Journal for STEM Education Research
https://doi.org/10.1007/s41979-024-00121-4

RESEARCH ARTICLE

Exploring Factors That Support Pre-service Teachers' Engagement in Learning Artificial Intelligence

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Accepted: 25 March 2024

Abstract
Artificial intelligence (AI) is becoming increasingly relevant, and students need to understand the concept. To design an effective AI program for schools, we need to find ways to expose students to AI knowledge, provide AI learning opportunities, and create engaging AI experiences. However, there is a lack of trained teachers who can facilitate students' AI learning, so we need to focus on developing the capacity of pre-service teachers to teach AI. Since engagement is known to enhance learning, it is necessary to explore how pre-service teachers engage in learning AI. This study aimed to investigate pre-service teachers' engagement with learning AI after a 4-week AI program at a university. Thirty-five participants took part in the study and reported their perception of engagement with learning AI on a 7-factor scale. The factors assessed in the survey included engagement (cognitive—critical thinking and creativity, behavioral, and social), attitude towards AI, anxiety towards AI, AI readiness, self-transcendent goals, and confidence in learning AI. We used a structural equation modeling approach to test the relationships in our hypothesized model using SmartPLS 4.0. The results of our study supported all our hypotheses, with attitude, anxiety, readiness, self-transcendent goals, and confidence being found to influence engagement. We discuss our findings and consider their implications for practice and policy.

Keywords Artificial intelligence · Pre-service teachers · Student engagement · Self-transcendent goals · School education

Introduction

Artificial intelligence (AI) is becoming increasingly relevant globally, integrated into various aspects of human life and sectors, including education (Long & Magerko, 2020). The growing importance of AI has led to a demand for its incorporation into school systems. While researchers, practitioners, and education policymakers

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have recognized the significance of teaching AI in K-12 systems (Ma et al., 2023, Touretzky et al., 2019), limited initiatives have been taken in the context of teacher education (Sanusi et al., 2022). Nevertheless, education stakeholders agree about the importance of AI education, as evidenced by the development of tools, curricula activities, and frameworks for effective implementation of AI as a subject or integrated throughout the curriculum (Casal-Otero et al., 2023; Mahipal et al., 2023; Sanusi, 2023). While these initiatives are crucial for promoting AI education in schools, focusing on teacher education is essential (Sanusi et al., 2023). Existing literature highlights a need for further work on teacher education programs for AI. Although there are a few initiatives for teacher education on AI, they are primarily conducted as professional development programs. However, to ensure the integration of AI within the K-12 system, future teachers must be prepared to facilitate AI, as it is now considered an essential skill for the future (Frimpong, 2022; Park et al., 2023).

As a new subject in schools and teacher education programs, learning AI requires new approaches to engage students with learning materials and activities. Engagement is crucial because studies have found a correlation between engagement and learning (Carroll et al., 2021; Fredricks et al., 2004; Poondej & Lerdpornkulrat, 2016). These studies suggest that more engaged students tend to have better learning outcomes. Bryson and Hand (2007) stated that engagement is key to student autonomy and improved learning overall. Given the importance of engagement, research has been conducted to understand how to increase students' engagement in learning. For example, Kim et al. (2015) explored the use of robotics to promote STEM engagement in pre-service teachers, while Volet et al. (2019) examined engagement in collaborative science learning among pre-service teacher students. Although research on pre-service teachers and engagement in STEM learning continues to grow, there is currently a limited research on student engagement in AI education. Xia et al. (2022) discussed student engagement from the perspective of self-determination theory, but no study has investigated the factors that influence pre-service teachers' engagement with AI. Therefore, this research aims to examine the factors that support students' engagement with AI in the context of teacher education. The framework used in this research combines the theory of planned behavior (Ajzen, 2020) with other constructs, including engagement. By exploring the factors that support pre-service teachers' engagement in learning AI, this study contributes to the limited literature on developing AI literacy within teacher education programs. The findings of this research will advance our knowledge of how to effectively engage students in learning AI.

To better understand the factors that impact student engagement with learning AI, we conducted an AI intervention for 35 pre-service teachers. We then collected their perspectives using a 7-factor scale, considering engagement (cognitive-critical thinking and creativity, behavioral, and social), intrinsic motivation, attitude towards AI, anxiety towards AI, AI readiness, self-transcendent goals, and confidence in learning AI. To analyze the participants' data, we utilized SmartPLS 4.0 to perform a variance-based structural equation modeling and evaluate our proposed model. This study is organized as follows: first, we outline the aim of the study; then, we review related research, discuss the theoretical framework, and develop hypotheses in the “Review of Related Work” section. The “Methodology” section provides a detailed explanation of the data collection method, participants, and analytical approaches. In the “Results” section, we present the findings of the data analysis, followed by a discussion of the implications of the study in the “Discussion” section. Finally, we conclude with a discussion of the study’s limitations and suggestions for future research.

Review of Related Work

In this section, we reviewed the related works and developed the study hypothesis. We specifically discussed the research that has explored pre-service teachers’ engagement within the STEM (science, technology, engineering, and mathematics) education context. We further explained the theoretical framework that inspired our research, highlighted why exploring engagement in learning AI is essential, and proposed a set of hypotheses based on Fig. 1.

Engagement in the STEM Teacher Education Program

Engagement in STEM teacher education programs is crucial for improving student outcomes in STEM subjects. Research has shown that active engagement in STEM

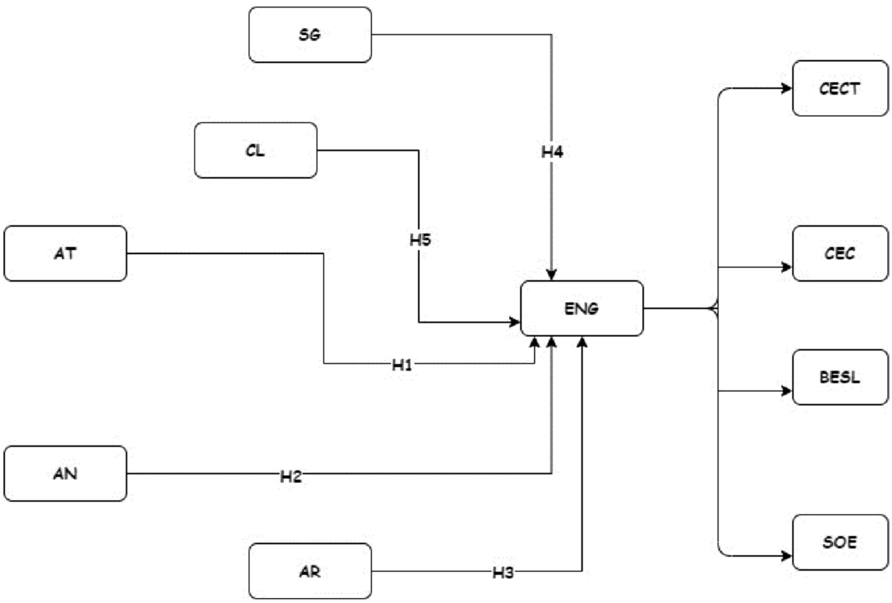

Fig. 1 Research conceptual framework. Note: *AT* attitude towards AI, *AN* anxiety towards AI, *AR* AI readiness, *SG* self-transcendent goals, *CL* confidence in learning AI, *ENG* student engagement in the AI program, *CECT* cognitive engagement—critical thinking, *CEC* cognitive engagement—creativity, *BESL* behavioral engagement—self-directed learning, *SOE* social engagement

