test measured a single underlying construct of AI literacy. The results of the differential item functioning analyses revealed that two items functioned differently across demographic groups, indicating potential bias, which led to their exclusion to ensure fairness and validity. Therefore, the final version of the test included a total of 28 items. Lastly, the researchers assessed the internal consistency of these 28 items and found an acceptable level of reliability (Cronbach's $\alpha = .74$) for the overall test, suggesting that the items consistently measured the underlying construct of AI literacy.

5.2.2. *AI Self-efficacy Scale (AISES)*

To assess participants' self-efficacy in AI in this study, the AI Self-Efficacy Scale (AISES), which was developed by Wang and Chuang (2024), was employed. The scale included a total of 22 items (e.g., "AI technologies/products help me to save a lot of time."). Responses were recorded on a 7-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). During the scale development process, Wang and Chuang (2024) collected data online from a relatively large sample of participants ($N = 318$), most of whom were college graduates. The researchers initially generated a pool of 72 items based on prior research on AI self-efficacy, which were reduced to 34 items following expert review by four specialists. During the item purification stage, exploratory factor analysis and reliability testing were iteratively conducted to refine the scale. Items with cross-loadings, low factor loadings (below .5), or insufficient representation within a factor were removed. As a result, 22 items were retained, representing four distinct dimensions: assistance, anthropomorphic interaction, comfort with AI, and technological skills. The researchers further conducted confirmatory factor analysis to validate the underlying factor structure. The internal consistency of the final scale was excellent, with Cronbach's alpha values ranging from .87 to .97 across the subdimensions and .96 for the overall scale.

5.2.3. *Interest in AI Scale*

In order to measure participants' level of interest in AI, we employed the 5-item Interest in AI scale, which was validated by Hornberger *et al.* (2023, 2025). The scale consists of Likert-type items that were rated on a five-point scale (1 = Strongly Disagree to 5 = Strongly Agree). Hornberger *et al.* (2023) adapted this instrument from another study that was originally developed to assess interest in science. In adapting the instrument for their research, the researchers replaced the term 'science' with 'artificial intelligence'. A sample item from the instrument included "I generally have fun when I am learning about artificial intelligence". The Interest in AI scale overall demonstrated good internal consistency, with a Cronbach's alpha of $\alpha = .90$ (Hornberger *et al.*, 2023). The researchers also performed an IRT analysis utilizing rating-scale models (Andrich, 1978). The scale demonstrated good reliability and the infit and outfit measures for all items were within the acceptable range.

5.2.4. *Attitudes toward AI Scale*

In order to measure participants' attitudes toward AI, we used the Attitudes toward AI scale validated by Hornberger *et al.* (2023), which was adapted from the General Attitudes towards AI scale developed by Schepman and Rodway (2020). The Attitudes toward AI scale consisted of eight items in total, with four items assessing positive attitudes (e.g., "There are many beneficial applications of artificial intelligence") and another four items assessing negative attitudes (e.g., "I think artificial intelligence is dangerous"). The items were responded to on a 5-point Likert scale (1 = Strongly disagree, 5 = Strongly agree). The instrument demonstrated an acceptable level of internal consistency, with Cronbach's alpha values of α = .77 (Hornberger *et al.*, 2023). The researchers used rating-scale models to conduct an IRT analysis, and the infit and outfit measures for all items came within the specified range and the scale showed an overall good reliability.

5.3. *Data Collection*

The data for this study was collected during the spring semester of 2024–2025 academic year. Initially, a formal approval was obtained from the university's Institutional Review Board (IRB) to conduct the study. Then, the data collection instruments were uploaded to Google Forms to facilitate the online data collection. All questions in the survey were configured as mandatory to ensure that there would be no missing responses from participants. On average, the entire survey took 30 minutes to complete. To compensate participants for their time, the researchers held a draw at the end of the data collection process, which included awarding an Amazon digital gift card (~$5) to ten randomly selected participants. After finalizing the online survey, the researchers began the data collection process. First, a poster describing the purpose of the study and inviting students to participate in the research was designed. It also included a shortened link as well as a QR code for the online survey. Several hard copies of the poster were placed on the bulletin boards in the two main buildings of the Faculty of Education to reach as many teacher candidates as possible. In addition to the posters, the researchers also sent a bulk email to all undergraduate students in the Faculty of Education, and the email included a short description of the study and the link to the online survey. Lastly, the researchers made in-person visits to several classes to inform teacher candidates about the study and invited them to participate.

5.4. *Data Analysis*

Regarding the data analysis, the one-parameter IRT model called the Rasch model (Boone *et al.*, 2014) was employed to analyze the participants' responses to all items of the scales in the survey after the data collection process was completed. The Winsteps (version 5.7.3) software (Linacre, 2024) was utilized for conducting Rasch analysis.

