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Exploring the mediating roles of self-control, management, and meaningful learning self-awareness in the relationship between academic self-discipline and GAI acceptance

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Abstract

This study investigated the relationships between academic self-discipline, self-control and management, meaningful learning self-awareness, and generative artificial intelligence (GAI) acceptance among 597 teacher candidates at nine Turkish universities. A serial mediation model was proposed, hypothesizing that academic self-discipline influences GAI acceptance indirectly through self-control and management and meaningful learning self-awareness. Data were collected using four established scales. Structural equation modeling, employing robust maximum likelihood estimation due to non-normality of the data, revealed an excellent fit between the hypothesized model and the data. Results supported the serial mediation model: academic self-discipline positively predicted self-control and management, which in turn positively predicted meaningful learning self-awareness, which subsequently positively predicted GAI acceptance. The findings highlight the important roles of self-control, management and meaningful learning in shaping teacher candidates' acceptance of GAI. Implications for teacher education programs and future research are discussed.

Keywords Generative artificial intelligence · AI acceptance · Self-control · Self-management · Meaningful learning · Self-awareness

1 Introduction

The rapid advancement and increasing accessibility of generative artificial intelligence (GAI) are transforming numerous sectors, including education (Kasneci et al., 2023). As GAI tools become increasingly sophisticated, their potential to reshape

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teaching and learning practices is undeniable (Li et al., 2023). Understanding the factors that influence the acceptance and adoption of these technologies by future educators is therefore crucial (Venkatesh et al., 2012). This study explores the role of individual characteristics, specifically academic self-discipline, self-control and management, and meaningful learning self-awareness, in shaping teacher candidates' acceptance of GAI. We posit that the relationship between academic self-discipline and GAI acceptance is not direct but rather mediated by these crucial intervening factors. Specifically, we propose a serial mediation model where academic self-discipline influences GAI acceptance indirectly through self-control and management, and subsequently, meaningful learning self-awareness. The serial mediation model was chosen to elucidate the specific pathways through which academic self-discipline influences GAI acceptance, revealing the sequential roles of self-control/management and meaningful learning self-awareness in this process. This study investigates these relationships among a sample of teacher candidates from nine Turkish universities, contributing to the growing body of knowledge on the psychosocial factors influencing GAI acceptance in the educational context. By illuminating these relationships, this research aims to inform strategies for fostering positive attitudes towards and effective integration of GAI in teacher education programs.

The rapid evolution and proliferation of GAI in education necessitate a deeper understanding of the psychosocial factors influencing its acceptance by future educators. This study addresses a critical gap in the literature by examining the role of academic self-discipline, self-control and management, and meaningful learning self-awareness in shaping teacher candidates' acceptance of GAI. While existing research establishes the importance of academic self-discipline for student success, linking it to behaviors like persistence and effort regulation (Duckworth & Gross, 2014; Duckworth & Seligman, 2005; Trautwein et al., 2009), its connection to technology acceptance remains unexplored, particularly in the context of rapidly evolving tools like GAI. Furthermore, the literature highlights the crucial role of self-management, encompassing self-monitoring, self-evaluation, and self-reinforcement (Bandura, 1991; Kanfer, 1970; Mezo & Short, 2012), in achieving behavioral change. This study proposes that these self-management skills, cultivated through academic self-discipline, are essential for navigating the complexities of GAI integration. Finally, given the emphasis on meaningful learning as an active process of connecting new information to existing knowledge (Ausubel, 2000; Koh, 2017), this research investigates how a teacher candidate's self-awareness of their own learning processes influences their willingness to embrace GAI as a tool for enhancing teaching and learning. By exploring these interconnected constructs through a serial mediation model, this study seeks to inform the development of effective strategies for fostering positive attitudes towards and successful integration of GAI in teacher education, ultimately contributing to the broader discourse on technology acceptance in education as outlined by Venkatesh et al. (2012).

Based on the theoretical framework and previous research, the following hypotheses were proposed:

H1: Academic self-discipline positively predicts self-control and management. Higher levels of academic self-discipline will be positively associated with greater self-control and management skills. Specifically, individuals with stronger academic self-discipline are expected to demonstrate increased proficiency in self-monitoring, self-evaluation, and self-reinforcement behaviors related to their academic pursuits. This hypothesis is grounded in self-regulation theory (e.g., Bandura, 1991; Kanfer, 1970) and the concept of academic self-discipline as a manifestation of broader self-control capacities. Self-regulation theory posits that individuals with higher self-discipline are more adept at setting goals, monitoring their progress, evaluating their performance, and adjusting their behavior accordingly (Zimmerman, 2000). Academic self-discipline, which involves regulating one's learning behaviors and resisting distractions, can be considered a specific application of these broader self-regulatory skills. Thus, individuals with stronger academic self-discipline are expected to exhibit greater proficiency in the core components of self-control and management: self-monitoring, self-evaluation, and self-reinforcement, as they apply these skills to their academic endeavors.