education leads to higher-order thinking skills, increased motivation, and improved achievement in learning activities (Kamarrudin et al., 2023). Engagement in STEM learning has been recognized as beneficial for preparing students to address real-world problems (Dong et al., 2019; Kim et al., 2015). Challenges in implementing integrated STEM curricula in schools due to the lack of teachers' experience have also been reported in the literature (e.g., Hamad et al., 2022). Several studies (Aydeniz & Bilican, 2018; Dong et al., 2019) investigated the relationship among different variables and engagement. However, few empirical evidence exists on what predicts pre-service teachers' engagement in STEM education programs.

Furthermore, there is a paucity of research that focuses on the factors that influence pre-service teachers' engagement in learning AI. As AI is considered a STEM-related concept, this study aims to fill this gap by investigating the factors influencing pre-service teachers' engagement in learning AI. Understanding these factors will provide valuable insights into how to effectively prepare pre-service teachers to integrate AI into their teaching practices. This study will also contribute to developing strategies and interventions to enhance pre-service teachers' learning experiences in AI. In addition, findings from this study will have practical implications for teacher education programs and curriculum development. By identifying the specific factors such as attitude towards AI, anxiety towards AI, AI readiness, self-transcendent goals, and confidence in learning AI that influence pre-service teachers' engagement in learning AI, pre-service teachers can tailor their pedagogical approach to meet their students' needs and interests better. Ultimately, the goal is to equip pre-service teachers with the necessary knowledge and skills to integrate AI effectively into their classrooms, ensuring they are prepared adequately for the ever-evolving technological landscape of education.

Extensive research indicates the importance of engagement in learning (Fredricks et al., 2004; Tarantino et al., 2013). Student engagement has also been referred to as a crucial means of fostering and enhancing student learning (Renninger & Bachrach, 2015; Sanusi et al., 2023). Engagement is characterized by the behavioral intensity and emotional quality of a person's active involvement in a task (Sun et al., 2019). Without engagement, meaningful learning remains elusive (Kim et al., 2015) and cannot accurately determine the extent to which a person has grasped a concept. Within the context of teacher education, particularly in STEM-related programs, we have identified literature that emphasizes the significance of engagement in promoting increased learning (Lange et al., 2022; Ryu et al., 2019). Previous research (e.g., Grimble, 2019; McClure et al., 2017) suggests that pre-service teachers' engagement with learning materials fosters a deep mastery of the subject matter and effective pedagogical practices that can stimulate their students' interest in STEM.

Teacher education programs can equip pre-service teachers with the skills and knowledge necessary to cultivate STEM literacy in the next generation by immersing them in hands-on experiences, encouraging them to explore real-world applications, and supporting collaborative learning (Suryadi et al., 2023). In this way, pre-service teachers become more than just conveyors of information; they also foster curiosity, problem-solving, and innovation in their classrooms, cultivating a lifelong interest in STEM disciplines. Moreover, integrating STEM courses into teacher education programs helps pre-service teachers develop a growth mindset and adaptability (Griful-Freixenet et al., 2021; Jones et al., 2017; Rowston et al., 2020), both of which are necessary for navigating the ever-changing landscape of science and technology. Pre-service teachers' engagement and learning of STEM subjects in teacher education programs are vital for their future performance in the classroom (Berisha & Vula, 2021; Bosica et al., 2021). These programs should emphasize acquiring topic knowledge and developing teaching practices that encourage students' active participation. By implementing active participation in STEM education programs, pre-service teachers better understand STEM concepts and learn how to create dynamic and interactive learning environments (Billington, 2023; Yllana-Prieto et al., 2023). Exposure to various teaching methods (Bin Abdulrahman et al., 2021) and the integration of technology provide students with the necessary capabilities to meet the evolving needs of STEM education. Similarly, encouraging pre-service teachers' engagement in STEM courses goes beyond the transfer of knowledge (Huang et al., 2022; Manasia et al., 2020). It instills a passion for these disciplines, inspires them to develop a growth mindset, and cultivates lifelong learners.

Berisha and Vula (2021) stated that the engagement and learning of pre-service teachers in STEM subjects are crucial for their professional development and the success of their future students. Teacher education programs strive to equip pre-service teachers with the knowledge and skills to effectively teach STEM subjects to their future students (Yang & Ball, 2022). It is important to foster their curiosity and enhance their problem-solving abilities. By actively engaging in STEM learning during these programs, educators become well-prepared to inspire the future of innovation and scientific discovery, ensuring a brighter future for STEM education. Encouraging pre-service teachers' interest in and learning of STEM courses helps build their confidence and competence in making these subjects accessible and enjoyable for their future students. As pre-service teachers become more adept in using STEM teaching methods, they are better equipped to address the challenges and misconceptions that often discourage students from pursuing STEM careers (Akaygun & Aslan-Tutak, 2020; Çinar et al., 2016; Delello, 2014). Ultimately, the success of STEM teacher education programs hinges on their ability to instill a genuine passion for these subjects in pre-service teachers, while providing them with the knowledge and skills to inspire the next generation of problem-solvers, critical thinkers, and innovators.

Theoretical Background

This study is based on the theory of planned behavior (Ajzen, 2020) and incorporates other relevant constructs. In the field of AI education, this theory has primarily been used to examine the intentions of various stakeholders in terms of learning (Chai et al., 2020a, 2020b; Sing et al., 2022) or teaching AI (Ayanwale & Sanusi, 2023; Ayanwale et al., 2022). These constructs have previously been used as predictors of behavioral intention. However, we have not found any studies that specifically utilize these constructs as predictors of engagement in the context of AI education, particularly in teacher education programs. Nonetheless, we briefly mention some instances where the variables examined in this study are related to engagement in similar fields.

