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Belief to behavior: how AI self-efficacy shapes AI acceptance through AI literacy

Onur İşbulan · Mehmet Uysal · Busra Caylan Ergene · Ozkan Ergene

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Abstract

The increasing integration of artificial intelligence (AI) technologies into higher education has raised important questions regarding students' acceptance of AI and the psychological and cognitive factors shaping their engagement with these systems. This study aimed to examine how university students' AI self-efficacy influences their acceptance of AI, whether AI literacy helps explain this relationship, and whether greater AI acceptance is associated with lower AI anxiety. For the present study, data were obtained from 622 undergraduate students at a public university. Empirical analyses were based on validated scales measuring AI self-efficacy, AI literacy, AI acceptance, and AI anxiety, and conducted using correlation analyses and regression-based mediation models via the PROCESS Macro. The results showed that AI self-efficacy was positively associated with AI acceptance, both directly and indirectly through AI literacy. Higher AI acceptance was also associated with lower AI anxiety; however, this relationship should not be interpreted as causal. These findings support a sequential motivational, cognitive and affective model of AI engagement and highlight the importance of integrating confidence-building interventions with literacy-focused instructional strategies to promote psychologically adaptive and sustainable AI integration in higher education contexts.

Introduction

Artificial intelligence has emerged as a transformative technology but it is still subject to significant debate, disagreement, and scrutiny in higher education, generating both substantial opportunities and critical challenges. Although AI in education has existed for approximately thirty years, significant gaps persist between technological advancement and meaningful educational impact (Zawacki-Richter et al., 2019). Research demonstrates concrete applications across four primary domains: profiling and prediction, assessment and evaluation, adaptive systems, and intelligent tutoring systems (Zawacki-Richter et al., 2019; Zhang and Aslan, 2021). However, Picciano (2019) raises a cautionary perspective, arguing that widespread AI adoption may fundamentally alter educators' roles and institutional purpose. A major shift in the conceptual understanding of AI has been noted in recent academic publications, from technology-directed learning where students are passive recipients, to AI-empowered models emphasizing learner agency and personalization (Ouyang and Jiao, 2021; Gašević et al., 2023). This paradigm shift reflects growing recognition that meaningful AI integration requires pedagogical grounding rather than mere technological sophistication.

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Effective implementation of AI in higher education increasingly centers on learner empowerment and literacy development. Kong et al. (2021) demonstrated that university students across diverse disciplines could develop conceptual understanding of machine learning and AI applications through structured literacy courses, reporting increased confidence engaging with AI systems. Simultaneously, Chiu et al. (2023) identified thirteen distinct roles AI plays in educational domains while highlighting ten major challenges, including concerns about equity, bias, and validity in AI-driven assessment. Kabudi et al. (2021) further documented substantial gaps between proposed adaptive learning systems and actual institutional implementation, suggesting that adoption lags considerably behind theoretical enthusiasm. Moving forward, research emphasizes that progress requires interdisciplinary collaboration addressing ethics, data governance, AI literacies among stakeholders, and policy development responsive to rapid technological change (Gašević et al., 2023; Zhang and Aslan, 2021).

At the same time, AI-driven personalization (Huang, Lu, and Yang, 2023) and 24/7 support through AI-based chatbots (Rackoff et al., 2025; Reyes-Portillo et al., 2025) can enhance students' engagement and well-being, while accessibility-oriented AI systems that tailor content, pacing, and feedback to individual needs further promote inclusive, student-centered learning environments (Huang et al., 2023). These developments collectively suggest that students' psychological responses, such as motivation, autonomy, and perceived support, and their AI literacies are critical to realizing AI's pedagogical benefits (Huang et al., 2023; Rackoff et al., 2025; Reyes-Portillo et al., 2025). Within this complex context, Bandura's (1986, 1997) Social Cognitive Theory proposes that human behavior is shaped by the ongoing interaction between personal beliefs, actions, and environmental conditions. From this perspective, students' engagement with AI can be viewed as a sequential process where motivational beliefs precede cognitive development, which then drives behavioral and affective outcomes (Bandura, 1997). Self-efficacy may influence whether individuals begin a learning activity, how much effort they invest, and how long they continue when they face difficulties (Bandura, 1982, 1997). From this perspective, the present study considers AI self-efficacy as a possible motivational basis for the development of AI literacy. Although previous studies suggest that literacy may also strengthen confidence over time (Chun et al., 2025; Zhang et al., 2025), students who feel more confident in using unfamiliar AI technologies may be more willing to engage with them and develop their knowledge and skills (Bandura, 1997). In contrast, limited confidence may reduce their willingness to take part in learning experiences that support AI literacy (Schutte and Li, 2025). These relationships are therefore examined within a sequential model involving AI self-efficacy, AI literacy, AI acceptance, and AI anxiety. In this study, these factors are represented by AI self-efficacy, AI literacy, AI acceptance, and AI anxiety, respectively.

AI self-efficacy: foundations, measurement, and educational outcomes

As artificial intelligence becomes more common in education, it is increasingly important to understand individuals' AI self-efficacy, defined as their confidence in their ability to use AI technologies effectively (Chun et al., 2025). Although AI self-efficacy is a relatively new concept, it is grounded in Bandura's (1982) work on self-efficacy, which emphasizes that people's beliefs about their capabilities are related to their motivation, thinking, and choices when they face unfamiliar tasks. Despite the growing use of AI in education, validated measures of AI self-efficacy have only recently been developed (Wang and Chuang, 2024). Wang and Chuang (2024) identified four core factors of AI self-efficacy: assistance, anthropomorphic interaction, comfort with AI, and technological skills. At the same time, institutional AI capability significantly influences students' self-efficacy, which in turn affects creativity and learning performance (Wang et al., 2023). Additionally, Schutte and Li (2025) found that general curiosity, particularly the exploration dimension, strengthens self-efficacy for AI use, which subsequently predicts increased student engagement with AI tools. Collectively, these findings indicate that AI self-efficacy functions as a critical psychological construct mediating between technological availability and meaningful learning outcomes in contemporary higher education.

Psychological and organizational factors further shape AI self-efficacy across educational stakeholder groups. Among EFL students, resilience and self-efficacy jointly predict 54.2% of learning motivation in AI-based contexts, with resilience proving the stronger predictor (Shi and Zhang, 2025). For educational leaders, a growth mindset

significantly predicts readiness to adopt AI through both direct and indirect pathways via self-efficacy and openness to change (Kılınç et al., 2025), while perceived usefulness and ease of use strengthen AI literacy and leadership self-efficacy (Bellibaş et al., 2025). Chun et al. (2025) reveal that AI literacy serves as a core condition influencing self-efficacy, creativity, and academic achievement through complex interrelationships. Consequently, cultivating AI self-efficacy requires multifaceted approaches that address technological design, individual psychological capacities, and institutional support systems, empowering diverse educational stakeholders.

AI acceptance: technology adoption models and human factors

Acceptance of artificial intelligence technologies is widely identified as a key condition for their successful integration in education, with recent studies stressing that uptake by students and educators largely determines whether AI-enhanced tools actually improve teaching and learning outcomes (Espinoza-Bravo et al., 2025; Nevárez Montes and Elizondo-Garcia, 2025; Helmiatin et al., 2024). At the same time, this adoption is shaped by complex psychological and contextual factors, including performance expectancy, self-efficacy, social influence, and facilitating conditions, as well as institutional readiness and broader cultural and ethical concerns in specific educational settings (Bai and Yang, 2025; Espinoza-Bravo et al., 2025; Sustaningrum and Haldaka, 2025). This is also reflected in recent research with Turkish university students, which found that social influence and ease of use are related to students' acceptance of generative AI (Gözüm et al., 2026).