H2: Self-control and management positively predicts meaningful learning self-awareness. Individuals with stronger self-control and management skills will demonstrate a greater awareness of their meaningful learning processes. Specifically, those proficient in self-monitoring, self-evaluation, and self-reinforcement will be more adept at recognizing when they are engaging in deep, conceptually connected learning as opposed to rote memorization. They will also be more aware of their own learning strategies, strengths, and weaknesses. This hypothesis draws upon the principles of metacognition and self-regulated learning (SRL) (Flavell, 1979; Zimmerman, 2000). Metacognition, the awareness and understanding of one's own cognitive processes, is a crucial component of SRL. Self-control and management skills, particularly self-monitoring and self-evaluation, are essential for developing metacognitive awareness. By monitoring their learning behaviors and evaluating their understanding, individuals gain insights into the effectiveness of their learning strategies and their level of conceptual understanding. This heightened awareness allows them to distinguish between meaningful learning, where new information is integrated with existing knowledge structures, and superficial learning or rote memorization. Therefore, individuals with stronger self-control and management skills are expected to exhibit greater meaningful learning self-awareness, as they can effectively monitor, evaluate, and regulate their learning processes to achieve deeper understanding.

H3: Meaningful learning self-awareness positively predicts generative artificial intelligence acceptance. Individuals with higher levels of meaningful learning self-awareness will demonstrate greater acceptance of generative artificial intelligence (GAI) in education. Specifically, they are expected to perceive GAI tools as valuable resources that can support and enhance their meaningful learning processes, rather than viewing them as threats or distractions. This hypothesis is based on the intersection of self-determination theory (SDT) (Deci & Ryan, 2000) and the concept of meaningful learning. SDT posits that individuals are more likely to accept and internalize new behaviors and technologies when they perceive those things as supporting their basic psychological needs for autonomy, competence, and relatedness. Individuals with high meaningful learning self-awareness are likely to recognize how GAI tools can foster autonomy by providing personalized learning experiences, enhance competence by offering tailored feedback and support, and promote relatedness by facilitating collaborative learning opportunities. By aligning with their inherent drive for meaningful learning, GAI tools are more likely to be perceived as valuable assets rather than impediments. Therefore, greater meaningful learning self-awareness is expected to predict higher GAI acceptance, as individuals recognize the potential of these tools to enhance their learning experiences and satisfy their basic psychological needs.

This study holds several important implications for the field of education. First, it contributes to a deeper understanding of the factors influencing teacher candidates' acceptance of GAI, a technology with the potential to significantly impact teaching and learning (Cooper, 2023; Fergus et al., 2023; Kasneci et al., 2023). By identifying the mediating roles of self-control and management, and meaningful learning self-awareness, the study provides valuable insights into the psychological processes underlying GAI acceptance. This knowledge can inform the design of effective interventions and professional development programs aimed at fostering positive attitudes and promoting the skillful integration of GAI in educational settings. Second, the focus on teacher candidates makes this study particularly relevant. As future educators, their acceptance and effective use of GAI are crucial for harnessing the technology's potential to enhance student learning outcomes. By exploring these relationships early in their professional development, this study can contribute to shaping future pedagogical approaches that leverage GAI effectively and responsibly. Finally, the study's context within Turkish universities provides valuable cross-cultural insights into GAI acceptance, contributing to a more nuanced and global understanding of this emerging phenomenon. The findings can inform policy decisions and educational initiatives related to GAI adoption in diverse cultural contexts, promoting a more equitable and inclusive approach to technological integration in education.

Understanding the factors influencing teacher candidates' acceptance of GAI holds significant implications for shaping future pedagogical strategies. Teacher candidates who embrace GAI are more likely to explore its potential for personalized learning, automated feedback, and content creation, leading to innovative teaching practices. Conversely, resistance or apprehension towards GAI may hinder the integration of these powerful tools into classrooms, potentially limiting students' exposure to cutting-edge learning experiences. By examining the precursors to GAI acceptance, this study aims to inform the development of targeted interventions and training programs that empower future educators to effectively and ethically leverage GAI, ultimately maximizing its potential to enhance student learning and transform educational landscapes.

This study makes several original contributions to the burgeoning field of AI in education. First, it directly addresses the nascent area of generative AI acceptance specifically, moving beyond general technology acceptance models like UTAUT and providing empirical evidence regarding teacher candidates' attitudes towards this rapidly evolving technology. Second, it investigates a novel serial mediation model, revealing the complex psychological mechanisms underlying GAI acceptance. The study demonstrates that academic self-discipline influences GAI acceptance indirectly through self-control and management, which in turn influences meaningful learning self-awareness. This nuanced approach highlights the importance of self-regulatory skills and metacognitive awareness in shaping technology adoption, a perspective largely unexplored in prior GAI research. Third, by focusing on teacher candidates in Turkish universities, the study offers a valuable cross-cultural perspective on GAI acceptance, contributing to a more global understanding of this phenomenon and expanding the limited existing research beyond predominantly Western contexts. Finally, the study's focus on the interplay between self-discipline, self-management, meaningful learning, and GAI acceptance provides a novel theoretical framework for understanding how individual characteristics interact to influence the adoption of emerging educational technologies.

Literature review.