Attitude Towards AI

In STEM programs, attitudes towards AI education play a crucial role in determining pre-service teachers' readiness for the evolving educational landscape. A positive attitude towards AI encourages acceptance of its value as a tool to enhance STEM instruction (Papadakis et al., 2021), while negative attitudes can lead to resistance and limited adoption (Balakrishnan et al., 2021). Pre-service teachers must develop an open-minded attitude towards AI, enabling them to leverage its potential for personalized learning and innovative teaching. This will also ensure that AI becomes a valuable tool in their future STEM classrooms. The engagement of pre-service teachers in AI education is grounded in educational theories and pedagogical principles (Celik, 2023). Constructivist theories emphasize the significance of active engagement, collaboration, and hands-on experiences in learning (Kaufman, 1996). AI education for pre-service teachers aligns with these theories, advocating for immersive and experiential learning opportunities. Furthermore, the literature (Celik, 2023; Shelman, 1987; Yau et al., 2023) draws upon the principles of technological pedagogical content knowledge (TPACK), suggesting that effective AI education involves the integration of technological knowledge, pedagogical skills, and subject matter expertise. Theoretical perspectives often emphasize the importance of pre-service teachers developing a positive attitude (Opesemowo et al., 2022) and a deep understanding of AI concepts and their applications in educational settings. However, studies (Al Darayseh, 2023; Kelly et al., 2023; Zhang et al., 2023) have demonstrated that attitude is a critical factor that influences teachers' acceptance or rejection of the use of AI. Some individuals hold a positive attitude towards AI technologies and recognize their potential, even if they do not fully comprehend the essence of these technologies (Yadrovskaia et al., 2023). Kaya et al. (2024) observed that personality traits, AI anxiety, and demographics significantly shape attitudes towards AI. The use of AI in the STEM context is an ongoing topic of public discourse, and there is a need for reliable measures to assess pre-service teachers' attitudes towards AI in STEM programs.

Anxiety Towards AI

Anxiety towards AI refers to the fear of using computers or technophobia, which is a term used to describe fear or aversion towards technology in general (Li & Huang, 2020; Wang & Wang, 2022). Various perspectives on anxiety towards AI and pre-service teachers' education in STEM programs have been proposed. Some argue that anxiety towards AI stems from a lack of understanding and fear of the unknown (Hopcan et al., 2023; Zhan et al., 2023). They suggest that pre-service teachers can better understand and overcome their anxiety by receiving comprehensive education in AI technologies. Others believe that anxiety towards AI among pre-service teachers is justified because they feel threatened by AI advancements' potential job market implications. Anxiety towards AI education in STEM programs can hinder pre-service teachers' acceptance of technology-driven teaching techniques. This apprehension may stem from concerns about their technological skills or anxieties that AI may replace traditional instructional responsibilities. Pre-service instructors can build confidence in AI tools by addressing these concerns through training and assistance (Jones et al., 2017). It is crucial to foster an environment that encourages experimentation while highlighting the complementary role of AI in improving STEM education, reducing anxiety, and promoting its beneficial integration. Kaya et al. (2024) noted that anxiety about learning AI significantly predicted positive and negative attitudes towards AI. According to Terzi (2020) and Wang and Wang (2022), anxiety about learning AI is the fear of being unable to acquire specific knowledge and skills about AI. Several studies have been conducted on anxiety towards AI, but few or none has explored the engagement of pre-service teachers, as used in this study. The relationship between anxiety towards AI and pre-service teachers' engagement with AI in STEM education is a crucial aspect that requires exploration. Pre-service teachers who experience anxiety towards AI may be less likely to embrace AI tools in their teaching practices (Chocarro et al., 2023; Wang et al., 2021). Therefore, we propose that anxiety towards AI can inversely affect student engagement in the AI program.

AI Readiness

AI readiness refers to the preparedness of pre-service teachers, individuals, organizations, and countries to adopt and utilize AI technologies effectively. It can be seen as the eagerness to use AI technological innovations (Garg & Kumar, 2017). The AI readiness of pre-service teachers in STEM programs demonstrates their willingness to use AI as an instructional resource. AI readiness entails technical proficiency and a proactive attitude towards incorporating AI technologies into instruction. It necessitates knowledge of AI-driven systems and a dedication to remaining current on AI breakthroughs. Educators who are well-prepared for the AI-infused future can exploit AI's potential (Hsu et al., 2019) to improve STEM instruction, adapt to changing educational demands, and give students creative and individualized learning experiences. Several studies have explored AI readiness in different contexts. Xuan et al. (2023) conducted a survey to evaluate medical AI readiness among undergraduate medical students and found that most participants had moderate readiness. Palade and Carutasu (2021) emphasized the need for organizations to adopt AI technologies to keep up with innovation. They suggested that AI readiness adoption can be normalized under an existing model for digitization. Baguma et al. (2023) proposed an AI readiness index specifically tailored to the needs of African countries, highlighting dimensions such as vision, governance and ethics, digital capacity, and research and development. Taskiran (2023) reported that an AI course in the nursing curriculum positively affected students' readiness for medical AI. These studies highlight the importance of assessing and enhancing AI readiness in various domains and contexts. Still, a drought of studies focused on the AI readiness of pre-service teachers to engage with STEM programs.

Self-transcendent Goals

Self-transcendent goals involve looking beyond oneself and adopting a larger perspective, including concern for others (Ge & Yang, 2023). Self-transcendence is a multifaceted psychological phenomenon that includes acts of kindness, philanthropy, and community service as individuals strive to go beyond their individual needs and desires to make a positive impact on the lives of others. It has been shown that self-transcendence is linked to mental health and nursing (Haugan et al., 2013; Nygren et al., 2005), spirituality (Bovero et al., 2023; Suliman et al., 2022), and performance in learning and motivation (Reeves et al., 2021; Yeager et al., 2014), social activism (Barton & Hart, 2023) among other fields. The self-transcendent aspirations of pre-service teachers in STEM programs encompass their desire to go beyond personal accomplishments (Naftzger, 2018) and contribute more significantly to the welfare of society through STEM education. These objectives frequently include instilling a love of STEM in their pupils, promoting diversity and inclusivity, and addressing real-world issues through STEM education (Okundaye et al., 2022). Embracing self-transcendent aspirations inspires pre-service teachers to consistently enhance their STEM topic knowledge, pedagogical abilities, and empathy, driving them to become inspirational educators who inspire future generations to engage profoundly with STEM and promote positive social change. With self-transcendence, pre-service teachers are motivated to continuously adapt and evolve their teaching practices, seeking innovative ways to integrate AI tools and resources into their lessons. By embracing the new trend of teaching and learning AI, pre-service teachers are preparing their students for the future and actively shaping the future of education. To the best of our knowledge, few studies (Ge & Yang, 2023; Sanusi et al., 2024a, 2024b; Yeager et al., 2014) have been conducted to examine whether pre-service teachers with a self-transcendent goal for engaging AI are more motivated to learn AI.

Confidence in Learning AI

Pre-service teachers' confidence in learning AI is a significant component of their readiness to integrate AI into STEM education (Roy et al., 2022). Confidence here refers to their belief in their ability to effectively learn AI-related knowledge and skills (Lin et al., 2023). When pre-service teachers feel confident in their ability to master AI, they are more likely to participate in AI-related professional development, investigate AI applications in their teaching practices, and adapt to the changing educational landscape. Building this confidence through professional development training is critical for equipping pre-service teachers to use AI as a beneficial resource for improving STEM instruction and preparing students for an AI-driven future. This study attempts to validate existing research (Sanusi et al., 2024a, 2024b) by investigating whether confidence in learning AI influences student engagement in an AI program.

