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The role of academic self-efficacy in pre-service mathematics and science teachers' use of generative artificial intelligence tools

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Abstract

Generative Artificial Intelligence (GenAI) has emerged as a transformative technology in recent years, fundamentally reshaping traditional pedagogical approaches and educational environments. The objective of this study was to investigate the adoption of AI tools by pre-service mathematics and science teachers in their learning processes, as well as to assess the influence of academic self-efficacy (ASE) on this adoption, framed through the Technology Acceptance Model (TAM). Specifically, this research evaluated the effect of ASE on the acceptance of AI technologies by pre-service mathematics and science teachers and their intentions to utilize these technologies in the future. Data were collected from a sample of 146 pre-service mathematics and 91 pre-service science teachers (N=237) at an educational faculty in a university located in Western Türkiye during the spring semester of 2024. The data collection employed two distinct instruments: the first instrument comprised items from the Academic Self-Efficacy Scale to assess levels of academic self-efficacy, while the second instrument included items adapted from the TAM, TAM2 (Technology Acceptance Model), and UTAUT (Unified Theory of Acceptance and Use of Technology) frameworks. The results of hypothesis testing indicated that pre-service teachers with elevated levels of ASE had a more favorable perception of the usefulness and ease of use of GenAI tools, which in turn positively influenced their intention to adopt AI-based technologies. Furthermore, the study revealed that perceived usefulness and ease of use significantly shaped pre-service teachers' attitudes and behavioral intentions toward AI. When pre-service teachers recognize GenAI as a beneficial learning resource and find it user-friendly, their willingness to engage with it increases. This study posits that ASE is a critical factor in the acceptance of GenAI-based tools among pre-service mathematics and science teachers, thereby affirming the TAM as a relevant and effective model for examining pre-service teachers' potential engagement with AI in educational contexts.

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Matematik ve fen bilgisi öğretmen adaylarının üretken yapay zeka araçlarını kullanmalarında akademik öz yeterliğin rolü

Öz

Üretken Yapay Zeka (ÜYZ), son yıllarda geleneksel pedagojik yaklaşımları ve eğitim ortamlarını temelden yeniden şekillendiren dönüştürücü bir teknoloji olarak ortaya çıkmıştır. Bu çalışmanın amacı, matematik ve fen bilgisi öğretmen adaylarının öğrenme süreçlerinde yapay zeka araçlarını benimsemelerini araştırmak ve Teknoloji Kabul Modeli (TAM) çerçevesinde akademik öz yeterliğin (AÖY) bu benimseme üzerindeki etkisini değerlendirmektir. Bu araştırma AÖY'in matematik ve fen bilgisi öğretmen adayları tarafından yapay zeka teknolojilerinin kabulü ve gelecekte bu teknolojileri kullanma niyetleri üzerindeki etkisini değerlendirmiştir. Veriler, 2024 yılı bahar döneminde Türkiye'nin batısında bir üniversitenin eğitim fakültesinde 146 matematik ve 91 fen bilgisi öğretmen adayından oluşan bir örneklemden toplanmıştır (N=237). Veri toplamada iki farklı ölçek kullanılmıştır: İlk ölçek akademik öz yeterlik düzeylerini değerlendirmek için Akademik Öz Yeterlik Ölçeği, ikinci ölçek TAM, TAM2 (Teknoloji Kabul Modeli 2) ve UTAUT (Teknoloji Kabul ve Kullanım Birleştirilmiş Modeli) çerçevelerinden uyarlanmış maddeler içermektedir. Hipotez testinin sonuçları, yüksek düzeyde AÖY'e sahip öğretmen adaylarının ÜYZ araçlarının kullanışlılığı ve kullanım kolaylığı konusunda daha olumlu bir algıya sahip olduklarını ve bunun da YZ tabanlı teknolojileri benimseme niyetlerini olumlu yönde etkilediğini göstermiştir. Ayrıca, çalışma, algılanan yararlılık ve kullanım kolaylığının öğretmen adaylarının ÜYZ'ye yönelik tutumlarını ve davranışsal niyetlerini önemli ölçüde şekillendirdiğini ortaya koymuştur. Öğretmen adayları ÜYZ'yi faydalı bir öğrenme kaynağı olarak gördüklerinde ve kullanıcı dostu bulduklarında, onunla etkileşim kurma istekleri artmaktadır. Bu çalışma, ASE'nin matematik ve fen bilgisi öğretmen adayları arasında ÜYZ tabanlı araçların kabulünde kritik bir faktör olduğunu ve böylece TAM'ın öğretmen adaylarının eğitim bağlamlarında ÜYZ ile potansiyel etkileşimlerini incelemek için uygun ve etkili bir model olduğunu doğrulamaktadır.

Anahtar kelimeler: *Matematik öğretmen adayları, fen bilgisi öğretmen adayları, akademik öz-yeterlik, teknoloji kabul modeli*

1. Introduction

Generative Artificial Intelligence (GenAI) has become a revolutionary technology in recent years, significantly altering traditional teaching methods and learning environments [1]. Incorporating GenAI into education has reshaped and transformed the strategies educators employ in various ways, including personalizing learning experiences, boosting student engagement, and improving assessment and feedback processes [2]. This paradigm shift requires pre-service teachers to be able to effectively integrate and use GenAI technologies efficiently. Pre-service teachers must stay informed about Generative AI (GenAI) as it is revolutionizing traditional teaching methods by personalizing learning, enhancing student engagement, and improving assessment practices [3]. As future educators, they need to incorporate AI-driven strategies from the outset to effectively navigate contemporary classrooms. Unlike in-service teachers who may need retraining, pre-service teachers can seamlessly integrate GenAI as a fundamental component of their pedagogy [4]. Academic self-efficacy is crucial for pre-service teachers in effectively adopting and utilizing novel technologies, including GenAI, as their confidence significantly impacts acceptance and use [5, 6]. Moreover, Zee and Koomen [7] emphasize that teachers' self-efficacy plays a vital role in shaping classroom dynamics, fostering student academic adjustment, and promoting teacher well-being, highlighting the importance of understanding how these beliefs influence various aspects of teaching. In this context, the Technology Acceptance Model (TAM) provides a theoretical framework for examining this phenomenon, positing that perceived ease of use and perceived usefulness of technology influence users' acceptance and engagement levels [8]. The acceptance and effective use of GenAI tools in education can enhance learning outcomes for both students and educators, making TAM particularly relevant in the GenAI-in-education context. Therefore, examining the impact of academic self-efficacy on GenAI engagement using the lens of TAM can significantly improve our comprehension of technology adoption in educational environments.

TAM is a theoretical framework developed by Davis [8] that elucidates how users come to accept and utilize technology. It posits that two primary factors influence an individual's decision to adopt a technology: Perceived Usefulness (PU) and Perceived Ease of Use (PEU). Perceived Usefulness refers to the degree to which a person believes that using a technology will enhance their performance, while Perceived Ease of Use indicates how effortless they find the technology to operate [8]. These perceptions subsequently influence an individual's attitude toward using the technology, which in turn shapes their behavioral intention and actual usage. Over time, TAM has evolved through modifications such as TAM2 and the UTAUT to incorporate additional variables, including subjective norms and facilitating conditions [9, 10].