Then, the IBM SPSS Statistics (version 29) software was used to generate descriptive statistics for the variables as well as to run the hierarchical regression analysis.

Once the data collection process ended, the researchers downloaded the raw data on an Excel file and checked for any irregularities in data (e.g., selecting the same answer choice for all items). After ensuring that no irregularities existed in the dataset, the researchers exported the data to Winsteps for running the Rasch analysis. First, item/person separation and reliability values along with Cronbach's alpha coefficients were generated for each instrument and carefully examined. In Rasch analysis, separation and reliability metrics for both items and persons are generally used to evaluate how well the instrument measures what it is supposed to measure, how consistent the obtained results are, and to what extent the instrument assesses different levels of person ability and item difficulty (Fox & Jones, 1998). Table 2 presents the separation and reliability values for items and persons along with Cronbach's alpha coefficients for the instruments used in this study. The separation and reliability values for both items and persons indicated that the instruments performed well overall. Person reliability values were found as .80 for AI Literacy, .94 for AI Self-Efficacy, .85 for Interest in AI, and .74 for Attitudes toward AI. The person reliability values ranging from .80 to .90 can be interpreted that the instrument is able to differentiate between two to three levels of respondent ability, while a value exceeding .90 indicates the instrument's ability to differentiate among three or more levels (Boone *et al.*, 2014). In addition, the item reliability values were found as .95 for AI Literacy, .99 for AI Self-Efficacy, .98 for Interest in AI and, and .98 for Attitudes toward AI, which is quite high for all instruments, suggesting strong stability in item difficulty ordering (Fox & Jones, 1998). A person separation value of 1.5 indicates an acceptable level, 2.0 represents a good level while a value of 3.0 or higher is considered excellent (Boone *et al.*, 2014). Person separation values were above 2 for all instruments except the Attitudes toward AI scale, which has an acceptable separation value of 1.70, meaning that it can still differentiate between at least two levels of respondent ability. In addition, an item separation value of 1.5 and above is needed for individual level analysis while a value for 2.5 and above is required for group level analysis. The results showed that all instruments had item separation values above these required thresholds, indicating strong item discrimination suitable for both individual and group analyses. Also, Cronbach's

Table 2
Separation and reliability values for items and persons and Cronbach's alpha coefficients for each instrument

Instruments	Person Separation	Person Reliability	Item Separation	Item Reliability	Cronbach's Alpha
AI Literacy Test	2.01	.80	4.57	.95	.79
AI Self-Efficacy Scale	3.92	.94	9.97	.99	.94
Interest in AI Scale	2.39	.85	6.85	.98	.87
Attitudes toward AI Scale	1.70	.74	7.67	.98	.71

alpha coefficients were obtained as .79 for AI Literacy, .94 for AI Self-Efficacy, .87 for Interest in AI, and .71 for attitudes toward AI, which means that the items in the scales demonstrated an acceptable to excellent level of internal consistency (George & Mallery, 2019). Lastly, the item fit indices (infit/outfit MNSQ and ZSTD) were carefully examined to check for any misfitting items in the instruments. The infit and outfit MNSQ values varied between .78 to 1.31 for the AI Literacy Test, which were in the acceptable range (i.e., .70 to 1.3) for multiple-choice tests (Boone *et al.*, 2014). Likewise, the infit and outfit MNSQ values for the Interest in AI, Attitudes toward AI, and AI Self-Efficacy were between 0.5 and 1.5, which is the acceptable range for rating scale items (Boone *et al.*, 2014). Only one item (item 22) in the AI Self-Efficacy scale had high infit and outfit MNSQ values (1.76 and 1.74, respectively), which suggests that this item may not align as well with the underlying construct as the other items in the scale and may require a revision.

To address the first and second research questions, descriptive statistics were generated for participants' logit scores derived from the Rasch analysis of the study's scales along with their raw scores. For ease of interpretation, logit scores were re-scaled on a 0–100 scale by using UMEAN and USCALE parameters on the Winsteps control files. In answering the third research question, a five-step hierarchical regression analysis was employed with the AI self-efficacy scores being the dependent variable, and demographic (i.e., age, gender), academic (i.e., major, GPA), behavioral (i.e., AI use frequency), cognitive (i.e., AI literacy), and affective (i.e., interest in AI, attitudes toward AI) variables as the independent variables. For the continuous variables related to AI (i.e., AI literacy, AI self-efficacy, interest in AI, attitudes toward AI), the logit scores generated from the Rasch analysis were used in the statistical analyses since logit scores provide a more accurate depiction of the measurement compared to raw scores. Since the 'major' variable is a categorical variable with three categories (i.e., science education, math education, CET), two dummy variables were created to represent it in the regression analysis: 'Major_MathEd' and 'Major_CET', with science education as the reference category. Thus, science education students were coded 0 on both dummies; math education students were coded 1 on Major_MathEd and 0 on Major_CET; and CET students were coded 0 on Major_MathEd and 1 on Major_CET. The predictors were entered in successive blocks corresponding to these categories, and the changes in R^2 were used to assess the unique contribution of each block in the explained variance. For each step in the hierarchical regression analysis, model fit statistics (e.g., R^2, adjusted R^2, and F-statistics) were reported, along with the significance of the change in the explained variance. An alpha level of .05 was used to determine statistical significance.