Traditional technology adoption frameworks, such as the Technology Acceptance Model (TAM) (Davis, 1989), explain technology acceptance mainly through perceived usefulness and ease of use (Al Darayseh, 2023; Chocarro et al., 2023; Zhang et al., 2023). However, these factors may not fully explain how individuals respond to complex technologies such as AI. First, traditional models often give limited attention to personal factors, including users' confidence and AI-related knowledge and skills (Schiavo et al., 2024). Second, acceptance is often treated as the final outcome of technology adoption, with less attention given to how it may relate to later emotional responses, such as AI anxiety. Recent studies support this broader view of AI acceptance. Schiavo et al. (2024) found that while AI literacy fosters positive attitudes toward acceptance, anxiety mediates this relationship, with learning and socio-technical dimensions of AI anxiety serving as partial mediators between literacy and acceptance. Trust operates as another significant factor; Choung et al. (2023) identified both human-like and functionality trust as distinct dimensions that significantly influence usage intention through perceived usefulness and attitude. This multi-dimensional understanding reveals that AI acceptance extends beyond mere technological features, encompassing psychological, social, and organizational dimensions.

Effective AI acceptance requires addressing barriers that extend beyond ease-of-use considerations. Nazaretsky et al. (2021) documented that teacher demonstrate reluctance to accept AI recommendations that contradict their prior knowledge and expect absolute correctness, even in inherently ambiguous contexts, revealing a confirmation bias in technology adoption. Among nursing students, anxiety about AI and acceptance attitude jointly mediate the relationship between AI perception and usage intention, underscoring the need for systematic educational interventions (Cho and Seo, 2024). Yu et al. (2022) emphasize that AI adoption from a socio-technical systems perspective requires attention to personnel, technical, organizational, and environmental factors affecting individual, organizational, and employment outcomes. To sum up, fostering meaningful AI acceptance demands interventions addressing human factors including trust, literacy, anxiety reduction, and alignment with professional judgment.

AI literacy: defining, teaching, and assessing AI competencies

Artificial intelligence literacy has emerged as an essential competency for students across all educational levels, yet the field continues to grapple with defining, teaching, and assessing this multifaceted construct. Ng et al. (2021) proposed a foundational framework for conceptualizing AI literacy through four interconnected aspects: knowing and understanding, using and applying, evaluating and creating, and addressing ethical issues. Despite this conceptual progress, Laupichler et al. (2022) found that research on AI literacy in higher and adult education remains in its

infancy, with little consensus on how to define AI literacy for non-experts or what content should be taught. At the K-12 level, Casal-Otero et al. (2023) identified two broad approaches to AI literacy integration: learning experiences focused on technical and conceptual skills and theoretical models framing AI literacy proposals, but noted that few programs systematically assess student conceptual understanding post-instruction. Notably, Kalantzis and Cope (2025) argue that the technological significance of Generative AI rivals that of the printing press, demanding a fundamentally reconceptualized literacy framework that addresses the cyber-social dimensions of AI engagement.

Translating AI literacy concepts into practice requires addressing substantial implementation challenges across educational contexts. Su et al. (2023) documented that early childhood education faces critical barriers, including teacher knowledge gaps, insufficient curriculum design, and inadequate teaching guidelines. Among primary and middle school teachers in China, Zhao et al. (2022) found that applying AI (i.e., using and implementing AI tools) positively influenced other dimensions of AI literacy, suggesting that experiential engagement with AI strengthens broader conceptual and ethical understanding. Zhang et al. (2024) developed and validated the Artificial Intelligence Literacy Concept Inventory to assess student understanding, which helped to address a critical measurement gap identified in prior reviews. Ultimately, effective AI literacy development hinges on a set of key requirements identified by this research: coherent curriculum frameworks, teacher professional development, validated assessment instruments, and pedagogical approaches that integrate technical skills, critical evaluation, and ethical reasoning.

AI anxiety: conceptualization, measurement, and psychological impact

Artificial intelligence anxiety has emerged as a significant psychological phenomenon affecting diverse populations, yet scholarly understanding remains fragmented across conceptual and measurement domains. Johnson and Verdicchio (2017) separate wild, science-fiction style fears about AI (based on mistaken ideas about machines "waking up" and acting like humans) from reasonable worries about how real AI systems are built, used, and controlled by people, especially when machine decision-making does not properly match human values or responsibilities. Li and Huang (2020) advanced this conceptualization by applying integrated fear acquisition theory to identify four dimensions of AI anxiety, personal experience, social influence, media exposure, and cultural context, encompassing eight distinct factors: direct experience, vicarious learning, verbal information, imagined scenarios, social norms, trust in technology, ethical concerns, and perceived loss of control, thereby proposing multiple pathways through which AI anxiety develops.

Wang and Wang (2022) developed the first standardized Artificial Intelligence Anxiety Scale, establishing reliable measurement of this construct and demonstrating that AI anxiety negatively predicts motivated learning behavior. More recently, Kim et al. (2023) conducted a comprehensive psychological analysis, showing that AI anxiety arises through interconnected cognitive, emotional, and behavioral mechanisms shaped by fears of replacement, loss of control, privacy erosion, misinformation, and bias. In combination, these studies establish AI anxiety as a measurable, multidimensional construct that requires nuanced understanding beyond simple fear responses, with important implications for educational and organizational contexts.

AI anxiety manifests differentially across stakeholder groups and carries significant consequences for technology adoption and well-being. Hopcan et al. (2024) found that teacher candidates express anxiety primarily regarding AI's employment and social impacts rather than learning difficulties, suggesting anxiety concentrates on existential rather than capability concerns. Among EFL learners, Wen et al. (2024) demonstrated that job replacement anxiety and learning anxiety indirectly predict reduced behavioral intention to use AI tools. Cantaş et al. (2024) revealed no significant correlation between AI anxiety and 21st-century skills or lifelong learning, indicating anxiety may not prevent skill development. However, Kaya et al. (2024) found that anxieties related to AI learning and configuration are significant predictors of both favorable and unfavorable attitudes toward artificial intelligence, while traits such as agreeableness and the frequency of computer use further shape individuals' overall perceptions of AI. These patterns suggest interventions addressing specific anxiety dimensions, enhancing AI literacy, and leveraging social influence could effectively promote adaptive engagement with AI technologies.

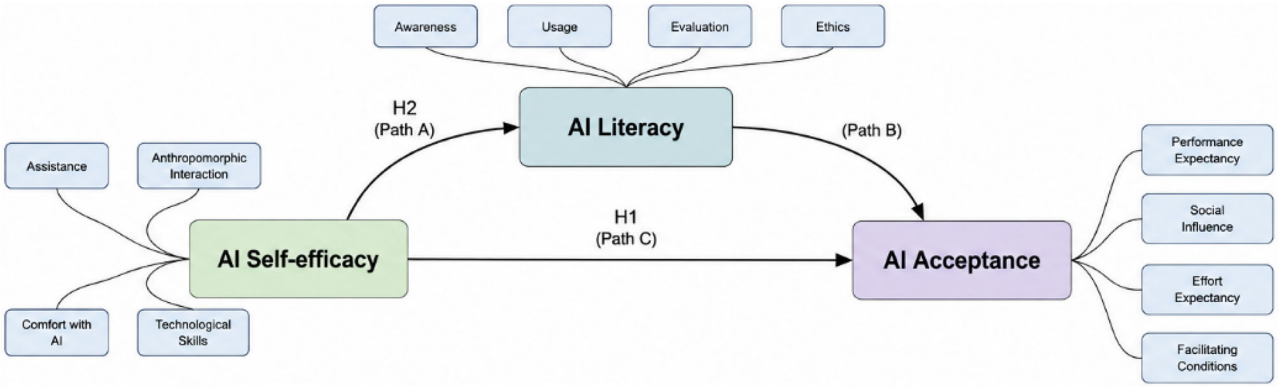

Fig. 1 Conceptual mediation model of AI self-efficacy, AI literacy, and AI acceptance.