TAM is widely utilized in educational technology research to investigate the factors that influence the adoption of emerging digital tools, including GenAI. In the context of teacher education, TAM aids in understanding how pre-service teachers perceive and adopt AI-based tools for learning and instruction. This model is particularly valuable as it identifies cognitive and psychological determinants that impact the willingness to integrate technology into educational practices [11]. By applying TAM, researchers can analyze the barriers and facilitators that shape teachers' attitudes toward AI-driven learning platforms, intelligent tutoring systems, and automated feedback mechanisms.

In this study, the TAM serves as a robust framework for examining the impact of self-efficacy on technology adoption. Academic self-efficacy—the belief in one's capability to successfully complete academic tasks—significantly influences perceptions of both the usefulness and ease of use of GenAI tools. Pre-service teachers with high levels of self-efficacy are likely to feel more confident in experimenting with AI-based applications, viewing them as valuable resources that enhance their teaching and learning effectiveness [12,13].

1.1. Using generative artificial ıntelligence for science and mathematics pre-service teachers

GenAI refers to a category of artificial intelligence models specifically designed to create new content, including text, images, audio, and video, by identifying patterns learned from extensive datasets. Unlike traditional AI systems that primarily focus on classification or decision-making, GenAI produces original outputs, making it highly versatile across various domains. GenAI is a subset of artificial intelligence that generates new content by learning patterns from large datasets. It utilizes deep learning architectures, particularly transformers, generative adversarial networks (GANs), variational autoencoders (VAEs), and diffusion models, to produce human-like text, images, audio, and code [2]. The process involves training on vast datasets, recognizing patterns, and generating outputs based on learned structures. Continuous refinement through techniques such as reinforcement learning ensures improved accuracy and coherence. GenAI can be categorized into several types based on its functionality and application. Text-based GenAI models, such as GPT-4 and BERT, generate human-like text and are widely used in chatbots, content creation, and language processing. Image-based GenAI, including DALL·E and Stable Diffusion, produces high-quality images from textual prompts, revolutionizing digital art and graphic design. Audio-based GenAI, exemplified by Jukebox and ElevenLabs, generates speech and music, facilitating advancements in voice synthesis and entertainment. Video-based GenAI, such as Runway Gen-2, creates and enhances video content, supporting applications in film production and media. Code-based GenAI, like GitHub Copilot, assists programmers by generating and debugging code, thereby improving software development efficiency. Lastly, 3D and design GenAI, represented by tools like NVIDIA Omniverse, enables the creation of 3D models and deepfake content, transforming industries such as gaming and virtual reality. GenAI has significant applications across education, healthcare, finance, and creative industries, reshaping traditional workflows through automation and personalization.

Integrating innovative technologies, such as GenAI, into the preparation of pre-service science and mathematics teachers is becoming essential. These tools offer substantial potential for revolutionizing teaching approaches and enhancing student learning [14]. GenAI can assist future teachers in completing their tasks more accurately. For instance, pre-service teachers can benefit from guidance and feedback to improve their writing style, grammar, and sentence structure [15]. Strong writing skills are essential for pre-service teachers to deliver clear instruction, communicate professionally, and provide meaningful feedback to students. GenAI can enhance their writing by refining grammar, structure, and clarity. These skills are essential for developing lesson plans, explaining complex concepts, providing feedback, publishing research, and engaging in professional communication. AI tools support pre-service teachers by enhancing the clarity and precision of their writing, thereby boosting teaching effectiveness and student learning outcomes. Additionally, these tools can personalize learning experiences for pre-service teachers, taking into account the diverse comprehension levels among students [16].

GenAI can assist future teachers in crafting innovative lesson plans and teaching materials [17]. AI-driven tools can generate a variety of examples, problems, and scenarios, allowing teachers to address diverse learning styles and needs [18,19]. These technologies can also support project-based and inquiry-based learning by providing real-time feedback and guidance, encouraging students to engage in deeper learning and critical thinking [20]. Additionally, AI can offer instant and detailed feedback on student performance, helping teachers identify where students struggle and need extra help. This leads to more effective and timely support [21]. Automated assessment tools can also reduce the time teachers spend on administrative tasks, giving them more time to focus on teaching and professional growth [22].

GenAI also promotes collaborative learning by facilitating communication and teamwork among pre-service teachers. AI-driven platforms accomplish this by analyzing pre-service teachers' learning styles, progress, and competencies to pair them with peers for effective peer tutoring, collaborative group projects, and structured discussions. These adaptive learning systems ensure that pre-service teachers work with partners whose strengths complement their learning needs, fostering a more dynamic and personalized educational experience [23]. Additionally, these technologies empower future educators to connect with experienced mentors and educators from around the globe. Through AI-powered professional learning networks, pre-service teachers can participate in virtual mentoring, attend interactive workshops, and receive personalized guidance tailored to their teaching preferences and career aspirations. This exposure enables them to benefit from a variety of teaching methodologies and best practices, thereby enhancing their professional development [24]. Furthermore, becoming familiar with advanced technologies prepares future educators for contemporary classrooms, where AI and other digital tools will play a crucial role in teaching and learning. By incorporating AI into lesson planning, student assessment, and classroom management, pre-service teachers gain practical experience in utilizing technology to enhance student engagement and improve learning outcomes. This ensures that they are well-equipped to integrate these tools effectively into their teaching practices [25]. Finally, understanding and utilizing AI in education positions teachers as leaders in educational innovation. Educators who actively engage with AI technologies can drive curriculum advancements, develop data-driven teaching strategies, and contribute to institutional digital transformation. This adaptability allows them to remain at the forefront of technological advancements and shape the future of education [26].

When examining literature, several studies indicate that the use of Generative Artificial Intelligence (GenAI) is associated with the academic self-efficacy of pre-service teachers, as well as its educational applications. The relationship between academic self-efficacy and GenAI usage is well-established within the frameworks of educational psychology and technology acceptance theory. Academic self-efficacy, defined as individuals' beliefs in their ability to successfully perform academic tasks, significantly influences pre-service teachers' willingness to engage with new and complex technologies [12]. In the context of the Technology Acceptance Model (TAM), perceived ease of use and perceived usefulness are the primary determinants of technology adoption [8]. Self-efficacy enhances these perceptions, enabling confident users to view GenAI tools as valuable resources for learning, lesson planning, assessment, and content creation [41]. Consequently, pre-service teachers with higher levels of academic self-efficacy are more likely to proactively engage with GenAI and utilize its features to enhance their teaching practices and academic outcomes [80, 81]. This relationship is crucial for two main reasons. First, it promotes equitable access: students with low self-efficacy may avoid GenAI tools due to fear of failure or misuse, potentially exacerbating existing inequalities in digital literacy and academic achievement. Second, high self-efficacy fosters deeper, more purposeful engagement with GenAI, supporting self-regulated learning and the development of professional identity [86]. Therefore, fostering academic self-efficacy among pre-service teachers is essential not only for their academic performance but also for preparing them to integrate GenAI into their future teaching practices in a meaningful and ethical manner. As educational systems evolve, the integration of GenAI should be viewed not merely as a technological enhancement but as a catalyst for reimagining pedagogy to foster deeper learning and enhance students' academic agency.