The key regression assumptions, including linearity, homoscedasticity, independence and normality of residuals, and the absence of multicollinearity were evaluated before running the hierarchical regression analysis. The normality of the predictor and dependent variables was assessed by examining skewness and kurtosis values for each variable. Absolute skewness values ranged from 0.045 to 1.44, and absolute kurtosis values ranged from 0.21 to 4.15, which were well below Kline's (2023) suggested thresholds for normality ($|\text{skewness}| < 3$, $|\text{kurtosis}| < 10$). In addition, Q-Q plots of residuals were also reviewed, which showed that the residuals closely followed the 45 degrees reference line without any systematic departures, indicating an acceptable approximation to normality. To assess the independence of residuals, the Durbin–Watson statistic was generated and found to be 2.024, which was quite close to the ideal value of 2 and indicated that the residuals were uncorrelated (Field, 2017). The normality of residuals was checked by examining the normal Q-Q plots of the studentized residuals, which showed the points closely followed the reference line. Lastly, the absence of multicollinearity was confirmed through reviewing the variance inflation factor (VIF) values that ranged from 1.001 to 1.472, which was well below the threshold value of 10 (Field, 2017).

6. Results

Firstly, in response to the question, 'Have you ever used an AI tool (such as ChatGPT)?', all participants answered 'Yes' without exception. Additionally, the majority of participants (72%) reported using AI tools either 'often' or 'very often' (see Fig. 2).

Based on Table 3, the Rasch logit scores, which were converted to a 0–100 scale with 50 being the exact midpoint, demonstrated that the respondents' AI literacy (*M* = 48.76, *SD* = 11.41) was closely aligned with the intended difficulty level of the test. This indicates that the items were neither too easy nor too hard and avoided both floor and ceiling effects (Bond & Fox, 2015). The fact that over two-thirds of individuals scored between about 37 and 60 logits demonstrates effective discrimination across different ability levels. Furthermore, interest in AI (*M* = 63.71, *SD* = 16.94) and attitudes toward AI (*M* = 60.89, *SD* = 9.81) were both above the midpoint, which suggests that AI is generally viewed favorably and with interest. Interest ratings showed a wider range, between roughly 47 and 81 logits, indicating greater variability in individual engagement than attitude scores, which ranged between around 51 and 71 logits. AI self-efficacy (*M* = 55.62, *SD* = 7.21) also fell above 50 but had the narrowest range, which was ap-

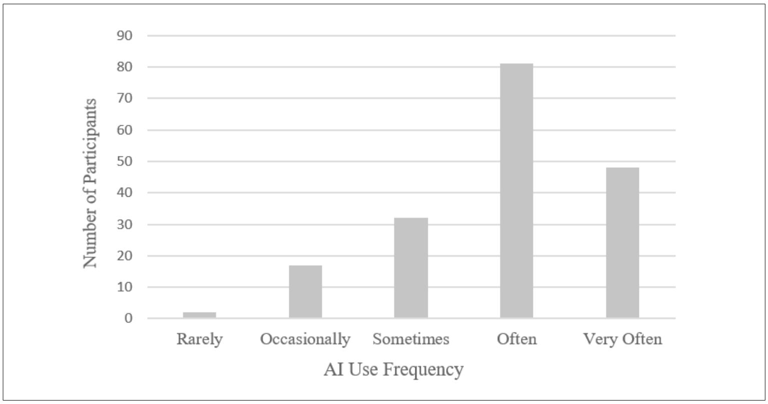

Fig. 2. How often participants used AI-based tools.