Problem, aims, and hypotheses

This study responds to the growing need to understand how university students perceive, use, and emotionally respond to artificial intelligence in higher education. Bandura's (1986, 1997) Social Cognitive Theory provides the main theoretical framework for the study. The theory suggests that human behavior is shaped by the ongoing interaction between personal beliefs, actions, and environmental conditions. In this study, these factors are represented by AI self-efficacy, which refers to students' confidence in using AI, AI literacy, which reflects their knowledge and skills, AI acceptance, which indicates their willingness to adopt AI, and AI anxiety, which refers to feelings of worry or discomfort about AI. From the perspective of Social Cognitive Theory, students' beliefs about their abilities may shape how they engage in learning and respond emotionally (Bandura, 1997). Although AI literacy may strengthen self-efficacy over time (Chun et al., 2025), self-efficacy may also encourage students to engage with AI and develop their knowledge and skills (Bandura, 1982, 1997). Based on this view, the study proposes a sequence in which AI self-efficacy is related to AI literacy, AI literacy is related to AI acceptance, and AI acceptance is associated with lower AI anxiety.

Response letter hazırla son yprum için

By examining these variables together, the study addresses three gaps in the literature. First, although previous studies have examined these factors separately (Al Darayseh, 2023; Wang and Wang, 2022), less is known about how motivational factors such as self-efficacy and cognitive factors such as literacy work together in relation to AI acceptance. Second, limited research has examined how students' confidence in using AI may be related to the development of AI knowledge and skills and how these skills may then be associated with greater acceptance. Third, little is known about whether AI acceptance is related to students' emotional responses, particularly their anxiety toward AI (Schiavo et al., 2024).

To address these gaps, the study proposes a sequential model of students' engagement with AI. In this model, AI self-efficacy is treated as a motivational factor associated with AI literacy. AI literacy is then examined as a factor that may help explain the relationship between self-efficacy and AI acceptance. AI acceptance is also examined in relation to AI anxiety as a secondary emotional outcome (Schiavo et al., 2024). In this way, the study extends technology acceptance research by considering both the motivational and cognitive factors related to acceptance and its possible relationship with students' emotional responses. Based on our theoretical framework and the reviewed literature, we proposed the following hypotheses:

H1: aI self-efficacy is positively associated with students' acceptance of AI.

H2: aI literacy mediates the relationship between AI self-efficacy and acceptance of AI.

H3: acceptance of AI is negatively related to students' anxiety toward AI.

The conceptual mediation model based on Social Cognitive Theory is presented in Fig. 1.

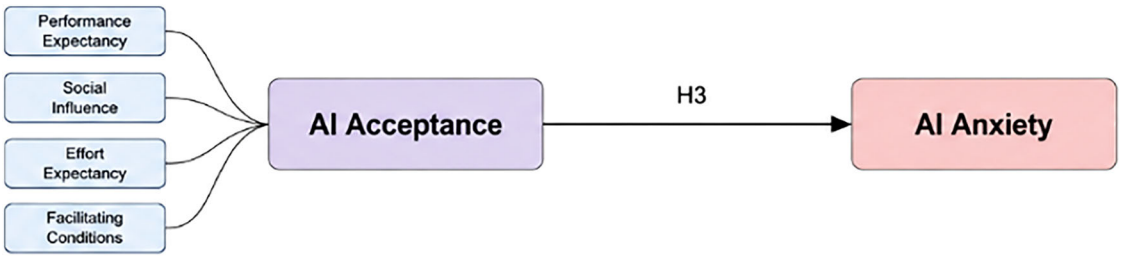

Fig. 2 Association between AI acceptance and AI anxiety.

Figure 1 shows the direct relationship between AI self-efficacy and AI acceptance, as well as the indirect relationship through AI literacy. The separate association between AI acceptance and AI anxiety is presented in Fig. 2. This association is examined as an additional outcome rather than as part of the mediation model.

Together, these relationships help explain how university students develop acceptance of AI and how this acceptance may relate to their anxiety toward AI.

Methodology

This study employed a quantitative research design to examine the relationships among AI self-efficacy, AI literacy, AI acceptance, and AI-related anxiety among undergraduate students enrolled at a public university. A conceptual model was developed to examine the direct relationship between AI self-efficacy and AI acceptance, as well as the indirect relationship through AI literacy. As shown in Fig. 1, these relationships were tested using correlation and regression-based mediation analyses. Specifically, the mediation model includes AI self-efficacy as the independent variable, AI acceptance as the dependent variable, and AI literacy as the mediator. AI-related anxiety is examined separately as a secondary outcome associated with AI acceptance through regression analysis.

Population and sample

The study was conducted with undergraduate students enrolled at a university in Türkiye. Participants were recruited from a public university located in the Marmara region using convenience sampling (Creswell and Creswell, 2018) during the Autumn semester of the 2025-2026 academic year. Although the data were obtained from a single institution, the sample represents a diverse profile of undergraduate students in terms of academic disciplines and grade levels, allowing cautious inferences to be drawn at the national level.

A total of 740 students were invited to participate, and 669 students completed the survey on a voluntary basis (representing a response rate of 90.4%). Because all scale items required a response in the online questionnaire, there were no missing data in the completed surveys. Following data screening, the responses were scored and standardized, and z-scores were examined to identify potential outliers. Of the 669 completed surveys, 47 were excluded because of highly repetitive response patterns (i.e., straight-lining) or extreme z-scores beyond ±3.29 (Hair et al., 2010). Consequently, the final sample included 622 students, whose data were retained for subsequent analyses. To evaluate the adequacy of the final sample size, we conducted a statistical power analysis based on Cohen's (1988) effect-size conventions using G*Power (Faul et al., 2007). For a multiple linear regression model with two predictors, approximately 485 participants are required to detect a small effect size of $f^2 = 0.02$ with 80% power at an alpha level of 0.05. The final sample of 622 students exceeded this requirement and provided approximately 89.3% power to detect an effect of this magnitude. It also provided nearly 100% power to detect medium ($f^2 = 0.15$) and large ($f^2 = 0.35$) effects. For the regression model with the smallest observed effect, namely the association between AI acceptance and AI anxiety ($R^2 = 0.048$, $f^2 = 0.0504$), the estimated statistical power exceeded 99.9%. These findings indicate that the sample size was sufficient to detect the hypothesized regression effects, including effects within the

Table 1 Demographics of the participants.

		N	%
Gender	Female	495	79.6%
	Male	127	20.4%
	Total	622	100%
Grade level	Freshman	98	15.8%
	Sophomore	260	41.8%
	Junior	148	23.8%
	Senior	116	18.6%
	Total	622	100%

small range. The indirect effects were also evaluated using bootstrapped confidence intervals, providing an appropriate assessment of their statistical precision. Participants' demographic characteristics are presented in Table 1.