1.2. Academic self-efficacy of science and mathematics pre-service teachers

According to Bandura's social cognitive theory, self-efficacy refers to an individual's belief in their ability to accomplish specific tasks [27]. Academic self-efficacy is a component of overall self-efficacy and a fundamental concept related to an individual's belief in their capacity to perform academic tasks effectively, achieve academic goals, and succeed in educational pursuits [28,29]. It encompasses individuals' confidence and perception of their academic abilities, their capacity to organize and carry out actions to attain desired levels of academic performance, and their assessments of their ability to excel in assignments, courses, or academic activities [30-33].

For pre-service teachers, self-efficacy significantly influences their teaching skills and practices [34]. Research by Burak [35] and Sultan et al. [36] has demonstrated the impact of self-efficacy beliefs on pre-service teachers' career choices and teaching abilities. When pre-service teachers lack self-efficacy in specific areas, such as science education, they may hesitate to engage in teaching practices related to these subjects, affecting their overall teaching skills and confidence in the classroom [37]. Studies by Velthuis et al. [38] and Slater and Main [39] further underscore the importance of self-efficacy in domains such as science teaching and classroom management. Self-efficacy influences pre-service teachers' willingness to engage in teaching actions and their ability to persevere through challenges. Pre-service teachers with higher self-efficacy in areas such as science teaching or classroom management are more likely to exhibit practical teaching skills and strategies in these domains.

Moreover, pre-service teachers' academic self-efficacy pertains explicitly to their confidence in effectively integrating technology into their teaching practices [40]. To comprehend the impact of pre-service teachers' academic self-efficacy on their technology usage, it is crucial to analyze the relationship between their confidence in academic tasks and their ability to utilize technology in educational settings effectively. Research by Holden and Rada [41] emphasizes the influence of perceived usability and technology self-efficacy on teachers' technology acceptance, highlighting individual differences and situational characteristics, including self-efficacy, in teachers' technology acceptance and use. Similarly, Pendergast et al. [42] offer insights into pre-service student-teacher self-efficacy beliefs, shedding light on foundational aspects of teachers' development, including their confidence in utilizing technology. Furthermore, Caner and Aydın [43] revealed a strong positive correlation between pre-service teachers' self-efficacy and technology integration tendencies. This suggests that higher levels of self-efficacy are associated with a greater inclination towards using technology. Keser et al. [44] compared pre-service teachers' TPACK competencies with their self-efficacy perceptions towards technology integration, emphasizing the correlation between these factors. These studies suggest that pre-service teachers' academic self-efficacy significantly influences their attitudes and behaviors towards technology usage in educational settings.

1.3. Research questions

The relationship between pre-service teacher’s academic self-efficacy levels and GenAI engagement may provide valuable information for teacher educators and practitioners. Since integrating new technologies into educational settings may require a basic level of academic self-efficacy, it is important to explore the potential influence of academic self-efficacy on the acceptance and use of GenAI among pre-service teachers. This study aims to offer essential insights into integrating AI in education to develop new approaches in the training of pre-service teachers. The relationship between pre-service teachers' academic self-efficacy and their level of acceptance of artificial intelligence tools was examined in the current study. A model was developed based on literature review.

RQ1: How does academic self-efficacy influence the acceptance and use of artificial intelligence tools among mathematics and science pre-service teachers?

RQ2: What insights can the relationship between academic self-efficacy and AI tool acceptance provide for developing effective AI integration strategies in teacher education programs?

2. Method

This study is a correlational survey, a type of descriptive research that aims to identify the relationships between variables as they exist. Correlational survey models aim to determine the existence or degree of correlation between two or more variables [45]. This study investigates the relationship between pre-service teachers' academic self-efficacy and their level of acceptance of artificial intelligence tools.

2.1. Proposed research model and hypotheses

In the proposed model, academic self-efficacy is addressed with three sub-dimensions. these are (1) ability to cope with academic problems, (2) academic effort and (3) academic planning. Pre-service teachers' ability to cope with academic problems significantly shapes their perception of technology's usefulness. Research demonstrates that individuals with high self-efficacy in problem-solving are more inclined to view new technologies as effective tools for addressing academic challenges [12, 46]. The confidence to overcome difficulties makes these students more receptive to technology's practical benefits in educational contexts. Liaw and Huang [46] found that students who are competent problem-solvers tend to report higher levels of perceived usefulness when engaging with e-learning platforms, underscoring the value of self-efficacy in promoting positive technology acceptance.

Similarly, academic effort influences the perceived usefulness of technology. Students who invest substantial effort in their academic work are more likely to appreciate the potential of AI and other technologies in streamlining learning processes [47, 48]. This sustained engagement with academic tasks fosters a mindset that values the utility of technological tools in managing workloads and achieving academic goals. Chemers et al. [47] found that students with strong academic self-efficacy were more proactive in engaging with resources, which shaped their perception of technology as a valuable learning aid.

In addition, academic planning plays a crucial role in shaping pre-service teachers' perceptions of how easy new technologies are to use. Planning skills enable students to organize their tasks efficiently, reducing the cognitive load associated with learning how to use new tools [49]. As a result, students with strong academic planning abilities are more likely to experience technology as intuitive and accessible. Zimmerman and Schunk [49] argued that well-planned learners adapt more quickly to technological environments, leading to a smoother and more positive user experience.

Once students perceive technology as useful and easy to use, these perceptions significantly influence their attitudes towards technology usage. According to the Technology Acceptance Model [8], perceived usefulness (PU) and perceived ease of use (PEU) are vital predictors of positive attitudes towards adopting new systems. Venkatesh and Davis [9] emphasized that when students recognize both the value and simplicity of technology, they are more likely to develop favorable attitudes towards its use in education. This alignment between usability and usefulness is essential for fostering a mindset that embraces innovation.

Finally, attitudes towards technology usage directly impact pre-service teachers' behavioral intention to use such tools. Ajzen [50] and Park et al., [52] posits that positive attitudes are potent motivators that translating into concrete behavioral intentions. Pre-service teachers with favorable views towards AI and digital tools are more likely to incorporate these technologies into their teaching practices. Venkatesh and Davis [9] confirmed that attitudes play a crucial role in predicting whether individuals will continue to use technology in their professional environments, highlighting the importance of fostering positive perceptions early in teacher education programs.