Table 3
Descriptive statistics for AI Literacy Test, Interest in AI, Attitudes toward AI, and AI Self-Efficacy scales

Scales	Mean	SD	Median	Mode	Min.	Max.	Range
AI Literacy (raw)[a]	13.13	5.17	13	13	2	28	26
AI Literacy (logit)[b]	48.76	11.41	48.17	48.17	20.68	99.98	79.30
Interest in AI (raw)[c]	3.73	0.77	3.8	4	1.40	5.00	3.60
Interest in AI (logit)[b]	63.71	16.94	63.42	67.57	16.72	99.95	83.23
Attitudes toward AI (raw)[c]	3.77	0.54	3.75	3.38	2.13	5.00	2.88
Attitudes toward AI (logit)[b]	60.89	9.81	59.27	54.07	37.56	99.96	62.40
AI Self-Efficacy (raw)[d]	4.60	0.99	4.61	4.45	2.23	7.00	4.77
AI Self-Efficacy (logit)[b]	55.62	7.21	55.13	54.20	39.90	100.00	60.10

N = 180
[a]Maximum score is 28.
[b]Maximum score is 100.
[c]Measured on a 5-point scale (1 = strongly disagree, 5 = strongly agree).
[d]Measured on a 7-point scale (1 = strongly disagree, 7 = strongly agree).

proximately between 48 and 63 logits, reflecting a consistently moderate confidence in the use of AI tools. Overall, these results confirmed that the survey items covered an appropriate difficulty range, reliably distinguished between lower- and higher-scoring individuals, and allowed for meaningful ranking of respondents in terms of literacy, interest, attitude, and self-efficacy dimensions.

Table 4 presents the zero-order correlations among the demographic, academic, behavioral, cognitive, and affective predictors entered into a hierarchical regression predicting AI self-efficacy. To guard against multicollinearity, predictor intercorrelations should stay below the established cut-offs. Pallant (2016) advised against including any two variables with r ≥. 70 in the same model, and Field (2017) recommended scanning for correlations of approximately .80–.90 to identify multicollinearity. In this study's data, all pairwise Pearson *r* values fell well beneath these thresholds, indicating that multicollinearity was unlikely to bias our regression results. Comparing the majors, CET majors reported higher AI self-efficacy (r = .245, p < .001), greater AI literacy (r = .154, p < .05), interest in AI (r = .133, p < .05) and AI use frequency (r = .235, p < .001). AI use frequency exhibited one of the strongest links to AI self-efficacy (r = .478, p < .001) and was also positively associated with interest in AI (r = .401, p < .001), attitudes toward AI (r = .394, p < .001) and, to a lesser extent, AI literacy (r = .163, p < .05). AI literacy also correlated with interest in AI (r = .176, p < .01) and attitudes toward AI (r = .227, p < .001). Interest in AI demonstrated particularly the strongest correlation with AI self-efficacy (r = .510, p < .001) and was further related to AI use frequency (r = .401, p < .001), AI literacy (r = .176, p < .01), and attitudes toward AI (r = .234, p < .001). Finally, attitudes toward AI was significantly and positively correlated with AI self-efficacy (r = .318, p < .001), AI use frequency (r = .394, p < .001), AI literacy (r = .227, p < .001), and interest in AI (r = .234, p < .001).

Table 4

Pearson correlation coefficients among the variables included hierarchical regression analysis

Variable	1	2	3	4	5	6	7	8	9	10
1. AI Self-Efficacy (logit)	—									
2. Gender[a]	–0.010	—								
3. Age	–0.113	–0.033	—							
4. GPA	0.041	–0.097	0.220^{**}	—						
5. Major_MathEd	$–0.165^{**}$	–0.009	0.137^{*}	–0.079	—					
6. Major_CET	0.245^{***}	0.221^{***}	–0.082	0.056	$–0.414^{***}$	—				
7. AI Use Frequency[b]	0.478^{***}	–0.072	–0.023	0.133^{*}	$–0.140^{**}$	0.235^{***}	—			
8. AI Literacy[c]	0.109	0.077	0.011	0.200^{**}	0.017	0.154^{*}	0.163^{*}	—		
9. Interest in AI[c]	0.510^{***}	0.074	–0.057	0.063	0.072	0.133^{*}	0.401^{***}	0.176^{**}	—	
10. Attitudes toward AI[c]	0.318^{***}	0.067	–0.054	0.052	–0.029	0.072	0.394^{***}	0.227^{***}	0.234^{***}	—

N = 180. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$, two-tailed.

[a]0 = female, 1 = male.

[b]Measured on a 5-point scale (0 = never, 5 = very often).

[c]Logit scores on a 0–100 scale.