Academic self-discipline is crucial for student success, enabling them to prioritize long-term goals over the immediate gratification of impulsive behaviors (Duckworth & Gross, 2014). This ability to regulate attention, thoughts, and behaviors, previously explored through the concept of "delay of gratification" (Mischel, 1974), is key for academic performance and personal development (Shoda et al., 1990). Self-disciplined students demonstrate specific behaviors like attentive listening, prioritizing homework, and persistence despite boredom or frustration (Duckworth & Seligman, 2005), reflecting a preference for goal-directed actions requiring effort and patience (Trautwein et al., 2009). This contrasts with those exhibiting lower self-discipline, who may prioritize short-term pleasures over personal growth. While earlier research equated self-discipline with delay of gratification (Funder, Block, & Block, 1983), more recent studies acknowledge broader components like concentration and impulse inhibition (Taylor et al., 2002), which contribute to the effort and persistence vital for academic success (Hagger & Hamilton, 2019). This capacity for self-control has been consistently linked to higher grades and achievement test scores (Zhao & Kuo, 2015), distinguishing high-achieving students from their peers (Duckworth & Seligman, 2005). The lack of self-discipline, conversely, has been associated with various negative outcomes, including antisocial behaviors and lower academic engagement (Duckworth & Seligman, 2005; Malouf et al., 2014).

Self-control, initially a concept from clinical psychology (Cautela, 1969 as cited in Neck & Houghton, 2006), evolved into the management science concept of self-management, where employees control their own involvement within an organization (Manz & Sims, 1980). Self-management involves strategies individuals use to manage behaviors and align them with external standards. Kanfer (1970) and Bandura (1991) proposed a three-component model of self-control and self-management: self-monitoring (SM), self-evaluating (SE), and self-reinforcing (SR). In SM, individuals monitor targeted behaviors; in SE, they compare these behaviors against internalized standards; and in SR, they administer self-rewards or self-punishments based on this evaluation (Mezo, 2009; Mezo & Short, 2012). This process forms a feedback loop that influences future behavior, as seen in the example of a shy woman gradually improving her social interactions through repeated cycles of SM, SE, and SR. Self-management also intersects with self-leadership in industrial/organizational psychology, self-control in health psychology, and mindfulness in clinical psychology, although the focus here is on the industrial/organizational context, emphasizing the idea that individuals must lead themselves before leading others (Houghton et al., 2003; Manz, 1992). While self-management utilizes behavioral and cognitive strategies and relies on external controls and rewards, self-leadership goes further by emphasizing intrinsic task value and natural rewards (Manz, 1986; Neck & Houghton, 2006). This distinction is important because self-management, as described by Neck and Houghton (2006), involves choosing less attractive options to maintain low-probability behavior without external support (Kanfer, 1970).

Meaningful learning is an active process where learners connect new information to existing knowledge structures. As Koh (2017) explains, it involves "the active participation of students in experiences that are cognitively engaging." This process of linking new information to prior knowledge, as described by Perlman et al. (2010), facilitates deeper understanding and retention. Ausubel (2000) pioneered this concept, emphasizing the acquisition of new meanings from presented material and highlighting the importance of a pre-existing organized cognitive structure. This structure allows learners to "associate the relationship of new material with the cognitive structure that is already owned by them." Meaningful learning is contrasted with rote memorization, where information is learned without connection to existing concepts (Ausubel, 2000). The benefits of meaningful learning extend to improved assessment performance (Huang & Chiu, 2015) and enhanced engagement in problem-based learning activities (Hakkarainen, 2011). Ultimately, meaningful learning empowers learners to transfer knowledge and apply it to real-world problems (Mayer, 2002). This involves a process of inquiry, analysis, comparison, self-control, and application, culminating in the ability to explain and use new knowledge in one's own words (Cakıcı et al., 2006).

GAI is rapidly gaining acceptance due to its potential to revolutionize various fields, particularly education. Its ability to create new data and content, ranging from text and images to music and videos, makes it a powerful tool (Harshvardhan et al., 2020). This capacity stems from generative AI's design, which allows pre-trained models to leverage input data to produce novel and authentic outputs, including natural language and imagery. In education, generative AI promises to personalize learning and feedback, create intelligent tutoring systems (Li et al., 2023), develop engaging content (Cooper, 2023), automate assessment (Fergus et al., 2023; Lo, 2023), and enhance knowledge and skill development (Kasneci et al., 2023).

GAI is rapidly transforming education, presenting both exciting applications and significant challenges. Several studies highlight the potential of GAI to personalize learning and improve student outcomes. For example, GAI can provide personalized feedback and support to students in various subjects, from writing (Golding et al., 2024) and translation (Zhang et al., 2025) to programming (Gong et al., 2024) and mathematics (Song et al., 2025). GAI-powered chatbots can act as virtual tutors, providing instant feedback and scaffolding for learning (Chien et al., 2024; Kim et al., 2025). This individualized support can be particularly beneficial for students with diverse learning needs and disabilities (Pierrès et al., 2025), promoting inclusivity in education. GAI can also assist teachers in creating engaging learning materials, such as generating read-aloud question prompts (Yang et al., 2025), designing lesson plans (Lee et al., 2025), and developing interactive simulations (Borge et al., 2024). This can free up teachers' time and allow them to focus on other important aspects of teaching, such as fostering critical thinking and creativity.