These interconnected factors illustrate how academic self-efficacy and key components of the technology acceptance model work together to influence technology adoption (see Figure 1). Devel oping self-efficacy through problem-solving, effort, and planning can enhance pre-service teachers' perceptions of technology, encouraging them to adopt new tools more confidently and effectively in their academic and professional lives. Below are the generated hypotheses indicating that higher academic self-efficacy level of pre-service teachers has a positive impact on the acceptance of AI technology:

- H1: Cope with academic problems (ASE1) positively affects perceived usefulness (PU).
- H2: Academic effort (ASE2) positively affects perceived usefulness. (PU).
- H3: Academic planning (ASE3) positively affects perceived ease of use (PEU).
- H4: Perceived ease of use (PEU) positively affects perceived usefulness. (PU).
- H5: Perceived usefulness. (PU). positively affects attitude towards use (ATU).
- H6: Perceived ease of use (PEU) positively affects attitude towards use (ATU).
- H7: Attitude towards use (ATU) positively affects Behavioural intention to use (BIU).

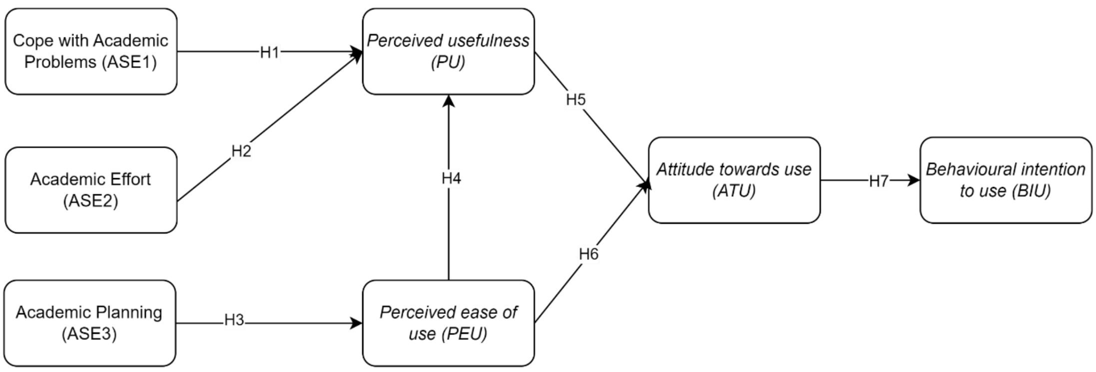

Figure 1. Academic self-efficacy and technology acceptance model (TAM) integration

2.2. Data collection tools

Data collection for this study involved two distinct forms. The first form utilized was the Academic Self-Efficacy Scale, developed by Kandemir [53], to measure pre-service teachers' academic self-efficacy levels. This scale comprises 19 items across three sub-dimensions: coping with academic problems (11 items), academic effort (4 items), and academic planning (4 items). The scale's internal consistency was confirmed with Cronbach's alpha coefficients of .90 for the first factor, .78 for the second, .77 for the third, and .92 for the total scale. Kandemir [53] reported fit indices for the scale as χ^2/sd = 3.74, RMSEA = .077, NFI = .96, CFI = .97, GFI = .89, AGFI = .86, and RMR = 0.056. In the present study, alpha coefficients were found .84, .81, .78 and .91, respectively, and the the fit indices were found to be χ^2/sd = 2.89, RMSEA = .087, CFI = .97, TLI = .94, and SRMR = .079 in CFA.

The second form includes items adapted from the TAM, TAM2 and UTAUT studies conducted by Venkatesh and Davis [9,54] and Venkatesh et al. [10] This scale comprises 15 items across four sub-dimensions: perceived usefulness (4 items), perceived ease of use (5 items), attitude towards use (2 items) and behavioural intention to use (3 items). In the present study the scale's internal consistency was confirmed with Cronbach's alpha coefficients of .88 for the perceived usefulness, .88 for the perceived ease of use, .87 for the third, and .92 for the total scale. The fit indices were found to be χ^2/sd = 2.64, RMSEA = .085, CFI = .96, TLI = .95, and SRMR = .078 in CFA.

2.3. Participants and data collection

The target group of the study comprised pre-service science (n = 91) and mathematics (n = 146) teachers (N = 237) enrolled at a university in western Turkey. Among the pre-service teachers, 169 were female and 68 were male. The participants were categorized by grade level, with 70 freshmen, 65 sophomores, 34 juniors, and 68 seniors. The data collection process followed a carefully structured protocol designed to ensure reliability and validity of results. Initially, a pilot test was conducted with a small subset of participants (n = 15) to assess the clarity of instrument items, estimate completion time, and identify potential procedural issues. Based on pilot test feedback, minor adjustments were made to the wording of several questionnaire items to improve comprehension. Two standardized instruments were administered in sequence. Both instruments utilized a 5-point Likert scale where participants selected from the following options: "(1) It does not reflect me at all, (2) It reflects me very little, (3) It reflects me a little, (4) It reflects me mostly, (5) It reflects me completely."

To minimize potential response bias, the questionnaires were administered by research assistants who were not associated with teaching the courses. Participants completed the surveys independently without discussion among peers. The research assistants remained available to clarify any questions about the procedure but were instructed not to provide interpretations of questionnaire items. Demographic information including gender, academic major, and year of study was collected on a separate form that was coded to maintain participant anonymity while allowing for demographic analysis. The response rate was 92%, with 257 surveys distributed and 237 valid surveys returned. Incomplete surveys (n = 11) and those with uniform response patterns indicating potential non-engagement (n = 9) were excluded from the final analysis. All data collection procedures were reviewed and approved by the university's Institutional Review Board (E.371663) prior to implementation.

2.4. Data analysis

Questionnaires were distributed to over 314 pre-service teachers, and 297 responses were received. After eliminating pre-service teachers who indicated that they did not use artificial intelligence technologies, as well as non-responders and incomplete responses, the data from 237 participants were deemed suitable for analysis. The proposed conceptual model was evaluated using structural equation modeling (SEM), and the structural model was analyzed with R software. SEM is a robust statistical technique widely employed to examine the relationships between observed and latent variables. Utilized across various scientific disciplines, SEM provides a comprehensive framework for testing and validating significant theories, particularly in evaluating relationships between variables and constructing and assessing structural models [55].

The study examined the relations between academic self-efficacy and technology acceptance and use among pre-service teachers through five steps. (1) Descriptive statistics, including mean, standard deviation, mode, median, skewness, and kurtosis, were computed for the variables. (2) The data's normality was assessed to confirm it met the necessary assumptions, and common method bias was also evaluated. Harman's single-factor test was employed to check for common method variance, as the data was collected through self-reports and two scales were administered at the same time [56]. (3) The fit of the measurement model to the actual data was evaluated. (4) Correlation coefficients were calculated to determine the strength of relationships. (5) Theoretical models derived from the literature were tested, with structural equation modeling (SEM) being the preferred method. SEM is a collection of statistical techniques used to analyze the relationships between one or more independent variables and one or more dependent variables [57]. It facilitates multiple regression analyses among factors, examining relationships between measured variables, such as academic self-efficacy and technology acceptance.