A hierarchical multiple regression analysis was used to demonstrate how the independent variables predicted AI self-efficacy among the participants by sequentially adding five blocks of predictors as seen in Table 5. Model 1 appeared to be non-significant, $F(2, 177) = 1.159$, $p > .05$, with $\Delta R^2 = 0.013$ and an adjusted R^2 of 0.002, indicating that neither gender ($\beta = -.013$) nor age ($\beta = -.113$) explained a meaningful amount of variance in AI self-efficacy. Model 2 yielded a significant improvement, with $\Delta R^2 = 0.065$, $F(5, 174) = 2.931$, $p < .05$, and adjusted $R^2 = 0.051$. In this step, only Major_CET emerged as a significant positive predictor ($\beta = .225$, $p < .01$) and it has a small to medium effect size (Kline, 2023). Model 3 incorporated AI use frequency and produced a substantial increase in explained variance ($\Delta R^2 = 0.180$), with $F(6, 173) = 9.999$, $p < .001$ and adjusted $R^2 = 0.232$, also AI use frequency was a strong positive predictor ($\beta = .443$, $p < .001$) and it has a large effect size (Kline, 2023). In Model 4, adding AI literacy did not significantly improve prediction ($\Delta R^2 = 0.001$), $F(7, 172) = 8.546$, $p < .001$, and adjusted R^2 slightly decreased to 0.228. Also, AI literacy ($\beta = .025$) failed to reach significance. Finally, in Model 5, the inclusion of the affective variables resulted in a further significant gain, $\Delta R^2 = 0.139$, $F(9, 170) = 12.422$, $p < .001$, raising the adjusted R^2 to 0.365. In this final model, AI use frequency ($\beta = .235$, $p < .001$), interest in AI ($\beta = .388$, $p < .001$) and attitudes toward AI ($\beta = .134$, $p < .05$) made statistically significant unique contributions in predicting AI self-efficacy among the participants. Lastly, in the final model, while interest in AI showed a medium-to-large effect size, AI use frequency had a roughly medium effect size, and attitudes toward AI had a small effect size (Kline, 2023). Fig. 3 visually summarizes the steps as well as the final model of the hierarchical regression analysis, indicating the significant predictors of AI self-efficacy.

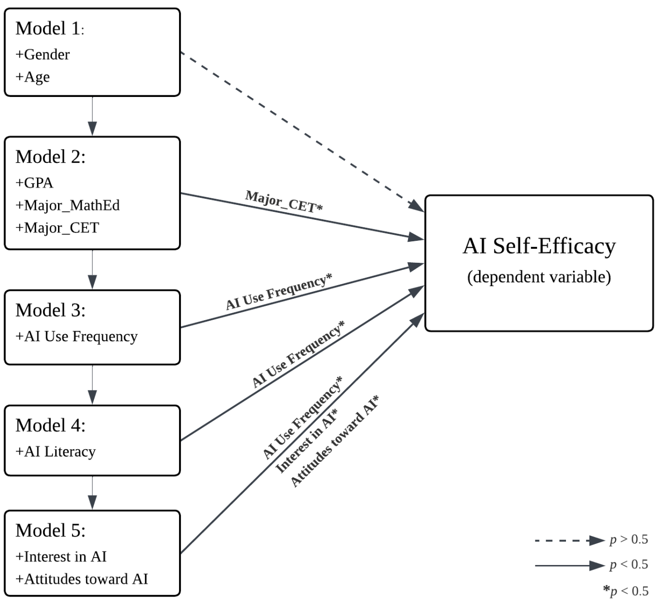

Fig. 3. A diagram representing the hierarchical regression analysis results.

Table 5

The results of the hierarchical regression analysis predicting participants' AI self-efficacy levels

Predictors	Model 1			Model 2			Model 3			Model 4			Model 5		
	B	SE	β	B	SE	β	B	SE	β	B	SE	β	B	SE	β
Constant	68.657	8.586		65.187	8.467		52.734	7.858		52.197	8.018		40.644	7.687	
Gender[a]	-0.207	1.167	-0.013	-0.924	1.178	-0.059	-0.126	1.067	-0.008	-0.155	1.073	-0.010	-0.845	0.981	-0.054
Age	-0.575	0.379	-0.113	-0.494	0.384	-0.097	-0.432	0.345	-0.085	-0.428	0.346	-0.084	-0.260	0.315	-0.051
GPA				0.600	1.146	0.040	-0.152	1.038	-0.010	-0.227	1.061	-0.015	-0.355	0.962	-0.023
Major_MathEd				-0.810	1.171	-0.056	-0.625	1.054	-0.043	-0.666	1.063	-0.046	-1.602	0.977	-0.111
Major_CET				4.346	1.593	0.225**	2.292	1.468	0.119	2.224	1.484	0.115	1.871	1.353	0.097
AI Use Frequency[b]							3.353	0.518	0.443***	3.330	0.523	0.440***	1.776	0.547	0.235***
AI Literacy[c]										0.016	0.044	0.025	-0.020	0.040	-0.032
Interest in AI[c]													0.165	0.029	0.388***
Attitudes toward AI[c]													0.099	0.049	0.134*
Adjusted R^2	0.002			0.051			0.232			0.228			0.365		
ΔR^2	0.013			0.065			0.180			0.001			0.139		
F total	1.159			2.931*			9.999***			8.546***			12.422***		

N = 180. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$, two-tailed.

[a]0 = female, 1 = male.

[b]Measured on a 5-point scale (0 = never, 5 = very often).

[c]Logit scores on a 0–100 scale.