However, the rapid development of GAI also brings forth numerous challenges. One major concern is academic integrity (Golding et al., 2024; Stone, 2024). The ease with which students can use GAI to generate essays and other assignments raises concerns about plagiarism and cheating. This necessitates a rethinking of assessment practices and the development of AI literacy among both students and teachers (O'Dea, 2024; Szabó & Szoke, 2024). Another challenge is the potential for over-reliance on GAI, which could hinder the development of students' critical thinking and problem-solving skills (Alzubi et al., 2025; Lindell & Modén, 2025). As students become more dependent on GAI for answers and feedback, they may lose the ability to think independently and critically evaluate information. Furthermore, there are concerns about the potential biases embedded in GAI models, which could perpetuate existing inequalities in education (Godwin-Jones, 2024). Ensuring fairness and equity in the use of GAI is therefore crucial. Finally, the rapid pace of GAI development has created a sense of uncertainty and ambiguity among educators and students alike (Stone, 2024). Many are struggling to keep up with the latest advancements and understand the implications of GAI for teaching and learning. This calls for ongoing research, professional development, and policy discussions to navigate the evolving landscape of GAI in education. Addressing the ethical implications of GAI use, as discussed by Higgs and Stornaiuolo (2024), is also vital for ensuring responsible implementation. Furthermore, considering the potential "Luddite" backlash against AI in education, as explored by Nichols et al. (2025), is essential for fostering a balanced and productive dialogue about the role of GAI in the future of learning.

Student acceptance of this technology is crucial for its successful integration, and the Unified Theory of Acceptance and Use of Technology (UTAUT) model provides a framework for understanding the factors influencing this acceptance (Venkatesh et al., 2012). UTAUT explains technology adoption through four key factors: performance expectancy (belief in the technology's benefits), effort expectancy (perceived ease of use), social influence (pressure from others), and facilitating conditions (available resources and support). Performance expectancy, effort expectancy, and social influence directly impact a person's intention to use a technology. This intention, combined with facilitating conditions, then determines actual technology use. Furthermore, individual characteristics like age, gender, and experience can moderate the relationships between these factors and technology adoption, meaning the impact of each factor might vary based on these individual differences.

The previous research, while not directly measuring the relationship between academic self-discipline and GAI acceptance, offers a strong foundation for inferring a complex and nuanced connection. Students demonstrating high academic self-discipline are typically more strategic and discerning in their approach to learning and, consequently, in their use of technology. They are more likely to evaluate GAI tools, based on their genuine potential to enhance learning and productivity, rather than viewing them as shortcuts to circumvent effort (Krumsvik, 2024; Merzifonluoglu & Gunes, 2025). This aligns directly with findings that perceived usefulness and perceived learning performance are significant predictors of GAI adoption (Saihi et al., 2024). Specifically, self-disciplined students are hypothesized to exhibit several key behaviors: critical evaluation of GAI output, recognizing its limitations and potential for inaccuracies (Elmas et al., 2024); maintaining control over their learning process, using GAI as a support mechanism rather than a replacement for their own cognitive efforts, consistent with research showing pre-service teachers adapting GAI suggestions to their preferences (Merzifonluoglu & Gunes, 2025); and a focus on long-term learning, prioritizing genuine understanding over immediate results, and being mindful of the ethical considerations surrounding AI use in academia (Krumsvik, 2024).

Conversely, a lack of academic self-discipline could reasonably lead to uncritical acceptance and over-reliance on GAI. Students who struggle with self-regulation and consistent effort might be more susceptible to using GAI as a crutch, bypassing the essential processes of learning and critical thinking, potentially leading to superficial understanding or even academic dishonesty. They might also be less discerning, accepting GAI-generated responses without critically evaluating their validity or accuracy, a concern highlighted by research demonstrating inaccuracies in GAI responses to scientific questions (Elmas et al., 2024).

Method.

1.1 Design

This study employed a correlational, ex post facto design. Given the nature of the variables under investigation (academic self-discipline, self-control and management, meaningful learning self-awareness, and GAI acceptance), direct manipulation or experimental control was not feasible or ethical. As highlighted by Cohen, Manion, and Morrison (2007) and Fraenkel, Wallen, and Hyun (2012), ex post facto designs are particularly valuable in situations where researchers cannot manipulate variables, instead examining pre-existing relationships between them. While this approach does not allow for definitive causal inferences, it provides crucial insights into the associations between variables, particularly when experimental designs are impractical or impossible. In this case, attempting to manipulate inherent personal characteristics like self-discipline or self-awareness would be both difficult and potentially ethically problematic. Therefore, the correlational approach adopted in this study was deemed the most appropriate method for exploring the relationships between these constructs and GAI acceptance among teacher candidates. This design allows for an initial exploration of these relationships, paving the way for future research utilizing more controlled methodologies if deemed appropriate and feasible.

1.2 Sample

Participants were 597 undergraduate teacher candidates recruited from nine universities across Türkiye to provide a diverse representation of pre-service teachers at various stages of their training programs. This sampling approach aimed to capture a range of perspectives and experiences relevant to GAI acceptance within teacher education. Participants were recruited from various education programs and included 140 male and 457 female students. The sample was distributed across different academic years, with 81 first-year students, 141 s-year students, 196 third-year students, and 179 fourth-year students participating. Initially, approximately 1,000 teacher candidates were invited to participate in the study. A total of 597 students completed and returned the scales.