3. Findings and discussion

The study utilized two different scales to gather information on students' academic self-efficacy, and technology acceptance. Table 1 shows the descriptive statistics of the variables analyzed in the study. The academic self-efficacy scale consists of three sub-dimensions (coping with academic problems, academic effort, and academic planning), and technology acceptance consists of four sub-dimensions (perceived usefulness, perceived ease of use, attitude towards use, behavioural intention to use). The table presents an analysis of mean, standard deviation, mode, median, Zskewness, and Zkurtosis values. The Z-scores for kurtosis and skewness of the variables were all within the range of -1.96 to 1.96, which suggests that the normality assumption was met [58].

Table 1. Descriptive Statistics

	Mean	Sd	Mode	Median	$Z_{kurtosis}$	$Z_{skewness}$
Coping with academic problems (ASE1)	3.27	0.521	3.17	3.25	1.11	0.24
Academic effort (ASE 2)	3.8	0.601	3.75	3.75	-1.84	2.32
Academic planning (ASE3)	3.51	0.598	3.25	3.5	-0.48	-0.16
Perceived ease of use (PEU)	3.56	0.709	3.4	3.6	-0.59	0.18
Perceived usefulness (PU)	4.04	0.63	4	4	-1.05	1.12
Attitude towards use (ATU)	3.51	0.741	4	3.67	-1.53	0.71
Behavioural ,ntetion to use (BIU)	3.98	0.696	4	4	-1.85	1.81

Furthermore, Harman's single-factor test was conducted to examine the presence of common method bias, and the threshold value was determined to be .305. The calculated threshold value, which is less than 0.5, indicates that there is no common method bias [59].

Structural equation modeling (SEM) is a statistical approach for evaluating the fit of both measurement models and constructed models. SEM relies on essential assumptions, such as normality, linearity, multicollinearity, multivariance, sample size, and outlier detection [60]. Failure to meet these assumptions can introduce errors in examining the relationships between observed and latent variables. To ensure valid confirmatory factor analysis, these assumptions must be satisfied beforehand. Therefore, the dataset was evaluated for univariate and multivariate normality, along with outliers. Univariate normality and outliers were checked using kurtosis, skewness values, and standardized z-scores, while multivariate normality and outliers were assessed through Mahalanobis distance and residuals. No outliers were found in the dataset. Table 1 presents the descriptive statistics for each variable, used to verify univariate normality. For multivariate normality, Mardia's coefficients for skewness and kurtosis, along with their p-values, were calculated. Mardia's test evaluates if a set of variables aligns with a multivariate normal distribution [61]. The results, with skewness ($\gamma 1p = 3.24$, $p = 0.256$) and kurtosis ($\gamma 2p = 7.41$, $p = 0.287$), confirm that the data meets the multivariate normality assumption. The multicollinearity assumption was examined using variance inflation factor (VIF) and tolerance values as Tabachnick et al. [62] outlined. Results showed VIF and tolerance values within acceptable limits (Academic Self-efficacy: VIF = 1.89, tolerance = .89; Technology Acceptance VIF = 1.92, tolerance = .88), indicating no multicollinearity issues since VIF was below 10 and tolerance exceeded .10.

Reliability and validity metrics were calculated to evaluate the conceptual model proposed in this study. The internal consistency and item reliability of each construct were assessed using Cronbach's α, composite reliability (CR), and average variance extracted (AVE) (Annex 1). Recommended thresholds for these values are 0.7 for Cronbach's α and CR and 0.5 for AVE [63, 64]. Results in Annex 1 indicate strong reliability and internal consistency, with Cronbach's α exceeding 0.7 [65]. CR values above 0.7 also confirmed sufficient internal consistency across constructs. Convergent validity was supported by factor loadings for each construct, with AVE values surpassing 0.5 [66, 63].

Discriminant validity was established by comparing the square roots of AVE values with the correlations shown in Table 2, where square roots of AVE values were higher than the corresponding correlations. This finding is consistent with discriminant validity standards outlined by Hair et al. [63].

In the measurement model, sub-dimensions of the scales were treated as observed variables, while academic self-efficacy and technology acceptance served as latent variables. Figure 2 illustrates the measurement model with seven observed variables and two latent variables with standardized factor loadings. Model fit indices showed a chi-square to degrees of freedom ratio of $X^2/df = 1.47$ ($X^2 = 19.2$, $df = 13$, $p = .118$), with RMSEA = .044 (90% CI: .001 - 0.084), CFI = .991, and TLI = .986, all indicating a well-fitting model [55, 67].

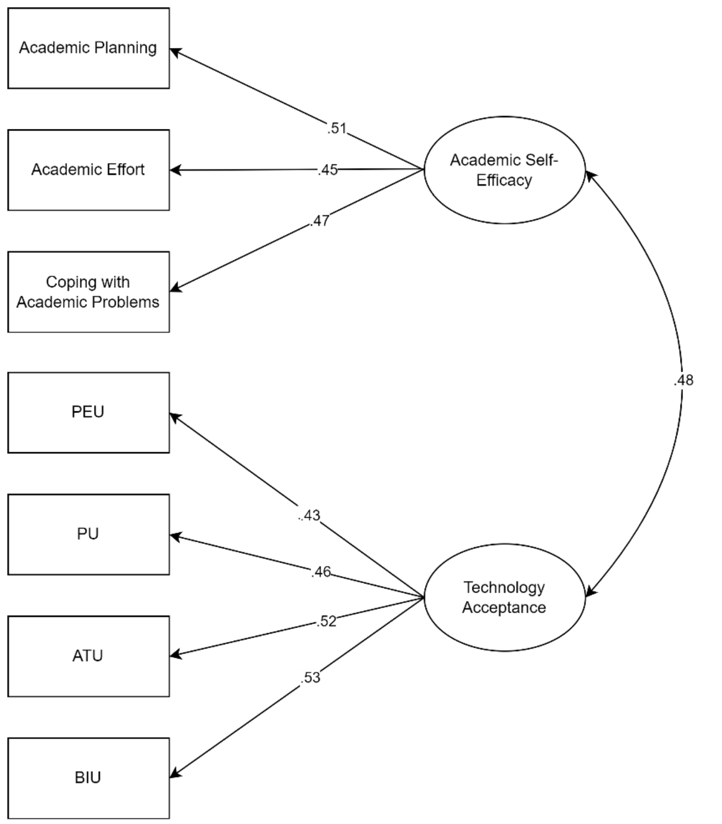

Figure 2. Measurement model

The correlation matrix (Table 2) reveals meaningful relationships between self-efficacy sub-dimensions (academic planning, academic effort, and coping with academic problems) and technology acceptance components (perceived usefulness, perceived ease of use, attitude towards use, and behavioral intention to use). Strong correlations were observed among the self-efficacy dimensions, suggesting that students who excel in one area of self-efficacy, such as academic planning, are likely to demonstrate strength in related areas like effort and coping skills. Within the technology acceptance dimensions, a moderately strong relationship was noted between perceived usefulness and perceived ease of use and between attitude towards technology use and behavioral intention to use, highlighting the link between positive perceptions of technology and the likelihood of intending to use it.