As shown in Table 1, the sample consisted predominantly of female students (79.6%, $n = 495$), while male students accounted for 20.4% ($n = 127$). In terms of grade level, 15.8% of the participants were Freshmen ($n = 98$), 41.8% were Sophomores ($n = 260$), 23.8% were Juniors ($n = 148$), and 18.6% were Seniors ($n = 116$).

Data collection tools

Data were collected using four validated instruments, including the AI Self-Efficacy Scale, AI Acceptance Scale, AI Literacy Scale, and AI Anxiety Scale.

AI self-efficacy scale

The AI Self-Efficacy Scale, originally developed by Wang and Chuang (2024) with 22 items, was adapted into Turkish by Uyan and Gültekin (2024). The adaptation process followed established cross-cultural validation procedures, including translation back translation, linguistic equivalence testing, and validity and reliability analyses. Linguistic equivalence results indicated a high correlation between the Turkish and original English versions. The Turkish form consists of 21 items rated on a 5-point Likert scale. Exploratory and confirmatory factor analyses provided evidence supporting the construct validity of the scale in the Turkish context. Sample items include "*I find it easy to get AI technologies/products to do what I want them to do*" and "*I can interact smoothly and comfortably with AI technologies/products*." The internal consistency coefficients reported for the subscales ranged between 0.71 and 0.78, indicating acceptable reliability.

AI acceptance scale

The AI Acceptance Scale was developed by Yılmaz, Yılmaz, and Ceylan (2023) based on the UTAUT framework. Exploratory factor analysis was conducted with data from 338 university students, followed by confirmatory factor analysis with a separate sample of 250 students. The resulting scale comprises 20 items across four factors, rated on a 5-point Likert scale, and accounts for 78.34% of the total variance. The scale includes items such as "*The use of generative AI applications makes my life easier*" and "*It is easy for me to become skilled in using generative AI applications*." The original study reported excellent overall reliability (Cronbach's $\alpha = 0.97$).

AI literacy scale

The AI Literacy Scale, developed by Wang et al. (2022), was adapted into Turkish by Çelebi, Yılmaz, Demir, and Karakuş (2023). The adaptation study was conducted with 402 adult participants who had no professional background in AI. Construct validity was examined through confirmatory factor analysis. The scale consists of 12 items across four dimensions. The CFA results demonstrated good model fit ($\chi^2/df = 1.82$, RMSEA = 0.04, RMR = 0.03,

NFI = 0.95, CFI = 0.98, GFI = 0.96, AGFI = 0.94). The scale includes items such as "*I can identify the AI technology used in the applications and products I use*" and "*I can evaluate the capabilities and limitations of an AI application or product after using it for a while*." The internal consistency coefficients for the subscales ranged from 0.72 to 0.76, while the overall reliability coefficient was reported as 0.85.

AI anxiety scale

The AI Anxiety Scale, originally developed by Wang and Wang (2022; first published online in 2019), consists of 21 items and was adapted into Turkish by Terzi (2020). The translation process involved independent forward translations by three academics who had completed doctoral training in English-speaking countries, followed by evaluation of translation consistency. The scale was subsequently back-translated by another independent academic and compared with the original version. Confirmatory factor analysis supported the four-factor structure, with acceptable model fit indices. The scale includes items such as *"Learning how an AI technique or product works makes me anxious"* and *"I am afraid that an AI technique or product may get out of control or malfunction."* The adaptation study reported an overall internal consistency coefficient of Cronbach's $\alpha = 0.96$, indicating excellent reliability.

In the present dataset, internal consistency coefficients (Cronbach's α) were 0.87 for the AI Self-Efficacy Scale, 0.90 for the AI Acceptance Scale, 0.77 for the AI Literacy Scale, and 0.92 for the AI Anxiety Scale. These values indicate satisfactory to excellent reliability across all measures, supporting their suitability for the subsequent regression and mediation analyses (Hair et al., 2010; Nunnally and Bernstein, 1994).

Data analysis

Data were analyzed using SPSS (Version 27). Prior to hypothesis testing, the dataset was screened for missing values, outliers, and normality. Standardized z-scores were examined to identify potential outliers, and cases exceeding acceptable thresholds were excluded from further analysis. Demographic variables such as gender and academic year were not included as control variables in the mediation analysis. Descriptive statistics were computed for all study variables, followed by Pearson correlation analyses to examine bivariate relationships among AI self-efficacy, AI literacy, AI acceptance, and AI anxiety. To test the hypothesized mediation model, regression-based mediation analyses were conducted using PROCESS Macro for SPSS (Model 4; Hayes, 2013). This procedure estimates total, direct, and indirect effects through ordinary least squares regression combined with nonparametric bootstrapping. Indirect effects were evaluated using a bias-corrected bootstrap procedure with 5000 resamples, and mediation was considered statistically significant when the 95% confidence intervals did not include zero (Hayes, 2013). All statistical tests were evaluated using an alpha level of 0.05 and 0.01. Effect sizes and variance explained (R^2 values) were reported for regression models to assess the strength of the relationships among variables. Regression assumptions were rigorously examined prior to hypothesis testing. Linearity and homoscedasticity were confirmed through visual inspection of scatterplots of standardized residuals against predicted values. The independence of errors was verified using the Durbin-Watson statistic, which fell within the acceptable range across the tested models (DW ranged from 1.869 to 1.975). Multicollinearity was assessed by examining Variance Inflation Factor (VIF) and tolerance values; the maximum VIF value was 1.213 and the minimum tolerance value was 0.825, indicating no severe multicollinearity among predictors. Finally, potential influential cases were evaluated using Cook's distance, with a maximum value of 0.128, which remains well below the critical threshold of 1, confirming that no single case unduly influenced the regression analyses.

Given that the data were collected cross-sectionally using self-report measures, Harman's single-factor test was conducted to assess the potential for common method bias. All items from the study's scales were entered into an unrotated principal component analysis constrained to extract a single factor. The results indicated that the single factor accounted for 20.17% of the total variance, which is well below the recommended threshold of 50%. Therefore, common method bias was not considered a significant threat to the validity of the findings in this study.

Table 2 Pearson correlations among the study variables.

Variables	Mean	SD	AI Literacy	AI Acceptance
AI Self-Efficacy	75.63	11.45	0.419**	0.536**
AI Literacy	46.87	5.35	-	0.591**

SD Standard Deviation.

* $p < 0.05$, ** $p < 0.001$.

Validity and reliability of the study

The validity of the present study was supported through a theoretically grounded research design and the use of previously validated measurement instruments. The conceptual model and hypotheses were derived from established literature on AI self-efficacy, AI acceptance, AI literacy, and AI-related anxiety, ensuring coherence between the research framework and analytical procedures. Reliability was assessed using Cronbach's alpha coefficients calculated for each scale in the present sample. Internal consistency estimates were 0.87 for AI Self-Efficacy, 0.90 for AI Acceptance, 0.77 for AI Literacy, and 0.92 for AI Anxiety. These values exceed the commonly accepted reliability threshold of 0.70 and indicate satisfactory to excellent internal consistency, supporting the suitability of the measures for subsequent correlation, regression, and mediation analyses (Hair et al., 2010; Nunnally and Bernstein, 1994). Data screening procedures and regression assumption checks further strengthened the methodological rigor of the study.

Results

Hypotheses were tested using a two-step analytic strategy. First, Pearson correlation analyses were performed to identify bivariate associations among the primary study variables. Second, regression-based mediation analyses were conducted using PROCESS to examine both the direct effects of AI self-efficacy on AI acceptance and the indirect effects transmitted through AI literacy, as specified in the proposed conceptual model.