Engagement in AI Learning

Engagement sparks curiosity and motivates individuals to actively participate in and absorb new information. When learners are engaged, they are more likely to ask questions, seek additional resources, and apply the material to their own experiences. According to Martin (2012), motivation is the basis of engagement, so AI can be used as a tool to engage pre-service teachers in integrated STEM learning and teaching (Kim et al., 2015). Exploring engagement in AI learning is essential, as it establishes a relationship between engagement and learning. Since there are indications that students engaged in learning activities benefit from increased learning, it is imperative to explore this relationship. This investigation is crucial because AI learning is a new initiative, and strategies must be examined to effectively communicate the concepts to students and teachers. Based on the description by Fredricks et al. (2004), engagement is a multidimensional construct that encompasses behavior, emotion, and cognition. We will briefly describe each engagement type (in relation to AI learning) highlighted below.

Cognitive Engagement—Critical Thinking: Cognitive (Looking at the Focused Effort Students Give to What Is Being Taught)

Learning and mastering artificial intelligence (AI) require critical thinking (Benvenuti et al., 2023), particularly in cognitive engagement. The CE details how students process information (Schnitzler et al., 2021). AI requires deep cognitive engagement from learners because of its complex algorithms (Jaiswal & Arun, 2021), diverse applications, and ethical implications. Critical thinking in this context involves analyzing data sources for potential biases, evaluating the ethical implications of AI decisions, and challenging the assumptions that underpin AI decisions. Additionally, it requires learners to explore and evaluate different approaches and methods to solve real-world problems using AI techniques. Developing critical thinking skills with cognitive engagement helps individuals understand AI concepts and provides them with the tools to innovate effectively and navigate the rapidly changing AI landscape. In addition, cognitive engagement through critical thinking catalyzes innovation in the fast-expanding field of AI. Cognitive engagement and critical thinking are important aspects of pre-service teachers' engagement in STEM education. Research has shown that active engagement in STEM education leads to higher-order thinking skills, increased motivation, and improved learning outcomes (Kamarrudin et al., 2023). In STEM education, pre-service teachers employ cognitive engagement via critical thinking skills to successfully teach STEM and achieve meaningful learning experiences for their students (HacioĞLu, 2021). Recently, Yıldız-Feyzioğlu and Kıran (2022) showed that collaborative group investigation (CGI) learning and self-efficacy have also been found to positively impact the critical thinking skills of pre-service science teachers. Therefore, cognitive engagement and critical thinking play a crucial role in pre-service teachers' engagement in

STEM education, leading to improved learning outcomes and the development of effective instructional strategies.

Cognitive Engagement—Creativity

Cognitive engagement via creativity is a dynamic and necessary part of learning AI. While AI is founded on mathematical and computational concepts, encouraging creativity in AI education is crucial for several reasons (Lin et al., 2023). Creativity enables students to conceive unique AI applications, leading to novel healthcare, economics, and entertainment solutions. Cognitive engagement for pre-service teachers in STEM education involves their continuous intellectual involvement, the design of stimulating instructional strategies, effective use of technology, and the promotion of a growth mindset (Kim et al., 2015). These cognitive aspects contribute to a dynamic and enriching STEM learning experience, preparing students to think critically, adapt to new challenges, and thrive in a knowledge-based society. Patar (2023) reveals that active engagement activities, such as exploration, sharing knowledge, and assessment, can enhance pre-service teachers' cognitive engagement. Pre-service teachers should champion the integration of digital tools and resources to enhance the learning experience, providing students with opportunities to explore, experiment, and apply their cognitive skills in a technology-driven world. This integration also supports the development of digital literacy skills, which is essential for successful STEM disciplines. Whether cognitive engagement through creative thinking will significantly affect pre-service teachers in STEM education remains to be investigated.

Behavioral Engagement—Self-directed Learning: Behavioral (Measuring Attendance and Participation)

Behavior engagement refers to measuring academic performance and participation in educational activities (Bowden et al., 2021). It is critical to understand the discipline of AI, particularly in the context of self-directed learning (Nazari et al., 2021). Pre-service teachers must consider behavioral engagement as an important aspect of STEM education. When pre-service teachers actively engage students in hands-on activities, discussions, and problem-solving tasks, students are more likely to understand STEM concepts better. However, taking the initiative indicates a high level of behavioral engagement (Kim et al., 2015). STEM education differs from conventional teaching, which treats students as passive listeners. To implement STEM innovations in the classroom, teachers must design inquiry activities and learning contexts to engage students in authentic problem-solving (Dong et al., 2019). Kim et al. (2015) found that using technology (robotics) significantly impacted students' behavioral engagement. Thus, this study supports behavioral engagement in STEM education for pre-service teachers.

Social Engagement

Social interaction can be referred to as social interaction, which is an essential component of learning (Okita, 2012). It entails working with peers, experts, and AI communities to exchange ideas, share knowledge, and get diverse viewpoints, ultimately improving the learning experience and driving creativity. Social engagement for pre-service teachers in STEM education involves building positive relationships within the school community, integrating collaborative learning experiences, actively participating in professional networks, and instilling a sense of social responsibility in students. These social aspects contribute to a holistic STEM education experience, fostering a collaborative and purpose-driven approach that prepares students for success in both academic and real-world STEM contexts. Ishmuradova et al. (2023) reported that pre-service science teachers have shown high awareness of social responsibility in human welfare, safety, and a sustainable environment. However, their awareness related to practice and participation is relatively low. To our knowledge, there is apparently no study on social engagement among pre-service teachers in STEM education.

Research Hypotheses

H1: Attitude towards AI will significantly positively influence student engagement in the AI program.
H2: Anxiety towards AI will significantly negatively influence student engagement in the AI program.
H3: AI readiness will significantly positively influence student engagement in the AI program.
H4: Self-transcendent goals will significantly positively influence student engagement in the AI program.
H5: Confidence in learning AI will significantly positively influence student engagement in the AI program.

Methodology

Research Context and Participants

This study was conducted at a public university of education in Ghana, specifically focusing on the students enrolled in the Information Communication and Technology (ICT) Education program. It is important to note that the student teachers had not completed any courses in AI. As shown in Table 1, 35 pre-service teachers participated in our research, with a majority being male and aged between 19 and 25 years. Most of the participants (57.1%) were in their second year of the teacher training program. For this research, we utilized a simple random sampling approach. We extended an invitation to all the students in the ICT department to participate in

Table 1 Study subjects characteristics

Variable	Category	Frequency	Percentages
Gender	Female	7	20
	Male	28	80
Age	19–25 years	23	65.7
	26–35 years	12	34.3
Study level	Year 1	11	31.4
	Year 2	20	57.1
	Year 3	2	5.7
	Year 4	2	5.7

our study, and their involvement was based on informed consent. We also assured the participants of their anonymity and the ability to withdraw from the project at any time.