Regarding cross-dimension relationships, the analysis shows that self-efficacy dimensions are weakly to moderately correlated with technology acceptance factors. For instance, students who demonstrate high academic effort and effective coping strategies may also be slightly more inclined to see technology as useful or easy to use and, thus, may be more likely to adopt it. However, these correlations are relatively lower, indicating that self-efficacy contributes to technology acceptance but not as strongly as internal relationships within each category.

Overall, the analysis suggests that both academic self-efficacy and positive perceptions of technology play roles in fostering an intention to use technology, but the influence of self-efficacy on technology acceptance appears to be more limited.

Table 2. Correlations and square roots of AVE scores

Factor	ASE1	ASE2	ASE3	PU	PEU	ATU	BIU
Coping with academic problems (ASE1)	(.71)						
Academic effort (ASE2)	0.68^{***}	(.72)					
Academic planning (ASE3)	0.77^{***}	0.65^{***}	(.72)				
Perceived Usefulness (PU)	0.36^{***}	0.30^{***}	0.29^{***}	(.87)			
Perceived Ease of Use (PEU)	0.31^{***}	0.23^{***}	0.28^{***}	0.47^{***}	(.80)		
Attitude Towards Use (ATU)	0.36^{***}	0.21^{**}	0.28^{***}	0.45^{***}	0.45^{***}	(.73)	
Behavioral Intention to Use (BIU)	0.31^{***}	0.29^{***}	0.22^{***}	0.54^{***}	0.49^{***}	0.56^{***}	(.91)

Note. * $p < .05$, ** $p < .01$, *** $p < .001$

The literature on academic self-efficacy and technology acceptance aligns closely with the findings in the correlation matrix, which reveals significant relationships between self-efficacy sub-dimensions (academic planning, effort, and coping with academic problems) and components of technology acceptance (perceived usefulness, perceived ease of use, attitude towards use, and behavioral intention to use). As established by Bandura and Zimmerman [68] and Chemers et al. [47], academic self-efficacy influences students' engagement and motivation, which, in turn, can positively affect how they perceive and intend to use educational technologies. The matrix's strong internal correlations among self-efficacy dimensions support this, suggesting that students confident in planning their studies are likely to excel in related self-efficacy areas, such as academic effort and coping abilities [48]. This mirrors the findings by Holden and Rada [41], who argued that high self-efficacy enhances openness to technology.

Within the technology acceptance model (TAM) framework, as proposed by Davis [8], perceived usefulness and ease of use are core to technology adoption. The matrix reflects this with a moderate correlation between perceived usefulness and ease of use and a notable connection between attitude toward use and behavioral intention to use—similar to the relationship highlighted in TAM literature, including Venkatesh and Bala [51]. Students who view technology as applicable are more likely to have a favorable attitude towards it and, thus, a stronger intention to use it, indicating that positive perceptions of technology play a significant role in its adoption.

The cross-dimension correlations between self-efficacy and technology acceptance factors in the matrix are relatively weaker, yet they suggest that students with high self-efficacy in academic effort or coping may perceive GenAI tools as slightly more useful or accessible, aligning with Pan's [69] findings on the influence of self-efficacy on perceived usefulness. However, the modest strength of these correlations implies that while self-efficacy can enhance technology acceptance, its impact is secondary to internal relationships within each domain. This aligns with Yulian et al. [70], who found that although self-efficacy contributes to technology use intention, it is not the primary driver. Overall, the analysis suggests that academic self-efficacy and positive technology perceptions both play essential, though somewhat distinct, roles in fostering the intention to use GenAI in educational contexts.

The SEM approach statistically analyzed the research model's path coefficients and tested for significance. The fit indices of the model $X^2/df = 4.04$ ($X^2 = 1964$, $df = 485$, $p < .001$), RMSEA = .114 with 95% CI [.108 ~.119], CFI = .963, and TLI= .960 respectively. Regarding parameter values, the fit measures were within acceptable limits [55, 67]. When Figure 3 displays regression coefficients and explained variances, it indicates that 28% of the variance accounts for the behavioral intention to use AI tools. Additionally, the model's PU, PEU and ATU structures are explained by variances of 60%, 87%, and 28%, respectively.

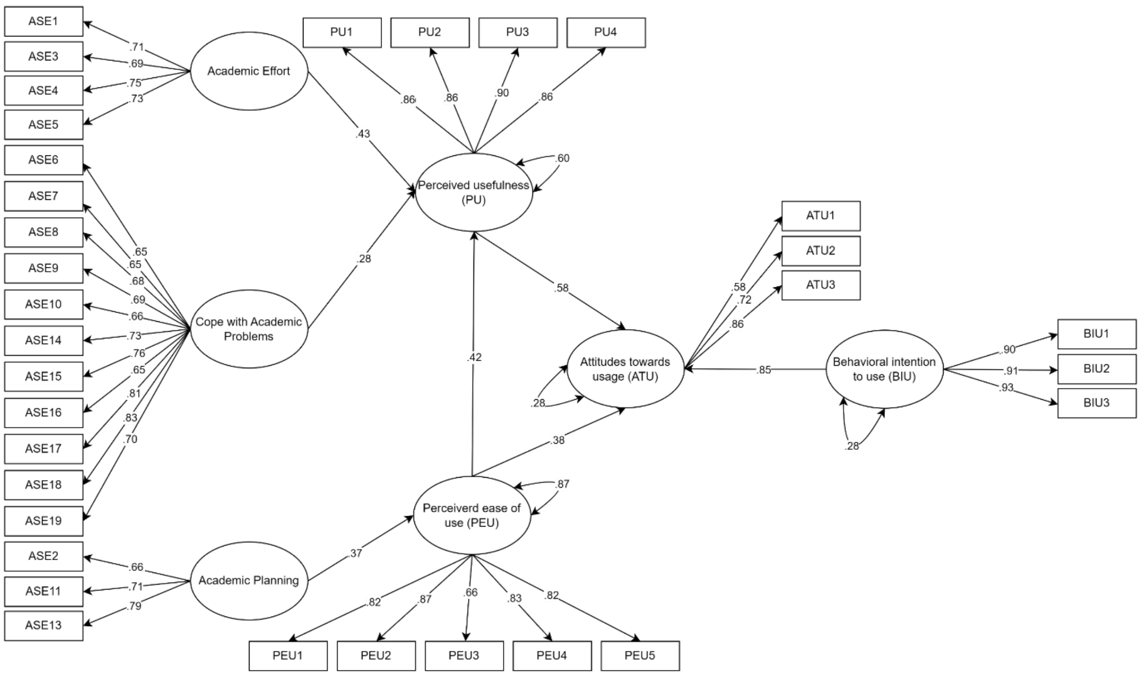

Figure 3. Structural equation modelling of the hypotheses

The data presented in Table 3 indicates a notable positive correlation among these variables. All proposed hypotheses were validated within the model.