Correlation analysis

Pearson correlation analyses were conducted to examine the relationships among AI self-efficacy, AI literacy, and AI acceptance. The results are presented in Table 2.

Pearson correlation analyses revealed significant positive associations among AI self-efficacy, AI literacy, and AI acceptance as shown in Table 2, Specifically, self-efficacy was moderately correlated with AI literacy ($r = 0.42$, $p < 0.01$) and AI acceptance ($r = 0.54$, $p < 0.01$). In addition, AI literacy was strongly correlated with AI acceptance ($r = 0.59$, $p < 0.01$). These findings indicate that greater self-efficacy and AI literacy are associated with higher levels of AI acceptance.

Mediation analysis

To examine the effect of AI self-efficacy on AI acceptance and the mediating role of AI literacy, mediation analyses were conducted using PROCESS Macro Model 4 (Hayes, 2013). Indirect effects were estimated through a bias-corrected bootstrap procedure with 5,000 resamples. Mediation was considered statistically significant when the 95% confidence interval did not include zero, consistent with established recommendations (Hayes, 2013; Preacher and Hayes, 2008).

H1 was examined using regression analysis, and the results are summarized in Table 3.

Table 3 Regression results for the predictive relationship between AI self-efficacy on AI acceptance.

Variables	*B*	SE	95% CI	R^2	*p*
AI Self-Efficacy-AI Acceptance	0.430	0.027	0.37–0.48	0.287	<0.001

As presented in Table 3, regression analysis indicated that AI self-efficacy exhibited a significant positive association with AI acceptance ($B = 0.43$, SE = 0.02, $t = 15.80$, 95% CI [0.37, 0.48], $R^2 = 0.29$, $p < 0.01$). Thus, H1 was supported.

H2 was examined using regression analysis, and the results are summarized in Table 4.

As shown in Table 4, mediation analysis demonstrated that AI literacy statistically mediated the positive association between AI self-efficacy and AI acceptance. The indirect effect of AI self-efficacy on AI acceptance through AI literacy was statistically significant ($B = 0.15$, SE = 0.018, 95% CI [0.12, 0.19]), as the confidence interval did not include zero. Accordingly, H2 was supported.

The predictive relationship between AI acceptance and AI anxiety

H3 was examined using regression analysis, and the results are summarized in Table 5.

Results reported in Table 5 indicate that AI acceptance was significantly and negatively associated with AI anxiety ($B = -0.34$, SE = 0.06, 95% CI [−0.46, −0.22], $R^2 = 0.05$, $p < 0.01$). This finding suggests that higher levels of AI acceptance are associated with lower levels of anxiety toward AI technologies. Therefore, H3 was supported.

Discussion

The present study explored the relationships among AI self-efficacy, AI literacy, AI acceptance, and AI anxiety among undergraduate students. Data were collected from 622 participants at a public university and analyzed using correlational and regression-based mediation procedures. Guided by a conceptual model, this study examined the direct relationship between AI self-efficacy and AI acceptance, the mediating role of AI literacy, and the association between AI acceptance and AI-related anxiety. Overall, the study aimed to explain how motivational and cognitive factors shape students' acceptance of AI and how this acceptance may relate to their emotional responses in higher education.

The strong positive effect of AI self-efficacy on AI acceptance observed in the present study ($\beta = 0.43$) underscores the central importance of motivational beliefs in shaping students' openness to emerging technologies. This result is highly consistent with prior empirical findings. Heydarnejad (2024) reported a nearly identical correlation between AI self-efficacy and attitudes toward AI-assisted language learning ($r = 0.433$, $p < 0.01$), demonstrating that students' confidence in their competence with AI translates into more favorable attitudes across learning contexts. Similarly, within a UTAUT framework, Pratama et al. (2025) found that self-efficacy enhanced perceived usefulness and perceived ease of use two critical predictors of behavioral intention and technology acceptance. Extending this perspective to behavioral engagement outcomes, Zhang et al. (2025) reported that AI learning self-efficacy significantly predicted willingness to communicate ($\beta = 0.151$, $p = 0.004$), a construct conceptually linked to acceptance-related participation and technology integration behaviors.

From a psychological standpoint, AI self-efficacy reflects students' perceived ability to effectively operate AI tools. When students believe that they can competently interact with technology, they are less likely to interpret AI systems

Table 4 Mediation results for AI literacy in the relationship between AI self-efficacy and AI acceptance.

AI Literacy	*B*	SE	95% CI	*p*
Total Effect (c)	0.430	0.027	0.37–0.48	<0.001
Direct Effect (c^{l})	0.280	0.026	0.22–0.33	<0.001
Indirect Effect (axb)	0.150	0.018	0.12–0.19	

Table 5 Regression results for the association between AI acceptance on AI anxiety.

Variables	*B*	SE	95% CI	R^2	*p*
AI acceptance-AI Anxiety	−0.340	0.061	−0.460 / −0.220	0.048	<0.001

as overwhelming or threatening and more likely to frame these tools as supportive learning resources. This reduced threat perception promotes persistence, experimentation, and active engagement with AI applications. Supporting this interpretation, Batool et al. (2025) showed that elevated self-efficacy levels were associated with more proactive involvement in AI-supported learning environments and improved learning effectiveness. Collectively, these converging findings position self-efficacy as a foundational motivational driver of AI acceptance among university students. These observations are consistent with recent findings among Turkish university students, showing that social influence and ease of interaction are related to their willingness to use conversational AI tools (Gözüm et al., 2026).

The present study also showed that AI literacy significantly mediated the relationship between AI self-efficacy and AI acceptance. Although AI self-efficacy was directly associated with AI acceptance, part of this relationship was also explained through AI literacy (indirect effect, $\beta = 0.19$). This finding suggests that students' confidence in using AI may support the development of AI knowledge and skills, which in turn may strengthen their acceptance of AI. This finding suggests that AI self-efficacy may serve as an important motivational basis for students. Students who feel more confident in their ability to use AI may be more willing to explore AI tools, persist when they face difficulties, and invest the effort needed to improve their knowledge and skills.

From the perspective of Bandura's (1997) Social Cognitive Theory, self-efficacy influences whether individuals begin a learning activity, how much effort they invest, and how long they persist when challenges arise. In this sense, confidence in using AI may support the later development of AI literacy. As students become more willing to engage with AI, they gain greater conceptual and practical knowledge, which may also contribute to stronger acceptance of these technologies (Schiavo et al., 2024). This sequence, in which AI self-efficacy contributes to AI literacy, differs from studies that position AI literacy as a predictor of self-efficacy (Chun et al., 2025; Zhang et al., 2025). Chun et al. (2025), for example, suggested that basic AI knowledge and skills help students feel more confident, while Zhang et al. (2025) reported that AI literacy strengthens learning self-efficacy. These findings indicate that the relationship may operate in both directions over time: greater knowledge can build confidence, while greater confidence can encourage further learning. However, the present model emphasizes self-efficacy as an initial motivational factor, particularly for students with limited experience of AI. In educational settings where AI tools are introduced rapidly, students may first need to believe that they are capable of using these technologies. Without this initial confidence, they may be less likely to engage in the learning experiences through which AI literacy develops. Therefore, the model positions AI self-efficacy as an important motivational basis for the development of AI literacy.