A post-hoc power analysis was conducted using G*Power 3 (Faul et al., 2007) to determine the achieved power for the observed effects in the serial mediation model. Given the sample size of 597, four observed variables, and an alpha level of 0.05, the analysis revealed a power of 1.00 for detecting the indirect effect (Fritz & MacKinnon, 2007). This indicates that the study was sufficiently powered to detect the observed mediated relationships, further supporting the robustness of the findings and their generalizability to the broader population of teacher candidates.

All teacher candidates participated in the study voluntarily. Prior to data collection, participants received information about the study's purpose, procedures, and their rights, including the right to withdraw at any time without penalty. Informed consent was obtained from all participants electronically before they proceeded to the online questionnaires, ensuring their understanding of the study's voluntary nature and the confidential handling of their responses. The study adhered to ethical guidelines for research involving human subjects.

1.3 Measures

Academic Self-Discipline Scale: Adapted into Turkish by Erduran Tekin and Sal (2023), the Academic Self-Discipline Scale is a tool developed to measure university students' levels of academic self-discipline. Originally created by Sal (2022), the scale comprises two subdimensions: "Planned Study" and "Attention." The scale consists of 18 items rated on a 5-point Likert scale, where "Always" scores 5 points, and "Never" scores 1 point. Items 6, 7, and 17 are reverse-coded. The total score ranges from 18 to 90, with higher scores indicating greater academic self-discipline.

The Planned Study subdimension evaluates students' regular study habits, time management skills, and goal-oriented planning. It encompasses behaviors such as waking up at the same time daily, reviewing lessons before and after class, being conscious and systematic while studying, and using time effectively.

The Attention subdimension measures students' ability to control distractions and maintain focus. This includes actions like eliminating distractions in the study environment and pre-determining topics and methods of study.

In the adaptation study by Erduran Tekin and Sal (2023), the linguistic equivalence, construct validity, concurrent validity, and reliability of the Turkish version were examined. Confirmatory factor analysis (CFA) supported the original two-factor structure of the scale. Additionally, the scale demonstrated significant positive correlations with the Academic Self-Efficacy Scale and the Beliefs and Emotions Towards Academic Potential Scale, confirming its concurrent validity. The Cronbach's alpha coefficient was 0.86, and the test–retest reliability coefficient was 0.84, indicating high reliability. The Cronbach's alpha coefficient of data collected in the present study was calculated as 0.88.

Self-Control and Self-Management Scale: Adapted into Turkish by Ercoşkun (2016), the Self-Control and Self-Management Scale was developed by Mezo (2009) to assess general characteristics of self-control and self-management skills in adults. The scale focuses on three independent components of self-management: Self-Reinforcement, Self-Evaluation, and Self-Monitoring.

The scale consists of 16 items rated on a 6-point Likert scale, ranging from "Does not describe me at all" (0 points) to "Describes me completely" (5 points). Total scores range from 0 to 80, with items 7, 8, 9, 10, and 11 reverse-coded.

Ercoşkun's adaptation study examined the linguistic validity, construct validity, and reliability of the scale. A bilingual group design confirmed high correlations between the Turkish and English forms. Exploratory factor analysis (EFA) validated the original three-factor structure of the scale for the Turkish version, explaining 54.09% of the total variance. CFA results confirmed a good fit for the three-factor model. Reliability analysis yielded a Cronbach's alpha coefficient of 0.87 and a test–retest correlation of 0.92, indicating high temporal stability. The Cronbach's alpha coefficient of data collected in the present study was calculated as 0.88.

Meaningful Learning Self-Awareness Scale: Developed by Meydan (2018), the Meaningful Learning Self-Awareness Scale measures individuals' self-awareness regarding meaningful learning processes. Based on Ausubel's meaningful learning theory, the scale consists of 24 items rated on a 5-point Likert scale and includes five subdimensions:

1. Cognitive Self-Regulation and Transfer: Assesses students' abilities to relate new information to existing knowledge, self-regulate, and transfer learning to new contexts.
2. Analyzing Newly Learned Information: Measures students' skills in analyzing, interpreting, and deeply understanding new information.
3. Connecting Learnings: Evaluates the ability to establish connections between new and prior learning, integrate information, and create meaningful knowledge networks.
4. Activating Prior Knowledge: Assesses students' skills in reviewing existing knowledge before starting a new topic and preparing for new learning.
5. Evaluating Learnings: Measures students' abilities to critically evaluate their learning, question its quality, and develop strategies for improvement.

Meydan's study confirmed the validity and reliability of the scale. EFA results supported the five-factor structure, explaining 59.45% of the total variance. The overall Cronbach's alpha coefficient was calculated as 0.913, indicating high internal consistency. Subdimension alpha coefficients ranged from 0.661 to 0.883. The Cronbach's alpha coefficient of data collected in the present study was calculated as 0.96.

Generative Artificial Intelligence Acceptance Scale: Developed by Yilmaz et al. (2023), the Generative Artificial Intelligence Acceptance Scale assesses students' acceptance levels regarding the educational use of generative AI. Based on the Unified Theory of Acceptance and Use of Technology (UTAUT), the scale comprises four subdimensions: Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Social Influence.