Table 3. Hypothesis test results

Structural relations of the proposed model	β	z	p-value	Decision
H1. ASE1 → PU	.28	2.43	.015	Accepted
H2. ASE2 → PU	.43	5.35	.025	Accepted
H3. ASE3 → PEU	.37	7.53	<.001	Accepted
H4. PEU → PU	.42	7.28	<.001	Accepted
H5: PU →ATU	.38	4.81	< .001	Accepted
H6: PEU → ATU	.58	5.60	< .001	Accepted
H7: ATU → BIU	.85	6.51	< .001	Accepted

This self-efficacy and technology acceptance model for Generative AI (GenAI) highlights how individual attitudes and perceptions influence behavioral intentions to adopt GenAI tools. Self-efficacy components such as Academic Effort, Coping with Academic Problems, and Academic Planning are shown to impact perceived ease of use (PEU) and perceived usefulness (PU), which, in turn, affect attitudes towards usage (ATU) and the ultimate behavioral intention to use (BIU) the technology. The model is statistically significant in all structural relationships, suggesting a robust interdependence between these factors. Five key topics have emerged when the results obtained from the model are analyzed in light of the existing literature. These topics are the role of self-efficacy in technology acceptance, adaptation of the Technology Acceptance Model (TAM) for Generative AI (GenAI), perceived usefulness and behavioral intention in GenAI usage, attitudes toward GenAI and adoption behavior, and the relationship between behavioral intention and actual use.

Self-efficacy is critical in technology acceptance, as it directly influences users' confidence in their ability to use new technology effectively. In a foundational study, Bandura [12] demonstrated that self-efficacy affects behavior through efficacy expectations and outcome expectations. This aligns with the model's emphasis on "Academic Effort" and "Coping with Academic Problems" in influencing GenAI acceptance. Research by Budu et al. [71] further reinforces this by showing that both academic and technology-specific self-efficacy significantly contribute to technology acceptance in higher education. Al Kurdi et al. [72] further explore these relationships, developing a model for e-learning technology acceptance that emphasizes the importance of both self-efficacy and social influence in students' perceived ease of use and perceived usefulness of technology, underscoring the broader relevance of self-efficacy across digital learning contexts.

The Technology Acceptance Model (TAM) is frequently adapted to fit specific technological contexts. Davis [8] identified Perceived Usefulness (PU) and Perceived Ease of Use (PEU) as critical predictors of attitudes toward using new technology. The current model adapts TAM constructs to analyze how academic self-efficacy impacts perceptions of GenAI's usefulness and ease of use, ultimately shaping attitudes and intentions toward usage. The research by Al-Adwan et al. [73] on extending TAM to metaverse-based platforms illustrates a similar adaptation, emphasizing that self-efficacy enhances students' perceptions of ease and usefulness for cutting-edge technologies. This suggests that as students become more confident in their abilities, they are more likely to adopt complex technologies like GenAI.

Perceived usefulness is a well-documented predictor of behavioral intentions to use technology, as evidenced by Venkatesh and Bala [51]. The current model links PU directly to BIU, suggesting that students who recognize the academic benefits of GenAI are more likely to incorporate it into their learning activities. This aligns with insights from Latip et al. [74], who found that self-efficacy moderates the acceptance of e-learning platforms, with higher self-efficacy correlating with greater acceptance and intention to use technology. For GenAI, this indicates that perceived utility, supported by self-efficacy, enhances pre-service teachers' intentions to integrate it into their academic work.

Positive attitudes toward technology (ATU) are frequently linked to increased behavioral intentions to adopt, as shown by Fishbein and Ajzen [75]. The current model captures ATU as a factor shaped by both PU and PEU, aligning with the broader body of research on technology adoption. The study by Yanto et al. [76] discusses how perceived ease of use (PEU) and perceived usefulness (PU) significantly influence students' attitudes toward using virtual laboratories, aligning with the broader research on technology adoption. It highlights that PU mediates the relationship between PEU and attitudes, reinforcing the importance of both factors in technology acceptance models. Another research by Jang et al. [77] illustrates how perceived usefulness (PU) and perceived ease of use (PEU) significantly influence attitudes toward technology use (ATU) in the context of integrating AR and VR in education. The study's findings underscore the importance of these factors in shaping teachers' willingness to adopt new technologies, aligning with broader research on technology adoption. In the context of GenAI, positive attitudes fostered by high self-efficacy and perceived ease of use can lead to broader adoption of these tools in academic environments.

Research has consistently demonstrated that behavioral intention (BIU) strongly predicts actual technology usage [50, 53, 78]. Current model aligns with these findings by positing that when students perceive GenAI as valuable and user-friendly, they are more likely to express a strong intention to use it, which translates to increased usage in academic contexts. This is further supported by the study of Al Kurdi et al. [72], which emphasizes the role of behavioral intention as a determinant of actual e-learning technology usage, reinforcing the model's conclusion that positive behavioral intentions can lead to sustained technology adoption. Research by Vinnikova et al. [79] demonstrates that behavioral intention significantly mediates the relationship between perceived usefulness, perceived ease-of-use, and actual usage behavior of smartphone fitness applications, indicating that BIU strongly predicts technology usage. The study's findings suggest that enhancing behavioral intention can effectively increase app adoption, supporting the assertion of BIU's predictive strength.

Proposed model accounts for these dynamics through the PEU and PU constructs, highlighting that self-efficacy is essential for overcoming initial barriers to GenAI adoption. The proposed model accounts for the dynamics of Generative AI (GenAI) adoption through the constructs of perceived ease of use (PEU) and perceived usefulness (PU), highlighting the essential role of self-efficacy in overcoming initial barriers to adoption. Self-efficacy, defined as an individual's belief in their capability to perform a specific task [12], has been widely recognized as a critical determinant in technology acceptance [78].

Recent studies have reinforced this notion by demonstrating how self-efficacy enhances GenAI adoption. Kong et al. [80] found that self-efficacy significantly influences teachers' behavioral intentions toward using GenAI tools in education. Their study, based on an extended TAM framework, demonstrated that as users develop confidence in their ability to utilize AI tools, their perceptions of ease of use and usefulness increase, thereby facilitating smoother adoption. Similarly, Eldakar [81] integrated TAM with the UTAUT and Social Cognitive Theory (SCT) to explore how self-efficacy, ethical considerations, and academic integrity shape scholars' willingness to adopt GenAI. The findings indicate that higher self-efficacy not only fosters adoption but also alleviates concerns regarding ethical compliance and the credibility of AI-generated content.