Data Collection Procedure

The data utilized for this study was gathered through an online survey shortly after a 4-week AI short course program organized between September and October 2022. The course was designed to expose pre-service teachers to AI knowledge and its ethical implications. The program is designed as an intervention of 2 h 30 min weekly, including assignments, and comprises four different learning sessions and five different topics. The topics include Introduction to AI and Ethical Dilemmas, Image Recognition, Algorithms and Bias, Convolution Neural Networks, k-Nearest Neighbor, and Decision Trees. We used different plugged and unplugged activities to demystify the topics to the study participants (Ma et al., 2023). We used AI tools like Google Teachable Machine (plugged activities) during the learning session, including a series of paper-based activities (unplugged) that support collaborative learning (Frimpong, Sanusi, Ayanwale, et al., n.d) After the sessions, the pre-service teachers filled out a survey to gather their perspectives about their learning.

Instrumentation

Our research instrument was adapted from different sources in the research literature (see "Appendix"). We modified some terms slightly to fit our research context. We adapted the items for engagement from the studies of Bowden et al. (2021), Reeve and Tseng (2011), and Sun et al. (2019). Confidence in learning AI scale was adapted from Xia et al. (2022). Finally, the scales for attitude towards AI, anxiety towards AI, AI readiness, and self-transcendent goals were derived from the study of Sanusi et al. (2023). A 6-point Likert scale ranging from "strongly disagree" to "strongly agree" was used to retrieve all the items' responses. We decided to use a 6-point Likert scale since it provides opportunities for more choice and may measure the participants' evaluation more accurately (Taherdoost, 2019).

Analytical Approach

In this study, we employed a variance-based structural equation modeling (VB-SEM) approach to assess our proposed model. This methodology allowed us to estimate both the measurement and structural models simultaneously. We chose VB-SEM over covariance-based structural equation modeling (CB-SEM) due to its suitability for our study's specific characteristics. These include dealing with small sample sizes, not having strict distribution requirements for the data, explaining variance, and managing a complex hierarchical component model. This complexity is evident in our study, which focuses on student engagement in the AI program (Benitez et al., 2020; Hair et al., 2014). To conduct our data analysis, we utilized SmartPLS software version 4.0.9.6 (Ringle et al., 2022). More so, various parameters were considered when estimating our model in partial least squares (PLS), including the use of the path weighting scheme as the estimation method, raw data for data metric, and default settings of the initial weight PLS-SEM algorithm (Hair et al., 2017). To validate our model, we employed the two-stage disjoint approach for higher-order constructs (Sarstedt et al., 2019) since the variable "engagement" is indeed a higher-order construct consisting of four lower-order constructs: cognitive engagement—critical thinking (CECT), cognitive engagement—creativity (CEC), behavioral engagement—self-directed learning (BESL), and social engagement (SOE).

In addition, our analysis process involved assessing the goodness of model fit for the measurement model, which was based on the saturated model, and for the structural model, which was based on the estimated model. We evaluated these models using various parameters, including the standardized residual mean square root (SRMR) and other fit indices like normed fit index (NFI), the distance of unweighted least squares (d_{ULS}), and the geodesic distance (d_G) to ensure adequate model fit (Benitez et al., 2020; Hair et al., 2017). In the evaluation of the measurement model, both first- and second-order constructs were examined for reliability and validity, looking at factors such as item factor loadings ($FL \geq 0.60$), construct reliability (i.e., Cronbach alpha and composite reliability indices—$CA \geq 0.70$; $CR \geq 0.70$), convergent validity (average variance extracted—$AVE \geq 0.5$), and discriminant validity (i.e., heterotrait-monotrait correlation—$HTMT < 0.85$ or $HTMT < 0.90$) (Ayanwale & Ndlovu, 2024; Hair et al., 2017, 2019, 2022; Henseler et al., 2015; Ringle et al., 2023; Sarstedt et al., 2019). Items with factor loadings below 0.60 and constructs with average variance extracted (AVE) below 0.50 were removed, and the models were subsequently refined. To test the hypotheses proposed in our study, we analyzed the relationships between constructs in the structural model using bootstrapping with 10,000 subsamples in PLS. We assessed the magnitude and statistical significance of direct effects to understand the relative importance of constructs in explaining others in the structural model (Amusa & Ayanwale, 2021; Hair et al., 2018; Hock et al., 2010; Ringle & Sarstedt, 2016). We also estimated the predictive power within the sample using the coefficient of determination (R^2), which should exceed 0.1 ($R^2 > 0.1$), and the predictive power outside the sample through the PLSpredict ($Q^2_{predict}$) obtained by comparing the RMSE (root mean square error) or MAE (mean absolute error) values of all the indicators in the PLS-SEM analysis to those of the LM (linear model) benchmark. When most of these indicators yield lower RMSE or MAE values than the LM benchmark, it demonstrates a moderate level of predictive power. On the other hand, if only a minority of the indicators exhibit lower prediction errors compared to the LM benchmark, the model's predictive capability is low. If none of the indicators shows lower prediction errors than the LM benchmark, the model lacks predictive power (Sanusi et al., 2023; Shmueli & Koppius, 2011; Shmueli et al., 2019).

Results

This section presents the results of the analysis. Thus, Table 2 evaluates the overall model fit for the measurement and structural models. This analysis indicates that the SRMR value falls below the recommended threshold (SRMR < 0.08), and the SRMR, NFI, d_{ULS}, and d_G values are all below the 95% quantile (HI95) of their reference distribution. These findings collectively suggest that the measurement model demonstrates an acceptable fit, and there is empirical evidence supporting the validity of the estimated model (Molefi & Ayanwale, 2023; Quintana & Maxwell, 1999).

In the measurement model, we conducted an evaluation of reliability and validity for both the lower-order constructs (LOC) and higher-order constructs (HOC). The results, as depicted in Table 3, indicate that the factor loadings for LOC range from 0.648 to 0.975, composite reliability (CR) values for LOC range from 0.826 to 0.980, Cronbach's alpha (α) values for LOC range from 0.783 to 0.962, and average variance extracted (AVE) values for LOC range from 0.541 to 0.923. Furthermore, the factor loadings for HOC range from 0.784 to 0.846, with a CR value for HOC of 0.888, a Cronbach's α value for HOC of 0.834, and an AVE value for HOC of 0.664.