The scale consists of 20 items rated on a 5-point Likert scale, with responses ranging from "Strongly Disagree" to "Strongly Agree." Total scores range from 20 to 100, with higher scores indicating greater acceptance of generative AI.

- Performance Expectancy measures the degree to which students believe using generative AI will enhance their academic performance.
- Effort Expectancy evaluates perceptions of the ease of use of generative AI tools.
- Facilitating Conditions assesses access to resources and infrastructure supporting AI use.
- Social Influence reflects the impact of significant others (e.g., teachers, peers) on students' AI usage.

The study by Yilmaz et al. examined the scale's construct validity, internal consistency, and test–retest reliability. EFA and CFA confirmed the four-factor structure, explaining 78.349% of the total variance. The Cronbach's alpha coefficient was 0.96, indicating excellent internal consistency. The test–retest correlation coefficient was 0.91, demonstrating high temporal stability. Item analysis showed that all items had strong discriminatory power. The Cronbach's alpha coefficient of data collected in the present study was calculated as 0.93.

1.4 Data analysis

The data were analyzed in R (Ihaka & Gentleman, 1996). Structural equation modeling (SEM) was performed using the lavaan package (Rosseel, 2012), and the mvn package (Korkmaz et al., 2014) was used to check for normality. Both multivariate and univariate normality tests (Doornik-Hansen, 2008; Henze-Zirkler, 1990; Anderson–Darling, 1954; Lilliefors, 1967) revealed significant deviations from normal distribution ($p < 0.001$). Therefore, robust maximum likelihood estimation with a correction factor of 1.30 was applied in the SEM analysis (Kline, 2012).

Potential Common Method Bias.

As all data were collected using self-report questionnaires, the potential for common method bias, which can inflate or deflate relationships between variables, was acknowledged. Several strategies were employed to mitigate this potential bias. First, the questionnaires included items worded both positively and negatively to reduce response bias tendencies. Second, during data collection, participants were assured of anonymity and confidentiality to encourage honest responses. Finally, Harman's single-factor test was conducted. This test involves conducting an exploratory factor analysis and examining whether a single factor accounts for the majority of the variance. If a substantial portion of the variance is not explained by a single factor, it suggests that common method bias is not a major concern. The results of this test are reported in the results section.

2 Results

The means, standard deviations and correlations of the scales used are presented in Table 1.

To address the potential for common method bias, Harman's single-factor test was performed. The results revealed that the first factor explained only 28% of the total variance, suggesting that common method bias was not a substantial issue in this study.

The SEM results, using robust maximum likelihood estimation, showed an excellent fit between the model and the data, as indicated by various fit indices (AGFI = 0.91, GFI = 0.94, CFI = 0.94, NFI = 0.94, IFI = 0.94, RFI = 0.93, RMSEA = 0.05, SRMR = 0.04). These strong fit indices confirm that the proposed factor structure is well-supported by the data (Hooper et al., 2008). For conciseness and simplicity, the path model is shown in Fig. 1. As the figure illustrates, academic self-discipline strongly affects self-control and self-management ($\beta = 0.73$, $p < 0.001$). Self-control and self-management strongly affects meaningful learning self-awareness ($\beta = 0.74$, $p < 0.001$), which then moderately affects generative artificial intelligence acceptance ($\beta = 0.38$, $p < 0.001$).

3 Discussion

This study investigated the relationships between academic self-discipline, self-control and management, meaningful learning self-awareness, and GAI acceptance among teacher candidates. Our findings support the hypothesized serial mediation model: academic self-discipline positively influences GAI acceptance indirectly through self-control and management, and subsequently, meaningful learning self-awareness. The robust fit indices of our structural equation model provide strong support for this mediated relationship.

This sequential relationship suggests a compelling narrative: teacher candidates with a strong foundation in academic self-discipline are better equipped to manage

Table 1 The means, standard deviations and correlations of the scales

Scales	Mean	SD	2	3	4
1. Academic Self-Discipline Scale	3.28	0.55	0.58	0.51	0.17
2. Self-Control and Self-Management Scale	3.72	0.52	1	0.63	0.31
3. Meaningful Learning Self-Awareness Scale	3.62	0.60	0.63	1	0.36
4. Generative Artificial Intelligence Acceptance Scale	3.64	0.57	0.31	0.36	1