Educationally, these findings indicate that students' acceptance of AI technologies is most effectively fostered through instructional approaches that address both motivational (i.e. self-efficacy) and cognitive (i.e. literacy) dimensions. Strengthening students' self-efficacy in using AI tools without simultaneously developing their AI literacy may yield limited effects. In contrast, integrated learning experiences that cultivate both competence beliefs and conceptual understanding appear essential for supporting informed and sustainable AI adoption in higher education contexts.

Consistent with the third hypothesis, higher AI acceptance was associated with lower AI anxiety. This finding is in line with previous research showing that anxiety toward advanced technologies tends to decrease when individuals view them positively and see their use as manageable rather than threatening (Batool et al., 2025). One possible explanation is that students who accept AI are more willing to use and explore these tools. Through repeated interaction, AI may become more familiar, understandable, and easier to manage. This may reduce uncertainty, fear of losing control, and concerns about using AI effectively (Batool et al., 2025; Kim et al., 2023). In this sense, greater familiarity and understanding may help students view AI as a useful resource rather than a source of threat.

However, AI acceptance explained only 5% of the variance in AI anxiety ($R^2 = 0.05$), indicating that the relationship was relatively weak. This suggests that AI acceptance is only one of several factors related to students'

anxiety and that other influences may play a larger role. AI anxiety is a complex construct that may involve concerns extending beyond the usefulness or ease of use of AI. For example, students may worry about job replacement (Hopcan et al., 2024; Wen et al., 2024), privacy, misinformation, algorithmic bias, or losing control over decisions made by AI systems (Kim et al., 2023). They may also experience concerns about learning how to use AI or dealing with technical difficulties (Kaya et al., 2024). Such concerns may remain even when students generally accept AI as useful. Therefore, AI acceptance appears to account for only a small part of students' broader emotional responses to AI.

Furthermore, the relationship between AI acceptance and AI anxiety may operate in both directions or may partly reflect other underlying factors. Although the present model treats AI acceptance as being associated with lower anxiety, students who already feel less anxious about AI may also be more willing to accept and use these tools (Cho and Seo, 2024; Schiavo et al., 2024; Wen et al., 2024). Over time, lower anxiety may encourage initial acceptance, while continued use and greater familiarity may further reduce anxiety. The observed relationship may also be influenced by other factors, such as personality traits (Kaya et al., 2024) or AI literacy (Schiavo et al., 2024), which may be related to both higher acceptance and lower anxiety.

The results of this study offer several important implications for higher education institutions seeking to integrate AI technologies in a psychologically sustainable manner. First, the strong predictive role of AI self-efficacy suggests that instructional interventions should prioritize strengthening students' confidence in interacting with AI tools, as self-efficacy has been consistently linked to more positive attitudes toward AI-supported learning (Heydarnejad, 2024). Scaffolded training activities, guided practice sessions, and mastery-oriented demonstrations can help students develop positive competence beliefs. Second, the mediating role of AI literacy highlights the need to incorporate systematic instruction on core AI concepts, applications, and ethical considerations into university curricula. Building conceptual understanding alongside practical skills enables students to interpret AI technologies more effectively, strengthening their perceptions of usability and usefulness, which are central to technology acceptance processes (Schiavo et al., 2024). Third, given the inverse relationship between acceptance and anxiety, educational programs should aim to create low-pressure, supportive learning environments that promote gradual engagement with AI applications, thereby alleviating emotional resistance; this approach aligns with evidence showing that increased AI literacy contributes to both enhanced self-efficacy and reduced anxiety (Zhang et al., 2025). Collectively, these findings underscore the importance of integrated pedagogical strategies that simultaneously target motivational, cognitive, and affective dimensions to promote adaptive and confident engagement with artificial intelligence.

Limitations and suggestions

Despite the valuable contributions of this study, some limitations should be acknowledged. The cross-sectional design limits causal interpretations of the relationships among AI self-efficacy, AI literacy, AI acceptance, and AI anxiety. Although the proposed relationships are grounded in theory, the findings should be interpreted as associations rather than clear cause-and-effect links. This is particularly important for the relationship between AI acceptance and AI anxiety, which may operate in both directions. Higher levels of AI acceptance may be associated with lower anxiety, but students with lower initial anxiety may also be more willing to accept AI. The high proportion of female participants in the sample, with 79.6% of the participants being female, and the exclusion of demographic variables from the mediation analysis are limitations of the study. Because gender and academic year may be related to AI acceptance and other psychological responses to AI (Kaya et al., 2024), future studies should include samples with a more balanced gender distribution and examine these variables as controls when testing the model. Moreover, the reliance on convenience sampling from a single public university limits the generalizability of the findings across different institutional, disciplinary, and cultural contexts. Building on these limitations, future studies should use longitudinal or experimental designs to better examine how motivational and cognitive factors develop over time and how they may influence students' emotional responses. Expanding samples across multiple universities, academic disciplines, and cultural contexts would enhance the external validity of the findings. In addition, future studies may benefit from incorporating performance-based assessments of AI literacy, behavioral indicators of AI use, and

qualitative approaches to capture students' lived experiences and emotional responses in greater depth. Future studies could examine whether factors such as gender, previous technology experience, or institutional digital culture influence AI acceptance and anxiety (Kaya et al., 2024). They could also analyze the subscales of AI self-efficacy and AI literacy to better understand how different types of confidence and knowledge relate to students' acceptance of and anxiety toward AI (Ng et al., 2021; Wang and Chuang, 2024).

Conclusion

This study provides evidence that undergraduate students' engagement with AI may develop through a sequence in which motivation and knowledge support AI acceptance, which may then relate to their emotional responses. The findings demonstrate that AI self-efficacy is a key motivational factor positively associated with AI acceptance, both directly and indirectly through its relationship with AI literacy, while higher levels of acceptance are related to reduced anxiety toward AI technologies. These results highlight the importance of integrating confidence-building interventions with literacy-focused instructional strategies to support psychologically adaptive and educationally meaningful AI integration in higher education. By clarifying the pathways linking self-beliefs to acceptance and emotional responses, the present study contributes to the growing body of research informing theoretically grounded and evidence-based approaches to the responsible implementation of artificial intelligence in educational contexts.

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Author contributions OI contributed to the conceptualization of the study, designed the methodology, performed the formal analysis, and reported the results. MU drafted the introduction and literature review sections and contributed to the critical review and editing of the manuscript. ÖE and BÇE wrote the discussion and conclusion sections and contributed to the correction of the manuscript. Additionally, BÇE performed the language editing. All authors read and approved the final manuscript.

Declarations

Competing interests The authors declare no competing interests.

Ethical approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards. Ethical approval for this study was obtained from the Sakarya University Educational Research and Publication Ethics Committee (Reference No: E-61923333-050.99-314689, Decision No: 26/05, Date: December 13, 2023). In addition, informed consent was obtained from all participants prior to their involvement in the study.

Informed consent Informed consent was obtained from all individual participants included in the study. Participants were informed about the study's purpose and procedures via online form between 21.05.2025 and 06.06.2025.