7. Discussion

The development of AI technologies and AI-based applications has considerably increased in recent years and began to drastically transform and reshape many areas of daily life and professional careers in a wide range of fields including education. For example, Manyika *et al.* (2017) predicted that around half of the jobs in the U.S. will be at risk of automation by 2030. As societies worldwide are entering into a new era driven primarily by AI, it is particularly important that K-12 teachers are not only knowledgeable about AI but also have high self-efficacy in AI when it comes to using it for daily tasks and meaningfully incorporate it into their instruction. As such, this study aimed to explore a sample of Turkish PSTs from STEM teaching disciplines regarding their AI literacy and self-efficacy levels as well as affective orientations toward AI, including interest and attitudes.

Firstly, the results showed that all participants in the sample have previously used an AI-based tool such as ChatGPT and the majority reported frequently using AI-based tools in their lives. This finding aligns with the findings of previous studies regarding the high penetration of AI-based tools and applications among higher education students (Schei *et al.*, 2024). This seemingly fast and widespread adoption of AI technologies among university students points to a broader societal trend in recent years toward an accelerating acceptance of AI-driven applications in many aspects of life. As such, this important shift underscores the revolutionary and disruptive potential of AI technologies in the future as well as the urgency for teacher training institutions to better prepare tomorrow's teachers for an increasingly AI-driven education landscape.

This study aimed to investigate AI literacy and self-efficacy levels among Turkish preservice STEM teachers by assessing their understanding about AI itself and their perceived capability and beliefs in utilizing AI-based tools and applications. To begin with, the results indicated that participants had a moderate level of understanding about AI, with a mean score of 48.76 logits (SD = 11.41) on a 0–100 scale from the AI Literacy Test. It can be argued that the participants demonstrated a level of foundational knowledge regarding the fundamental concepts in AI. However, they appeared to lack an in-depth understanding of AI beyond the basics. This finding is in line with the findings of similar studies conducted with university students or preservice teachers in the literature (Černý, 2024; Hornberger *et al.*, 2023, 2025; Mansoor *et al.*, 2024; Teng *et al.*, 2022; Younis, 2024). For example, in a large-scale and multinational study, Hornberger *et al.* (2025) investigated AI literacy among university students from Germany, the U.K., and the U.S. (N = 1465) by utilizing the AI Literacy Test that was also used in the present study. Their results showed that while German students demonstrated higher AI literacy, overall, their sample had a limited understanding of AI, with a raw mean score of 15.0 (SD = 4.8) out of a maximum of 28 points. In another large-scale study with undergraduate and graduate students in four countries (N = 1800), including Saudi Arabia, Egypt, Malaysia, and India, Mansoor *et al.* (2024) found a moderate level of AI literacy among the participants by utilizing a previously validated scale. Since AI is a relatively novel and rapidly evolving technology that is primarily driven by advancements in technical fields such as computer science and data analytics, it is understandable that university students and especially those who are outside of these disciplines may not yet possess a deep and comprehensive understanding of its principles and applications. However, it is crucial that preservice teachers particularly in STEM areas develop a more comprehensive understanding of what really constitutes AI, how it functions overall, and the ethical, societal, and economic challenges it presents in both the near and long term. A deeper knowledge of these dimensions will enable future educators to make more informed pedagogical decisions in the classroom regarding when and how to integrate AI-based tools and applications into their lessons, as well as to establish clear ethical boundaries for students' use of such technologies responsibly in their learning processes and daily lives. Given that today's preservice teachers will shape the educational experiences of future generations, fostering AI literacy among them is imperative. As schools continue to serve as formal environments where children develop a variety of literacy skills and as AI is here to stay and even progress more, equipping teachers with the ability to critically engage with AI is particularly critical in ensuring that broader society develops a balanced, informed, and ethically grounded perspective on AI and its implications. Therefore, teacher training programs should consider designing and offering courses to foster AI literacy among teacher candidates.