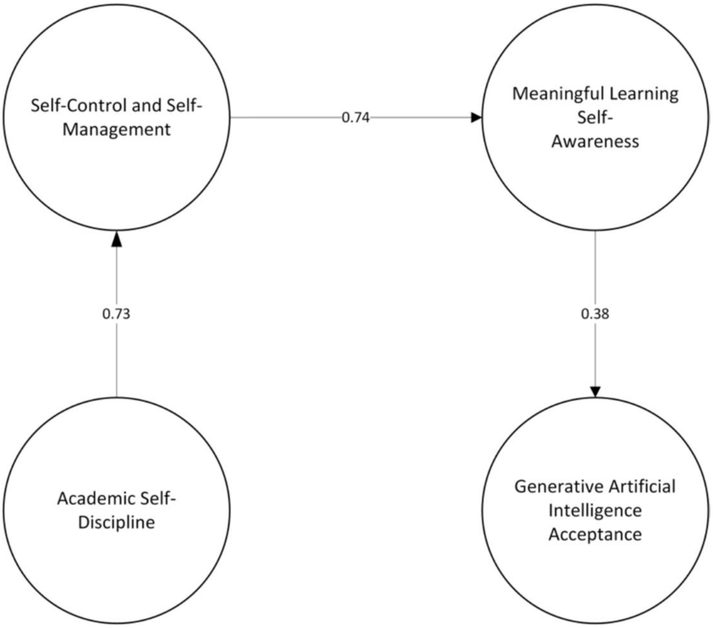

Fig. 1 The path model

their learning process, leading to increased self-awareness about their learning. This heightened metacognitive awareness, in turn, appears to foster a greater openness to integrating new technologies like GAI into their pedagogical practices. This finding aligns with broader research emphasizing the importance of self-regulated learning and metacognition in adopting innovative educational approaches (Bulut & Delialioglu, 2024; Ma & Lee, 2019; Mandari et al., 2024). However, the nature of this connection warrants further investigation. While our model suggests a causal pathway, it is possible that other factors, such as prior experience with technology or pedagogical beliefs about technology integration, also contribute to GAI acceptance.

The finding that self-control and management mediate the relationship between academic self-discipline and meaningful learning self-awareness underscores the crucial role of self-regulatory skills in fostering metacognition. This is consistent with research highlighting the connection between self-regulation and metacognitive development (Kilis & Yildirim, 2018; Robson, 2016). By effectively managing their learning process, teacher candidates may develop a deeper understanding of their own learning strengths and weaknesses, leading to increased self-awareness.

While previous research has established the positive impact of self-control and self-management on various learning outcomes (Hamutoglu et al., 2021; Sen, 2016), this study extends that understanding to the specific context of GAI acceptance. The positive relationship between meaningful learning self-awareness and GAI acceptance is particularly noteworthy. It suggests that individuals who are more reflective and aware of their own learning processes are more likely to perceive the potential benefits of GAI for enhancing learning. This finding emphasizes the importance of fostering metacognitive awareness in teacher education programs, not only for promoting effective learning in general but also for facilitating the integration of new technologies like GAI.

The findings of this study hold significant implications for teacher education programs. Specifically, they underscore the need to incorporate targeted interventions aimed at fostering self-control skills, including academic self-discipline, self-control and management, and promoting meaningful learning self-awareness. By explicitly addressing these areas, teacher education programs can better prepare future teachers for the effective integration of GAI into their pedagogical practices. This could involve incorporating workshops, seminars, or integrated coursework focused on developing self-regulatory strategies and metacognitive skills. For example, programs could incorporate reflective practices, self-assessment activities, and time management training to enhance self-discipline and control. Similarly, promoting activities that encourage self-reflection on learning processes, such as journaling or peer feedback, could foster meaningful learning self-awareness.

The study highlights the importance of framing GAI within the context of meaningful learning. Rather than simply introducing GAI as a new technological tool, teacher education programs should emphasize how GAI can be leveraged to enhance meaningful learning experiences for students. This could involve showcasing examples of how GAI can be used to personalize learning, provide targeted feedback, and create engaging learning activities. By connecting GAI to pedagogical principles of meaningful learning, teacher candidates are more likely to perceive its value and embrace its potential to transform their teaching practices. This approach also necessitates equipping teacher candidates with the critical thinking skills necessary to evaluate the ethical and pedagogical implications of using GAI in education. They should be encouraged to consider issues of bias, privacy, and accessibility when implementing GAI-driven tools and strategies.

Recognizing the dynamic nature of the technological landscape, teacher education programs must cultivate a mindset of lifelong learning among teacher candidates. This involves fostering a willingness to adapt to emerging technologies and continuously update their skills and knowledge. By promoting a growth mindset towards technological advancements, teacher education programs can empower future teachers to effectively navigate the evolving educational landscape and embrace innovative tools like GAI to enhance teaching and learning.

To foster these crucial skills, teacher education programs should integrate targeted interventions and learning experiences grounded in established pedagogical principles. Research highlights the strong connection between self-discipline and self-management (Zhang et al., 2017; de Jong et al., 2013), providing a rationale for focusing on these skills. Practical strategies could include workshops on time management and self-control techniques, aligning with the importance of self-management for meaningful learning as emphasized by Garrison (1997). Embedding reflective practices and self-assessment activities into coursework, coupled with opportunities for mindful technology integration, can further enhance self-awareness and learning, echoing the findings of Hamutoglu et al. (2021) and Sen (2016) regarding the positive impact of self-control on learning outcomes. For instance, teacher candidates could engage in microteaching exercises using GAI tools, followed by reflective discussions on their pedagogical choices, referencing the importance of pedagogical goals in AI integration highlighted by Rismani and Moon (2023). This approach could leverage the potential of GAI to support learning and development within Vygotsky's Zone of Proximal Development as discussed by Cai et al. (2024). By explicitly cultivating self-control skills and providing guided practice with GAI, focusing on the connection between meaningful learning and AI as suggested by Lin et al. (2024), Kim and Cho (2023), and Koc-Januchta et al. (2022), teacher education programs can empower future educators to approach this technology with confidence and a deeper understanding of its potential to enhance teaching and learning.