Significantly, all these values surpass the recommended thresholds, signifying that the lower-order and higher-order constructs exhibit strong validity, reliability, and internal consistency. Additionally, we confirmed discriminant validity, as indicated in Table 4, demonstrating that each reflective construct shows more robust associations with its indicators than any other construct within the PLS path model. In other words, the constructs are distinguishable from one another, with correlation values well below the suggested threshold. This underscores the effectiveness of the measurement model in establishing good discriminant validity (Ayanwale & Oladele, 2021; Hair et al., 2022).

Table 2 Overall model fit statistics

	Saturated model		Estimated model		
Discrepancy	Value	HI95	Value	HI95	Remarks
SRMR	0.046	0.041	0.058	0.051	Supported
d_{ULS}	1.693	0.883	1.785	1.637	Supported
d_G	0.546	0.362	0.592	0.571	Supported
NFI	0.624	0.604	0.831	0.801	Supported

Table 3 Measurement model assessment for first- and higher-order constructs

Constructs	Manifested variable	Factor loadings	CA	CR	AVE
Attitude towards AI			0.835	0.890	0.674
	AT1	0.914			
	AT2	0.653			
	AT3	0.733			
	AT4	0.946			
Lower order constructs: Behavioral engagement—self-directed learning			0.832	0.890	0.672
	BESL1	0.859			
	BESL2	0.704			
	BESL3	0.948			
	BESL4	0.746			
Cognitive engagement—creativity			0.916	0.941	0.800
	CEC1	0.931			
	CEC2	0.923			
	CEC3	0.867			
	CEC4	0.854			
Cognitive engagement—critical thinking			0.906	0.934	0.781
	CECT1	0.849			
	CECT2	0.859			
	CECT3	0.886			
	CECT4	0.938			
Social engagement			0.783	0.852	0.541
	SOE1	0.764			
	SOE2	0.648			
	SOE3	0.826			
Confidence in learning AI			0.785	0.826	0.613
	CL1	0.794			
	CL2	0.809			
	CL3	0.745			
AI readiness			0.888	0.921	0.744
	AR3	0.863			
	AR4	0.882			
	AR5	0.828			
	AR6	0.875			
Anxiety towards AI			0.962	0.980	0.923
	AN1	0.939			
	AN2	0.975			
	AN3	0.954			
	AN4	0.974			
Self-transcendent goals			0.869	0.900	0.603
	SG1	0.650			
	SG2	0.866			

Table 3 (continued)

Constructs	Manifested variable	Factor loadings	CA	CR	AVE
	SG3	0.688			
	SG4	0.863			
	SG5	0.866			
	SG6	0.689			
Higher order construct: Student engagement in the AI program			0.834	0.888	0.664
	BESL	0.846			
	CEC	0.816			
	CECT	0.807			
	SOE	0.784			

Table 4 Discriminant validity—HTMT

Constructs	AN	AT	BESL	CEC	CECT	CL	AR	SG	SOE	ENG
AN										
AT	0.174									
BESL	0.479	0.628								
CEC	0.482	0.225	0.615							
CECT	0.527	0.434	0.670	0.820						
CL	0.156	0.231	0.635	0.271	0.170					
AR	0.186	0.121	0.346	0.429	0.401	0.242				
SG	0.242	0.047	0.608	0.222	0.381	0.220	0.178			
SOE	0.356	0.611	0.669	0.663	0.510	0.616	0.350	0.657		
ENG	0.577	0.530	-	-	-	0.550	0.406	0.362	-	

*HTMT < 0.85 or HTMT < 0.90, *ENG* student engagement in the AI program (HOC)

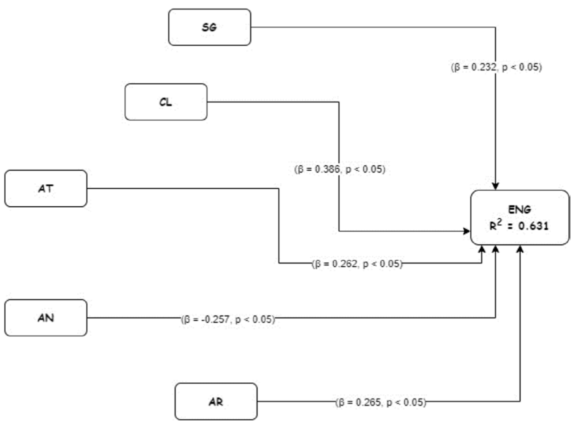

Fig. 2 Structural model result

The findings from the structural model are illustrated in Table 4 and Fig. 2. Following the results, attitude towards AI has a significant positive effect on student engagement in the AI program ($\beta = 0.262$, $t = 3.814$, $p < 0.05$), supporting H1. Anxiety towards AI is found to exert a negative influence on student engagement in the AI program ($\beta = -0.257$, $t = -3.438$, $p < 0.05$), validating H2. AI readiness positively influences student engagement in the AI program ($\beta = 0.265$, $t = 4.420$, $p < 0.05$), so H3 is supported. Self-transcendent goals positively impact student engagement in the AI program ($\beta = 0.232$, $t = 4.171$, $p < 0.05$), thus supporting H4. At the same time, confidence in learning AI is positively associated with student engagement in the AI program ($\beta = 0.386$, $t = 6.037$, $p < 0.05$), supporting H5. Attitude towards AI, anxiety towards AI, AI readiness, self-transcendent goals, and confidence in learning AI jointly explain 63.1% of the variance in student engagement in the AI program. Hence, the model's ability to explain variance within the sample is deemed adequate, as the coefficient of determination (R^2) values surpass the threshold of 0.10 (Ayanwale & Molefi, 2024; Falk & Miller, 1992; Molefi & Ayanwale, 2023).

In addition, the effect size (f^2) was calculated to assess how much removing each exogenous variable from the model influences the model's ability to explain variance. The f^2 values were interpreted according to Cohen (1988)'s guidelines, which classify effect sizes as small ($f^2 >= 0.02$), medium ($f^2 \geq 0.15$), or large ($f^2 \geq 0.35$). The effect sizes for the different exogenous variables, as shown in Table 5, revealed that AT ($f^2 = 0.292$) had a substantial effect size. This means that removing variable AT from the model would significantly reduce the model's ability to explain variance. Therefore, variable AT plays a crucial role in explaining variance in the model, and its inclusion is essential for an accurate model. Variable CL ($f^2 = 0.214$) also had a notable effect size, indicating its substantial contribution to the model's explanatory power. Its removal would significantly diminish the model's capacity to explain variance. Also, AR ($f^2 = 0.179$) had a moderate effect size. Removing variable AR would moderately decrease the model's ability to explain the variance, underlining its importance in the model, and AN ($f^2 = 0.042$) and SG ($f^2 = 0.031$) had relatively smaller effect sizes. While these variables contribute to the model's ability to explain the variance, their removal would have a minor impact on its overall performance. Prioritizing and retaining variables AT and CL are crucial to maintaining the model's accuracy and explanatory power. Although not as