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References

Al Darayseh A (2023) Acceptance of artificial intelligence in teaching science: science teachers' perspective. Computers Educ: artif Intell 4: 100132. https://doi.org/10.1016/j.caeai.2023.100132

Bai, X, & Yang, L (2025) Research on the influencing factors of generative artificial intelligence usage intent in post-secondary education: an empirical analysis based on the AIDUA extended model. Frontiers in Psychology, 16. https://doi.org/10.3389/fpsyg.2025.1644209
Bandura A (1982) Self-efficacy mechanism in human agency. Am Psychologist 37(2):122–147. https://doi.org/10.1037/0003-066X.37.2.122
Bandura, A (1986) Social foundations of thought and action: a social cognitive theory. Prentice-Hall
Bandura, A (1997) Self-efficacy: The exercise of control. W. H. Freeman
Batool K, Noreen HR, Akram S, Naseem A, Zenab S, Mehboob I, Javed R (2025) Artificial Intelligence Anxiety, Self-Efficacy and Academic Performance Among University Students. Int J Soc Sci Bull 3(5):491–494. https://doi.org/10.5281/zenodo.15448571
Bellibaş, MŞ, Özgenel, M, & Bozkurt, A (2025) Principals' artificial intelligence literacy and leadership self-efficacy: the technology acceptance model. The Asia-Pacific Education Researcher. https://doi.org/10.1007/s40299-025-01059-w
Cantaş Ç, Soyer C, Batur Ö (2024) Examination of undergraduate students' artificial intelligence anxiety, multidimensional 21st century skills, and lifelong learning levels in terms of various variables. Turkish Online J Educ Technol 23(3):130–154
Casal-Otero L, Catala A, Fernández-Morante C, Taboada M, Cebreiro B, Barro S (2023) AI literacy in K-12: a systematic literature review. Int J STEM Educ 10(1):29. https://doi.org/10.1186/s40594-023-00418-7
Çelebi C, Yılmaz F, Demir U, Karakuş F (2023) AI literacy: an Adaptation Study. Instructional Technol Lifelong Learn 4(2):291–306. https://doi.org/10.52911/itall.1401740
Chiu TKF, Xia Q, Zhou X, Chai CS, Cheng M (2023) Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. Computers Educ: Artif Intell 4: 100118. https://doi.org/10.1016/j.caeai.2022.100118
Cho KA, Seo YH (2024) Dual mediating effects of anxiety to use and acceptance attitude of artificial intelligence technology on the relationship between nursing students' perception of and intention to use them: a descriptive study. BMC Nurs 23: 212. https://doi.org/10.1186/s12912-024-01887-z
Chocarro R, Cortinas M, Marcos-Matas G (2023) Teachers' attitudes towards chatbots in education: a technology acceptance model approach considering the effect of social language, bot proactiveness, and users' characteristics. Educ Stud 49(2):295–313. https://doi.org/10.1080/03055698.2020.1850426
Choung H, David P, Ross A (2023) Trust in AI and its role in the acceptance of AI technologies. Int J Hum–Computer Interact 39(9):1727–1739. https://doi.org/10.1080/10447318.2022.2050543
Chun Z, Ning Y, Chen J, Wijaya TT (2025) Exploring the interplay among artificial intelligence literacy, creativity, self-efficacy, and academic achievement in college students: Findings from PLS-SEM and FsQCA. Educ Inf Technol 30(15):21283–21316. https://doi.org/10.1007/s10639-025-13617-2
Cohen, J (1988) Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates
Creswell, JW, & Creswell, JD (2018) Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). SAGE
Davis, FD (1989) Technology acceptance model: TAM. In M. N. Al-Suqri & A. S. Al-Aufi (Eds.), Information Seeking Behavior and Technology Adoption: Theories and Trends (pp. 205–219). IGI Global. https://doi.org/10.4018/978-1-4666-8156-9.ch013
Espinoza-Bravo MG, Cabezas-Cabezas R, Perez-Cepeda M, Carvache-Franco O, Carvache-Franco W (2025) AIDUA (Artificial Intelligence Device Use and Acceptance) model to assess the acceptance of AI in the learning practices of higher education students. Cogent Educ 12(1):2560618. https://doi.org/10.1080/2331186X.2025.2560618
Faul F, Erdfelder E, Lang A-G, Buchner A (2007) G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. Behav Res Methods 39(2):175–191. https://doi.org/10.3758/BF03193146
Gašević D, Siemens G, Sadiq S (2023) Empowering learners for the age of artificial intelligence. Computers Educ: Artif Intell 4: 100130. https://doi.org/10.1016/j.caeai.2023.100130
Gözüm, A İ., Strzelecki, A, & Kaya, ÜÜ (2026) Adoption of ChatGPT for learning-related information access: a comparative UTAUT2 analysis of Turkish and Polish university students. Information Systems Frontiers. 1-20 https://doi.org/10.1007/s10796-026-10785-5
Hair, JF, Black, WC, Babin, BJ, & Anderson, RE (2010) Multivariate data analysis (7th ed.). Prentice Hall
Hayes, AF (2013) Introduction to mediation, moderation, and conditional process analysis: a regression-based approach. Guilford publications
Helmiatin, Hidayat A, Kahar MR (2024) Investigating the adoption of AI in higher education: a study of public universities in Indonesia. Cogent Educ 11(1):2380175. https://doi.org/10.1080/2331186X.2024.2380175
Heydarnejad, T (2024) Beyond Whiteboard EFL Classrooms: Uncurtaining the Links between AI Self-efficacy, AI Cognitive-emotion Regulation, AI-assisted L2 Learning Attitude, and AI Psychological Flow in Higher Education. Applied Linguistics Inquiry
Hopcan S, Türkmen G, Polat E (2024) Exploring the artificial intelligence anxiety and machine learning attitudes of teacher candidates. Educ Inf Technol 29(6):7281–7301. https://doi.org/10.1007/s10639-023-12086-9
Huang AYQ, Lu OHT, Yang SJH (2023) Effects of artificial Intelligence–Enabled personalized recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom. Computers Educ 194: 104684. https://doi.org/10.1016/j.compedu.2022.104684
Johnson DG, Verdicchio M (2017) AI anxiety. J Assoc Inf Sci Technol 68(9):2267–2270. https://doi.org/10.1002/asi.23867