While acquiring a genuine understanding of different aspects of AI is important for prospective teachers, it is equally essential to ensure that they also develop strong self-efficacy beliefs regarding their ability and capability to effectively use AI-based tools and applications in their lives as well as in educational settings. Self-efficacy beliefs significantly shape individuals' goal-setting practices and responses to challenges along with their persistence in the face of difficulties, which makes it a crucial factor in understanding human motivation and behavior (Bandura, 2000). Individuals' self-efficacy beliefs regarding information and communication technologies (ICT) such as computers have been frequently studied in the past in different contexts and the findings consistently indicated that persons with higher levels of ICT self-efficacy had greater acceptance and tendency to use ICT tools as well as lower anxiety when using these tools (Saadé & Kira, 2009; Teo, 2009; Wilfong, 2006). With the rapid penetration of AI technologies into educational settings, researchers have recently started investigating preservice and in-service teachers' self-efficacy beliefs pertaining to AI (Al Darayseh, 2023; Bergdahl & Sjöberg, 2025; Du *et al.*, 2024; Guan *et al.*, 2025; Hoya *et al.*, 2024). For example, in a study with science teachers in the UAE, Al Darayseh (2023) found that participants' perceived ease of use of AI and self-efficacy in AI had a positive effect on their attitudes toward AI-based tools that significantly influenced their behavioral intention to adopt and use these technologies in their own science teaching. The results of the present study showed that participants had a moderate level of AI self-efficacy, with a mean logit score of 55.62 ($SD = 7.21$) on a 0–100 scale (Table 3). This indicates that participants on average felt reasonably confident and capable in their ability to use AI-based tools and applications in both personal and educational contexts. Considering the growing proliferation of AI technologies in K-16 educational settings (Zafari *et al.*, 2022; Zawacki-Richter *et al.*, 2019), this finding points to a critical area of improvement for preservice STEM teachers in Türkiye. Teachers who lack strong self-efficacy in the context of AI may be less likely to explore, learn, and meaningfully integrate novel AI-based tools in their teaching practice (Hoya *et al.*, 2024; Sanusi *et al.*, 2024). Thus, it is necessary for teacher education programs to prioritize targeted evidence-based interventions and experiences specifically designed to enhance preservice STEM teachers' AI self-efficacy beliefs. Strengthening their AI self-efficacy is not merely beneficial, but also essential for preparing tomorrow's educators who can leverage the potentials of AI technologies to transform STEM learning in the rapidly evolving educational landscape.

Regarding the third research question, the results of the five-step hierarchical regression analysis showed that only the affective (i.e., interest in AI, attitudes toward AI) and behavioral (i.e., AI use frequency) variables were significant predictors of participants' AI self-efficacy levels, with interest in AI emerging as the strongest predictor ($\beta = 0.388$). The final model explained 36.5% of the variance in AI self-efficacy (Adjusted $R^2 = .365$, $F(7,172) = 12.422, p < .001$). Academic and demographic variables along with AI literacy did not emerge as significant predictors in the final model. It is noteworthy that being in the Computer Education and Educational Technology (CET) department (Major_CET) initially appeared as a significant predictor in Model 2 ($\beta = 0.225, p < .01$), but this effect diminished and became non-significant when psychological variables were added in the subsequent steps. Overall, the findings of the present study are partially aligned with previous research that has examined factors influencing AI self-efficacy among university students. For instance, in their study with a large sample of university students ($N = 1465$) from Germany, the U.K. and the U.S., Bewersdorff *et al.* (2025) found through a path analysis that AI literacy and interest in AI positively affected AI self-efficacy while the use of AI and positive attitudes predicted AI interest, which in turn mediated their effects on AI self-efficacy. This points to the central role of interest as a key psychological driver in the development of AI self-efficacy among university students. In another study with undergraduate students in the Philippines, Asio (2024) found that AI self-efficacy varied significantly among the sample according to some demographic (e.g., gender) and academic variables (e.g., year in the program). Hornberger *et al.* (2023) found that AI self-efficacy was significantly correlated with AI literacy, interest in AI, and attitude toward AI among German undergraduate students who were mostly from the engineering field. In a study with in-service teachers, Du *et al.* (2024) also found AI literacy had a direct influence on AI self-efficacy among participants. In a study with Austrian university students, most of whom were preservice teachers, Bećirović *et al.* (2025) found that a technical understanding of AI significantly predicted AI self-efficacy. Overall, the findings of the present study do not align with the findings of previous studies (Asio, 2024; Bećirović *et al.*, 2025; Bewersdorff *et al.*, 2025; Hornberger *et al.*, 2023; Du *et al.*, 2024) that AI literacy significantly influenced AI self-efficacy. However, the findings of the present study regarding the influence of affective (i.e., interest in AI, attitudes toward AI) and behavioral factors (i.e., the use of AI) are supported by the findings of similar studies in the literature (Bergdahl & Sjoberg, 2025; Bewersdorff *et al.*, 2025; Hornberger *et al.*, 2023; Viberg *et al.*, 2023). For instance, based on survey responses from 508 K–12 teachers across six countries, Viberg *et al.* (2023) reported a significant relationship between AI self-efficacy and attitudes toward AI. In another study with Swedish teachers, Bergdahl and Sjoberg (2025) found that teachers with more prior experiences with AI tools demonstrated greater AI self-efficacy.