Table 5 Summary of structural model assessment

Hypothesis	Relationships	β	t value	5%	95%	p values	f^2	Remarks
H1	AT—> ENG	0.262	3.814	0.140	0.418	0.001	0.292	Supported
H2	AN—> ENG	−0.257	−3.438	−0.170	0.191	0.031	0.042	Supported
H3	AR—> ENG	0.265	4.420	0.210	0.427	0.000	0.179	Supported
H4	SG—> ENG	0.232	4.171	0.196	0.531	0.000	0.031	Supported
H5	CL-> ENG	0.386	6.037	0.124	0.648	0.000	0.214	Supported
	Construct	R-squared						
	ENG	0.631						

Table 6 Summary of PLSpredict assessment of indicators

Indicator	$Q^2_{predict}$	PLS-SEM_RMSE	PLS-SEM_MAE	LM_RMSE	LM_MAE
BESL	0.315	0.720	0.428	0.743	0.468
CEC	0.360	0.548	0.324	0.616	0.345
CECT	0.406	0.512	0.375	0.603	0.404
SOE	0.505	0.488	0.328	0.558	0.373

influential as AT and CL, variable AR still plays a moderate role in explaining variance and should be retained in the analysis.

Furthermore, when examining the results of $Q^2_{predict}$ (see Table 6), we noticed that all the metrics associated with the endogenous construct (student engagement in the AI program) exhibited lower values for RMSE (root mean square error) and MAE (mean absolute error) in comparison to a simple linear model benchmark that was based on the means of the indicators from the training sample. These metrics yielded $Q^2_{predict}$ values that exceeded 0. This suggests that the indicators used in our PLS-SEM analysis produced fewer prediction errors when compared to the linear model benchmark, thereby indicating a strong predictive capability for our model.

Discussion

While previous research has explored constructs such as AT, CL, AR, AN, and SG and their links to behavioral intention in the context of AI and education (Ayanwale et al., 2022; Chai et al., 2021, 2020a, 2020b), this study contributes to the existing literature by investigating how these constructs affect pre-service teacher engagement with AI. The novelty of this research lies in its examination of the relationship between these constructs and the engagement of pre-service teachers, addressing a gap in literature. This paper adopts a holistic approach to measuring pre-service teacher engagement in AI programs, which includes four dimensions: cognitive engagement (critical thinking and creativity), behavioral engagement (self-directed learning), and social engagement. Additionally, composite-based structural equation modeling is employed to unravel the intricate interrelationships among student engagement with AI learning, attitude towards AI, anxiety towards AI, self-transcendent goals, AI readiness, and confidence in learning AI.

The findings affirm the validity of all proposed hypotheses (H1–H5) as antecedents to pre-service teachers' engagement with AI content. Collectively, these constructs account for 63.1% of the observed variance in teachers' engagement with AI. Among the predictor variables, confidence in learning AI emerges as the most influential predictor of pre-service teachers' engagement, followed by AI readiness, attitude towards AI, and self-transcendent goals. These findings resonate with the previous research (e.g., Ayanwale, 2023; Lin et al., 2023; Papadakis et al., 2021; Roy et al., 2022). Confidence in one's ability to learn AI and use technology has been a recurring theme in technology adoption literature. Bandura's theory (1977) underscores the significance of self-efficacy in adopting and effectively using new technologies. Thus, confidence in learning AI plays a pivotal role in driving engagement with AI activities. These findings align with Chen et al. (2018), which found that undergraduate students' confidence in their ability to grasp AI significantly predicted their intention to learn AI. Consistent with our findings, Sun et al. (2019) asserted that confidence, as one of the intrinsic motivation components, significantly predicts students' engagement in MOOC courses. When students perceive learning in MOOCs as enjoyable and are confident in their abilities, they are more motivated and engaged in their studies. Therefore, it is imperative to prioritize building confidence in pre-service teachers concerning their capacity to learn AI and to create supportive learning environments and practical training to enhance their engagement in AI programs.

As the second most influential variable, AI readiness has been identified as critical in enhancing student engagement in learning AI (Tang & Chen, 2018). While existing studies have primarily explored the relationship between AI readiness and intention (Ayanwale et al., 2022; Chai et al., 2020a, 2020b), this study delves into how individuals' preparedness and willingness to engage with and adapt to AI influence engagement with AI learning materials. It examines whether their comfort level with AI technology contributes to their active involvement in AI-related educational programs, including attendance, coursework engagement, and participation in AI-related projects (Dai et al., 2020; Hsu et al., 2019; Sun et al., 2019). The positive coefficient uncovered in our findings indicates that higher AI readiness positively correlates with increased engagement in learning AI. This suggests that pre-service teachers are more likely to engage in AI-related activities when they feel prepared and willing to embrace AI. Therefore, it emphasizes the importance of adequately preparing pre-service teachers to work with AI. AI readiness is critical in teacher training to enhance engagement and effectiveness in AI education.

In addition, previous research (Ayanwale et al., 2022; Kumar & Mantri, 2021; Weng et al., 2018) has consistently highlighted the significance of one's attitude in predicting the intention to learn AI. Our study also observes a substantial positive relationship between a positive attitude towards AI and pre-service teacher engagement with AI. This finding aligns with the work of Papadakis et al. (2021), emphasizing that a positive attitude towards AI promotes its acceptance as a valuable tool for enhancing STEM instruction and increasing engagement. It further corroborates the findings of Kim and Park (2019), who reported that individuals with more positive attitudes towards AI were more likely to plan the use of AI-based technologies. Ayanwale (2023) and Ng and Chu (2021) also underscore the importance of a positive attitude, as students with such an attitude were more inclined to learn AI. Our results indicate that pre-service teachers are more likely to actively participate in AI-related educational activities when they view AI more favorably. This underscores the critical role of instilling positive attitudes and perceptions about AI in teacher training programs, urging educators and institutions to prioritize this aspect to enhance engagement with AI-related content.

We also examine the impact of self-transcendent goals, encompassing objectives beyond personal well-being. Our results reveal a significant positive coefficient, indicating that having self-transcendent goals positively correlates with pre-service teacher engagement in learning AI. This outcome aligns with the findings of Naftzger (2018) and Okundaye et al. (2022), who found that pre-service teachers in STEM programs often harbor aspirations to make a broader societal impact, transcending personal accomplishments. In practical terms, their engagement increases when teachers are motivated by goals benefiting their students, including the society. Therefore, emphasizing self-transcendent goals in pre-service teachers may enhance their commitment to AI-related education and its potential impact on students.