In student populations, self-efficacy plays a similar role. Tantivejakul et al. [82] applied the Diffusion of Innovations (DOI) model alongside TAM to investigate students' perspectives on GenAI usage in academic writing. Their study revealed that students with higher self-efficacy were more likely to perceive GenAI as a beneficial tool for creative and technical writing. Similarly, Hsiao and Tang [83] identified personal innovativeness and self-efficacy as key factors influencing GenAI adoption in higher education, emphasizing the role of individual and technological determinants in shaping learning experiences. The insights from Al-Adwan et al. [73] regarding TAM adaptations for metaverse platforms suggest that as students' self-efficacy grows, their perceptions of ease and usefulness for complex technologies like GenAI improve, facilitating smoother adoption.

Moreover, faculty perspectives on GenAI adoption align with these findings. Shata and Hartley [84] examined the relationship between faculty self-efficacy and AI adoption, concluding that educators with higher self-efficacy were more likely to trust and integrate AI-powered tools into their teaching and research practices. Furthermore, Tan [85] explored students' long-term intentions to use GenAI through the lens of the Task-Technology Fit (TTF) model integrated with TAM. This study highlighted that self-efficacy, alongside the perceived fit between the task and the technology, significantly influenced continued AI adoption.

Taken together, these studies affirm that self-efficacy is a pivotal factor in the acceptance and sustained use of GenAI across educational and professional domains. Enhancing self-efficacy among students, educators, and professionals may serve as a strategic approach to fostering a more seamless integration of AI-driven technologies.

4. Conclusion and recommendations

The findings of this study support the proposed model, demonstrating the significant impact of self-efficacy on mathematics and science teachers' acceptance of Generative AI (GenAI) technology in academic settings. The positive correlations among the dimensions of academic self-efficacy—such as Academic Effort, Coping with Academic Problems, and Academic Planning—and the core constructs of technology acceptance (Perceived Ease of Use (PEU), Perceived Usefulness (PU), Attitude Toward Usage (ATU), and Behavioral Intention to Use (BIU)) validate the model's hypotheses and align with established theories in the literature on self-efficacy and technology acceptance. Self-efficacy was found to enhance pre-service teachers' perceptions of GenAI's ease of use and usefulness, which, in turn, fostered positive attitudes and stronger intentions to utilize the technology. The strong relationship between ATU and BIU further suggests that positive attitudes toward GenAI can effectively predict pre-service teachers' intentions and likelihood of adoption, indicating a robust framework for understanding the factors influencing GenAI acceptance.

To encourage the broader adoption of Generative AI (GenAI) in educational contexts, several strategies are recommended. First, institutions should enhance pre-service teachers' academic self-efficacy through targeted interventions, such as skills training, problem-solving workshops, and self-regulated learning activities. These interventions can increase their confidence in their academic abilities, thereby supporting more positive perceptions of GenAI tools. Second, integrating training programs that emphasize the practical benefits and ease of using GenAI may strengthen pre-service teachers' perceived usefulness and perceived ease of use, further fostering favorable attitudes toward adoption. Since the data also highlights the predictive role of behavioral intention, educational institutions and technology developers should consider creating supportive environments that sustain pre-service teachers' positive intentions, such as offering ongoing technical support and user-centered design in GenAI applications. Finally, as self-efficacy strongly influences attitudes and intentions, promoting a culture of technological confidence and capability-building among pre-service teachers will be essential for maximizing the effectiveness and adoption of GenAI tools in educational settings.

Future research on the relationship between self-efficacy and the acceptance of Generative AI (GenAI) in education should explore several avenues to enhance understanding and broaden applicability. Longitudinal studies could provide insights into the stability of self-efficacy's influence on GenAI adoption over time. Comparative studies across different educational contexts (e.g., STEM versus humanities) may also reveal discipline-specific needs for fostering technology acceptance. Furthermore, examining the role of instructional support—such as peer networks or interactive tutorials—could identify resources that enhance the perceived ease of use and usefulness of GenAI. Social dynamics, including peer influence and social learning, should also be investigated to understand their moderating effects on self-efficacy and GenAI adoption, as supportive environments may facilitate technology uptake.

Future research should also focus on technology-specific self-efficacy—defined as the confidence in using Generative AI (GenAI) tools—since it may uniquely influence attitudes and behaviors toward GenAI. Experimentally evaluating interventions aimed at enhancing GenAI self-efficacy, such as structured training modules, could identify the most effective methods for increasing confidence and intentions to adopt these technologies. Additionally, understanding the barriers pre-service teachers face with low self-efficacy, such as technology-related anxiety or lack of motivation, could lead to more inclusive strategies for GenAI adoption. Furthermore, cross-cultural studies may reveal how various cultural contexts affect self-efficacy and acceptance of GenAI, while exploring psychological factors such as anxiety, motivation, and growth mindset could provide a comprehensive understanding of individual differences that impact technology acceptance. Collectively, these research avenues can inform targeted strategies to enhance self-efficacy, promote GenAI adoption, and support equitable technology integration in education.

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ANNEX -1

Descriptive Statistics, Internal Consistency, Convergent Validity and Reliability of Items.

Constructs	Item	Factor Loadings	Mean	Sd	Cronbach's α	CR	AVE
Cope with Academic Problems (ASE1)	ASE6	.65	3.78	0.777	.859	.92	.51
	ASE7	.65	3.24	0.965			
	ASE8	.68	3.58	0.947			
	ASE9	.69	3.48	0.981			
	ASE10	.66	3.23	1.042			
	ASE14	.73	3.76	0.856			
	ASE15	.76	3.57	0.854			
	ASE16	.65	3.5	0.886			
	ASE17	.81	3.65	0.764			
	ASE18	.83	3.84	0.75			
	ASE19	.70	3.6	0.826			
Academic Effort (ASE2)	ASE1	.71	3.98	.725	.729	.81	.52
	ASE3	.69	3.95	.665			
	ASE4	.75	3.85	.809			
	ASE5	.73	3.41	.999			
Academic Planning (ASE3)	ASE2	.66	3.67	.840	.713	.76	.52
	ASE11	.71	3.28	1.088			
	ASE13	.79	3.70	.791			
Perceived usefulness (PU)	PU1	.86	4.05	0.735	.889	.92	.75
	PU2	.86	4.04	0.75			
	PU3	.90	4.02	0.736			
	PU4	.86	4.06	0.689			
Perceived ease of use (PEU)	PEU1	.82	3.56	0.889	.886	.90	.64
	PEU2	.87	3.89	0.751			
	PEU3	.66	3.39	0.944			
	PEU4	.83	3.42	0.92			
	PEU5	.82	3.54	0.875			
Attitudes towards usage (ATU)	ATU1	.58	3.27	1.006	.705	.76	.53
	ATU2	.72	3.5	0.9			
	ATU3	.86	3.75	0.894			
Behavioral intention to use (BIU)	BIU1	.90	3.9	0.783	.892	.93	.83
	BIU2	.91	4.01	0.745			
	BIU3	.93	4.01	0.773			