Kabudi T, Pappas I, Olsen DH (2021) AI-enabled adaptive learning systems: a systematic mapping of the literature. Computers Educ: Artif Intell 2: 100017. https://doi.org/10.1016/j.caeai.2021.100017
Kalantzis M, Cope B (2025) Literacy in the time of artificial intelligence. Read Res Q 60(1):e591. https://doi.org/10.1002/rrq.591
Kaya F, Aydin F, Schepman A, Rodway P, Yetişensoy O, Demir Kaya M (2024) The roles of personality traits, AI anxiety, and demographic factors in attitudes toward artificial intelligence. Int J Hum–Computer Interact 40(2):497–514. https://doi.org/10.1080/10447318.2022.2151730
Kim, J, Kadkol, S, Solomon, I, Yeh, H, Soh, JY, Nguyen, TM, Choi, JY, Lee, S, Srivatsa, AV, Nahass, GR, & Ajilore, OA (2023) AI anxiety: a comprehensive analysis of psychological factors and interventions https://doi.org/10.2139/ssrn.4573394
Kong S-C, Man-Yin Cheung W, Zhang G (2021) Evaluation of an artificial intelligence literacy course for university students with diverse study backgrounds. Computers Educ: artif Intell 2: 100026. https://doi.org/10.1016/j.caeai.2021.100026
Kılınç, AÇ, Özdemir, S, Sezgin, F, Savaş, G, & Dolapcı, E (2025) Are turkish school principals ready to use artificial intelligence? Exploring the roles of growth mindset, self-efficacy and openness to change. Educational Management Administration & Leadership, 17411432251393449. https://doi.org/10.1177/17411432251393449
Laupichler MC, Aster A, Schirch J, Raupach T (2022) Artificial intelligence literacy in higher and adult education: a scoping literature review. Computers Educ: Artif Intell 3: 100101. https://doi.org/10.1016/j.caeai.2022.100101
Li J, Huang J-S (2020) Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory. Technol Soc 63: 101410. https://doi.org/10.1016/j.techsoc.2020.101410
Nazaretsky, T, Cukurova, M, Ariely, M, & Alexandron, G (2021) Confirmation bias and trust: Human factors that influence teachers' attitudes towards AI-based educational technology. https://osf.io/dzqju
Nevárez Montes, J, & Elizondo-Garcia, J (2025) Faculty acceptance and use of generative artificial intelligence in their practice. Frontiers in Education, 10. https://doi.org/10.3389/feduc.2025.1427450
Ng DTK, Leung JKL, Chu SKW, Qiao MS (2021) Conceptualizing AI literacy: an exploratory review. Computers Educ: Artif Intell 2: 100041. https://doi.org/10.1016/j.caeai.2021.100041
Nunnally JC, Bernstein IH (1994) The assessment of reliability. Psychometric Theory 3:248–292
Ouyang F, Jiao P (2021) Artificial intelligence in education: The three paradigms. Computers Educ: Artif Intell 2: 100020. https://doi.org/10.1016/j.caeai.2021.100020
Picciano AG (2019) Artificial intelligence and the academy's loss of purpose. Online Learn 23(3):182–201. https://doi.org/10.24059/olj.v23i3.2023
Pratama, R, Sulistiyo, U, Sadikin, A, & Wijaya, HA (2025) Understanding AI acceptance among Indonesian pre-service teachers: the mediating role of anxiety and self-efficacy in a UTAUT framework. Journal of Applied Research in Higher Education. Advance online publication. https://doi.org/10.1108/JARHE-05-2025-0358
Preacher KJ, Hayes AF (2008) Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. Behav Res Methods 40(3):879–891. https://doi.org/10.3758/BRM.40.3.879
Rackoff GN, Zhang ZZ, Newman MG (2025) Chatbot-delivered mental health support: attitudes and utilization in a sample of U.S. college students. DIGITAL HEALTH 11: 20552076241313401. https://doi.org/10.1177/20552076241313401
Reyes-Portillo JA, So A, McAlister K, Nicodemus C, Golden A, Jacobson C, Huberty J (2025) Generative AI–powered mental wellness chatbot for college student mental wellness: open trial. JMIR Formative Res 9(1):e71923. https://doi.org/10.2196/71923
Schiavo, G, Businaro, S, & Zancanaro, M (2024) Comprehension, apprehension, and acceptance: Understanding the influence of literacy and anxiety on acceptance of artificial Intelligence. Technology in Society, 77(C). https://doi.org/10.1016/j.techsoc.2024.102537
Schutte NS, Li H (2025) The role of self-efficacy and curiosity in student use of artificial intelligence (AI). Int J Educ Technol High Educ 22(1):73. https://doi.org/10.1186/s41239-025-00574-6
Shi S, Zhang H (2025) EFL students' motivation predicted by their self-efficacy and resilience in artificial intelligence (AI)-based context: from a self-determination theory perspective. Learn Motiv 91: 102151. https://doi.org/10.1016/j.lmot.2025.102151
Su J, Ng DTK, Chu SKW (2023) Artificial intelligence (AI) literacy in early childhood education: The challenges and opportunities. Computers Educ: artif Intell 4: 100124. https://doi.org/10.1016/j.caeai.2023.100124
Sustaningrum R, Haldaka M (2025) Student utilization and perceptions of AI technology for academic purposes: a mixed-method analysis. Cogent Educ 12(1):2553835. https://doi.org/10.1080/2331186X.2025.2553835
Terzi R (2020) An adaptation of artificial intelligence anxiety scale into Turkish: reliability and validity study. Int Online J Educ Teach 7(4):1501–1515
Uyan U, Gültekin SU (2024) Turkish Adaptation of Artificial Intelligence Self-Efficacy Scale: Validity and Reliability Study. J Res Bus 9(1):135–148. https://doi.org/10.54452/jrb.1415212
Wang B, Rau P-LP, Yuan T (2022) Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale. Behav Inf Technol 42(9):1324–1337. https://doi.org/10.1080/0144929X.2022.2072768
Wang S, Sun Z, Chen Y (2023) Effects of higher education institutes' artificial intelligence capability on students' self-efficacy, creativity and learning performance. Educ Inf Technol 28(5):4919–4939. https://doi.org/10.1007/s10639-022-11338-4
Wang Y-Y, Chuang Y-W (2024) Artificial intelligence self-efficacy: Scale development and validation. Educ Inf Technol 29(4):4785–4808. https://doi.org/10.1007/s10639-023-12015-w

Wang YY, Wang YS (2022) Development and validation of an artificial intelligence anxiety scale: an initial application in predicting motivated learning behavior. Interact Learn Environ 30(4):619–634. https://doi.org/10.1080/10494820.2019.1674887

Wen F, Li Y, Zhou Y, An X, Zou Q (2024) A study on the relationship between AI anxiety and AI behavioral intention of secondary school students learning English as a foreign language. J Educ Technol Dev Exch 17(1):130–154. https://doi.org/10.18785/jetde.1701.07

Yu X, Xu S, Ashton M (2022) Antecedents and outcomes of artificial intelligence adoption and application in the workplace: The socio-technical system theory perspective. Inf Technol People 36(1):454–474. https://doi.org/10.1108/ITP-04-2021-0254

Yılmaz FGK, Yılmaz R, Ceylan M (2023) Generative AI acceptance scale: a validity and reliability study. Int J Hum–Computer Interact 40(24):8703–8715. https://doi.org/10.1080/10447318.2023.2288730

Zawacki-Richter O, Marín VI, Bond M, Gouverneur F (2019) Systematic review of research on artificial intelligence applications in higher education – where are the educators? Int J Educ Technol High Educ 16: 39. https://doi.org/10.1186/s41239-019-0171-0

Zhang C, Schießl J, Plößl L, Hofmann F, Gläser-Zikuda M (2023) Acceptance of artificial intelligence among pre-service teachers: a multigroup analysis. Int J Educ Technol High Educ 20(1):49. https://doi.org/10.1186/s41239-023-00420-7

Zhang, H, Perry, A, & Lee, I (2024) Developing and validating the artificial intelligence literacy concept inventory: an instrument to assess artificial intelligence literacy among middle school students. International Journal of Artificial Intelligence in Education. https://doi.org/10.1007/s40593-024-00398-x

Zhang K, Aslan AB (2021) AI technologies for education: Recent research & future directions. Computers Educ: Artif Intell 2: 100025. https://doi.org/10.1016/j.caeai.2021.100025

Zhang Q, Nie H, Fan J, Liu H (2025) Exploring the Dynamics of Artificial Intelligence Literacy on English as a Foreign Language Learners' Willingness to Communicate: The Critical Mediating Roles of Artificial Intelligence Learning Self-Efficacy and Classroom Anxiety. Behav Sci 15(4):523. https://doi.org/10.3390/bs15040523

Zhao L, Wu X, Luo H (2022) Developing AI literacy for primary and middle school teachers in China: Based on a structural equation modeling analysis. Sustainability 14(21):14549. https://doi.org/10.3390/su142114549

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Authors and Affiliations

Onur İşbulan[1] · **Mehmet Uysal**[1] · **Busra Caylan Ergene**[1] · **Ozkan Ergene**[1]

[1] Faculty of Education, Sakarya University, Adapazarı, Turkey