Most related studies indicating that AI literacy directly influences AI self-efficacy investigated samples of in-service teachers or general university student populations, which often included technical fields such as engineering (e.g., Bewersdorff *et al.*, 2025; Hornberger *et al.*, 2023). In current teacher education programs in Türkiye, a dedicated coursework on either AI or pedagogy related to the infusion of AI into instruction is still in its infancy and this implies that Turkish preservice teachers in STEM areas are getting minimal or mostly no formal exposure to AI specifically in teaching and learning contexts. So, this may explain to some extent the moderate levels of AI literacy and self-efficacy found in the sample of this study. In contrast, in-service teachers may be provided with professional development opportunities related to the technical and pedagogical aspects of AI by the schools or school districts as AI tools became popular among students, and teachers are expected to develop strategies such as detecting and preventing AI-based cheating in assignments (Brandão *et al.*, 2024). As such, in the respective studies, AI literacy might have contributed to their AI self-efficacy beliefs to some extent. However, for preservice teachers, who get minimal or no exposure to AI in formal settings, as in the case of this study, their nascent AI literacy alone may not substantially influence their AI self-efficacy beliefs, while their interest and attitudes along with their personal informal experience of AI likely serve as the primary determinants of their AI self-efficacy. It is also important to acknowledge that social desirability bias might have led some participants to report higher degrees of interest in AI or positive attitudes toward AI taking into consideration AI's growing role in education. Additionally, prior exposure to AI applications might have also led them to overestimate their interest in or attitudes toward AI.

The findings of the present study have important policy and practice implications for teacher education regarding fostering AI self-efficacy among preservice teachers in STEM areas. This study found that interest in AI and attitudes toward AI along with the personal experience in using AI-based tools were significant predictors of AI self-efficacy among participants. This suggests that promoting positive attitudes and genuine interest in AI among teacher candidates is important for enhancing their AI self-efficacy beliefs. Therefore, teacher preparation programs should consider offering opportunities for preservice teachers to actively engage them in hands-on and meaningful experiences with AI-based tools and applications as part of their mandatory coursework. These experiences may stimulate their curiosity and interest and help them build positive attitudes about AI. Such targeted experiences are also likely to enhance AI self-efficacy more effectively than extensive theoretical instruction. Additionally, although AI literacy did not emerge as a direct significant predictor of AI self-efficacy among the participants in the final model of the regression analysis, it should not necessarily be interpreted as unimportant. As AI literacy has recently emerged as a key competency for everyone to function effectively in an increasingly AI-driven world (Ng *et al.*, 2021), tomorrow's educators should acquire a genuine understanding of how AI works and its limitations along with the ethical challenges it poses. Therefore, as an implication for policy, teacher education institutions should also consider designing innovative coursework to introduce the fundamental concepts of AI and meaningfully engage learners with AI, without emphasizing its technical complexities, to further AI literacy levels among preservice teachers.

8. Conclusion

In conclusion, this study provided important insights about the current state of AI literacy and self-efficacy among a sample of preservice STEM teachers in Türkiye. The findings showed that participants demonstrated moderate levels of foundational knowledge about AI. Additionally, the participants' perceived confidence and capability to effectively use AI tools in educational and non-educational contexts were largely shaped by their previous experiences with AI tools as well as their affective orientations toward AI (i.e., interest and attitudes). These findings highlighted the critical role of affective and experiential factors in shaping AI self-efficacy while demographic and academic background along with knowledge of AI-related concepts (i.e., AI literacy) did not significantly predict AI self-efficacy levels among the teacher candidates. The results point to the need for teacher education programs to not only promote constructing knowledge related to the basics of AI but also cultivate preservice teachers' positive interest, favorable attitudes, and meaningful engagement with current AI-based technologies through practical, hands-on experiences.

Given the rapid integration of AI tools in educational settings and professional workplaces worldwide, equipping future educators with both confidence and competence to employ these disruptive new technologies in their instruction is imperative. As such, the findings of this study have several implications for teacher education. Within teacher training method courses, program designers can prepare innovative coursework that aims to increase AI literacy and confidence progressively. For example, this coursework can begin with key concepts of AI and hands-on experiences where practical AI tools and applications are infused. Subsequently, preservice teachers can apply this knowledge by designing and implementing learning activities that include a variety of contemporary AI-based tools. Lastly, reflective assessments can be included for preservice teachers to critically evaluate their experiences with AI. By scaffolding learning this way, preservice teachers are provided opportunities to move from basic understanding of AI to stronger AI literacy and self-efficacy. Although the present study was limited to a non-random sample in only one higher education institution within a specific national context, its findings have broader implications for designing and implementing evidence-based interventions and professional development programs aimed at fostering AI readiness of teacher education programs globally. In future studies, researchers may consider working with larger and more representative samples to generalize findings to the target population and also employing mixed-methods designs to explore preservice teachers' personal experiences and unique perceptions in greater depth, which can yield richer contextual data and help further clarify how to best prepare prospective teachers for an increasingly AI-driven educational landscape.

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