In addition to previous studies that explore the relationship between anxiety and intention (Ayanwale et al., 2022; Chai et al., 2020a, b), our study delves into how self-perceived fear and discomfort concerning AI tools affect engagement in AI programs. The results support our hypothesis, showing a negative coefficient, indicating that anxiety towards AI is negatively associated with pre-service teacher engagement in learning AI. This finding resonates with the work of Katsarou (2021) and Kin (2020), which also found a significant negative relationship between anxiety and intention regarding AI. Jones et al. (2017) also note that apprehension might arise from concerns about technological skills or fears that AI might replace traditional instructional roles. To address this anxiety, pre-service instructors can build confidence in AI tools through training and support. Creating an environment that encourages experimentation and emphasizes AI's complementary role in improving STEM education is crucial. Reducing anxiety and promoting AI's beneficial integration is essential for encouraging engagement. While some scholars find anxiety less predictive of behavioral intention, our study suggests that anxiety towards AI significantly impacts pre-service teacher engagement with learning AI. This insight underscores the importance of recognizing and addressing AI-related anxiety among pre-service teachers. It highlights the need for strategies to reduce anxiety and enhance comfort with AI to promote engagement in AI education programs. Notably, while our study specifically targets pre-service teachers, we recognize the importance of exploring how these findings could be replicated across various academic disciplines. By discussing the relevance of our results to broader educational contexts, we provide insights into potential variations that might arise in different settings. This discussion facilitates a more comprehensive understanding of the generalizability and applicability of our findings.

Implication for Practice and Policy

Understanding the factors influencing pre-service teachers' engagement with AI has significant implications for both educational practices and policy development. Based on this study's findings, we recommend that educational institutions and policymakers prioritize integrating AI-related content within pre-service teacher education programs. This integration will facilitate the development of essential AI literacy and skills, equipping teachers to incorporate AI technologies into their teaching methods effectively. To ensure a well-rounded and practical approach, schools should offer opportunities for teachers to engage in ongoing professional development focused on AI. Additionally, we emphasize the importance of exposing pre-service teachers to various AI-powered teaching tools and methodologies. This exposure will empower them to create more engaging and personalized learning experiences for their students. Consequently, policies should encourage the adoption of AI tools that can cater to the unique needs of each student, fostering more inclusive and accommodating learning environments.

Furthermore, pre-service teachers must comprehend the ethical implications associated with AI technologies. They should be well-prepared to guide their students in the responsible utilization of AI. Policymakers can contribute by allocating school resources to acquire AI technologies and providing teachers with the necessary tools and training. This includes investments in AI software, hardware, and technical support to ensure teachers can effectively integrate AI into their classrooms. Robust policies should be established to safeguard student data when employing AI tools. Pre-service teachers should be well-versed in data privacy and security measures and adhere to regulations when incorporating AI technologies into their teaching practices.

Promoting cross-disciplinary learning that incorporates AI concepts is also crucial. Pre-service teachers should be primed to teach AI not only as a standalone subject but also as a complementary tool in various disciplines. Policies can foster collaboration among pre-service teachers, experienced educators, and AI experts. Such interactions can yield valuable insights and drive innovation in AI education. Encouraging pre-service teachers to engage in action research to assess the impact of AI on student learning and their teaching practices can be pivotal. This research can inform best practices and contribute to a growing knowledge of AI in education. On the policy front, both policymakers and educators should strive to ensure that AI resources and training are accessible to all, regardless of a student's socioeconomic background or geographical location. This may entail initiatives aimed at bridging the digital divide and promoting equitable access to AI education. The policy framework should also account for ongoing support and professional development for teachers as AI technologies evolve. Teachers must possess the skills to adapt to changes and stay current with developments in AI in education. Also, our study offers practical recommendations for practitioners. Emphasizing the critical role of building confidence in pre-service teachers, enhancing AI readiness in teacher training, fostering positive attitudes towards AI, and incorporating self-transcendent goals, we provide actionable steps for educators and institutions. These recommendations offer a roadmap for creating supportive learning environments and practical training to enhance pre-service teacher engagement in AI programs.

Limitation and Future Work

Some limitations should be noted despite the valuable results this study generates. First, the selection of study participants is restricted to the ICT education department at a university in Ghana. Hence, it is necessary to consider subjects across different disciplines within the teacher education program as well as other regions to understand students' engagement from a broader perspective. Second, our sample size may limit the generalizability of our results. Future research should consider a relatively large sample size across different contexts. Third, using only a quantitative approach limits the insight we may generate from students' explanations during the learning process. To this end, a qualitative or mixed-method approach should be considered for triangulation purposes. Lastly, the AI program in this study spans over a few weeks. Future research should investigate student engagement across an academic session and a longitudinal study of the candidates.

Appendix

AI Readiness

Applications and services that use the latest AI technologies are much more convenient to use.

I prefer to use the most advanced AI technologies.

I am confident that AI technologies will follow my instructions.

I can use different software to support AI learning.

I can use appropriate hardware to support AI learning.

I have access to relevant content on AI.

Confidence in Learning AI

I am confident that I can succeed if I work hard enough in learning AI.

I am certain that I can learn the basic concepts of AI.

I am certain that I can understand the most difficult AI resources.

I am certain that I can design AI applications.

AI Anxiety

Learning to understand all of the special functions associated with an AI technique/product makes me anxious.

Learning to use AI techniques/product makes me anxious.

Learning how an AI techniques/product works makes me anxious.

Learning to interact with an AI technique/product makes me anxious.

Attitude Towards AI

I look forward to using AI in my daily life.

I would like to use AI in my learning.

It is important that my future students learn AI.

It is important that my future students acquire the necessary abilities to take advantage of AI.

Self-Transcendent Goals

I wish to use my AI knowledge to serve others.

I wish I use AI to help people with physical and mental difficulties.
I wish I could design AI applications that can benefit people.
I am ready to learn design thinking to enhance my ability to use AI for helping others.
I want to learn AI knowledge to help me to have a positive impact on the world.
I want to master AI technologies to become a citizen who contributes to society.

Cognitive Engagement—Critical Thinking

In this AI course, I use different possible ways to complete the task.
In this AI course, I think the good and bad of different methods.
In this AI course, I provide different reasons and evidence for my opinions.
In this AI course, I consider different opinions to see which one makes more sense.

Cognitive Engagement—Creativity

In this AI course, I generate many new ideas.
In this AI course, I create different solutions for a problem.
In this AI course, I suggest new ways of doing things.
In this AI course, I produce ideas that are likely to be useful.

Behavioral Engagement—Self-Directed Learning

In this AI course, I explore the online resources on my own.
In this AI course, I set goals to complete this AI class.
In this AI course, I think about different ways or methods I can use to improve my learning.
In this AI course, I adjust my learning method based on my learning progression.

Social Engagement

In this AI course, my colleagues and I actively work together to learn new things.
In this AI course, my colleagues and I actively discuss different views we have about things we are learning.
In this AI course, my colleagues and I actively work together to complete tasks.
In this AI course, my colleagues and I actively share and explain our understanding.
In this AI course, my colleagues and I develop complex ideas.

Funding Open access funding provided by University of Johannesburg.

Declarations

Conflict of Interest The authors declare no competing interests.

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