While the sample includes teacher candidates from various programs and academic years, providing some level of demographic variability, this study did not explicitly collect detailed demographic information beyond gender and academic year. Future research should collect more comprehensive demographic data, including but not limited to age, socioeconomic status, prior experience with AI technologies, and specific teacher training program (e.g., science, mathematics, language arts), to explore potential moderating effects of these variables on the relationships between self-control constructs and GAI acceptance. This will contribute to a more nuanced understanding of how individual differences and background factors interact to shape attitudes towards GAI in the context of teacher education.

While this study provides valuable insights within the Turkish educational context, the generalizability of the findings to other cultural settings requires careful consideration. Cultural values and educational systems can significantly influence individual characteristics like self-discipline and learning approaches, as well as attitudes towards technology adoption. For example, cultures emphasizing collectivism might exhibit different relationships between self-control and technology acceptance compared to individualistic cultures. Similarly, the availability of resources and infrastructure supporting technology integration within a given educational system can influence perceptions of GAI's usefulness and ease of use. Future research should explore these relationships across diverse cultural and educational contexts to determine the extent to which the current findings can be generalized. Comparative studies involving teacher candidates from different countries with varying educational systems would be particularly valuable in this regard.

This study lays the groundwork for several promising areas of future research, all centered around understanding the interplay between self-control, meaningful learning, and the acceptance and implementation of GAI in education. One crucial direction involves extending the focus from teacher candidates to in-service teachers. Examining how these factors influence practicing teachers' actual classroom behavior would provide valuable insights. This could involve observing teachers with varying levels of self-regulation and meaningful learning self-awareness as they integrate GAI, and assessing the long-term impact on their GAI usage and pedagogical approaches.

Further research should also explore the underlying mechanisms connecting self-control and meaningful learning to GAI acceptance. Qualitative methods, such as interviews and focus groups, could illuminate the thought processes and beliefs that drive teachers' receptiveness to GAI. Understanding the specific challenges and opportunities teachers perceive related to GAI integration would be particularly helpful in designing targeted professional development programs. Complementing this, future research should also evaluate the effectiveness of interventions designed to improve self-control, meaningful learning, and, consequently, GAI acceptance. This could involve creating and assessing professional development programs focused on these constructs, and comparing different intervention strategies to identify the most impactful approaches.

Beyond acceptance, it's vital to investigate the actual impact of GAI on student learning outcomes. Future studies should examine how GAI, when used by teachers with varying levels of self-control and meaningful learning self-awareness, affects student engagement, motivation, and academic achievement. This would provide empirical evidence of GAI's pedagogical effectiveness and its potential to transform the educational landscape. Expanding the research scope further, cross-cultural studies comparing GAI acceptance and integration across different educational systems and cultural contexts would offer valuable insights into the influence of cultural factors on teachers' perceptions and use of GAI.

Finally, several longitudinal and practical application inquiries are warranted. Investigating the stability of the relationships between self-control, meaningful learning, and GAI acceptance over time is critical. Longitudinal studies, tracking teacher candidates through their training and into their early careers, would reveal how these relationships evolve with experience. These studies could also assess the long-term effectiveness of interventions designed to foster self-control and meaningful learning. Also, future research is to connect the dots between GAI acceptance and classroom to determine its real-world impact. Examining how teacher candidates' positive attitudes toward GAI translate into concrete pedagogical choices and classroom practices is essential. This could involve classroom observations, lesson plan analysis, and teacher interviews to understand how GAI is being used to support teaching. Ultimately, exploring the relationship between GAI acceptance, pedagogical approaches, and student learning outcomes will provide valuable insights into effective GAI integration and inform the development of evidence-based best practices.

4 Conclusions

The findings of this study contribute to the growing body of research on technology acceptance in education by highlighting the critical role of self-control and meaningful learning. The results suggest that interventions aimed at enhancing academic self-discipline, self-control and management, and meaningful learning self-awareness may positively influence teacher candidates' openness to embracing GAI. Future research should explore the specific ways in which these skills can be cultivated in teacher education programs to promote the effective integration of GAI in educational settings. Furthermore, investigating the long-term impact of these factors on actual GAI usage and pedagogical practices among teachers would provide valuable insights for informing professional development and policy decisions.

This study reveals a crucial link between self-control, meaningful learning, and generative AI acceptance among teacher candidates. The findings confirm that academic self-discipline, acting through self-control and management, and subsequently meaningful learning self-awareness, plays a significant role in shaping positive attitudes towards GAI. This suggests that cultivating these attributes in teacher candidates is essential for fostering successful integration of GAI in future educational practices. By emphasizing the development of self-regulatory skills and promoting meaningful learning within teacher education programs, we can empower future teachers to effectively navigate the evolving technological landscape and harness the potential of GAI to enhance teaching and learning. Ultimately, this research underscores the importance of focusing on the human element—the teacher—in the successful integration of transformative technologies like GAI in education. By equipping teachers with the necessary skills and fostering a mindset of openness and adaptability, we can pave the way for a future where technology empowers both educators and learners.

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Declarations

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