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Original Research Article

The Effect of Academics' AI Literacy on Generative Artificial Intelligence Acceptance in Higher Education: Evidence from Türkiye

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Abstract

Developments in artificial intelligence (AI) technologies have become increasingly important for educational innovations supported by generative AI (GenAI). This study examines the effects of AI literacy on the acceptance of GenAI technologies. To this end, this study developed a model based on the Unified Theory of Acceptance and Use of Technology (UTAUT). Structural equation modeling was used to conduct regression analyses and determine the effect of academics' AI literacy on GenAI acceptance. In addition, the study examined whether significant differences existed in academics' AI literacy levels and GenAI acceptance according to their demographic characteristics. The findings indicate that academics' AI literacy has a significant, direct, and positive effect on their GenAI acceptance. Accordingly, the UTAUT-based subdimensions of GenAI acceptance, including performance expectancy, effort expectancy, facilitating conditions, and social influence, are significantly influenced by academics' AI literacy levels. Analyses of demographic variables, including gender, age, academic title, and field of study revealed significant differences in AI literacy and GenAI acceptance across age groups and academic titles. The growth of AI in higher education in Türkiye has been supported by national AI strategies prepared and increasing international interest. The findings suggest that AI literacy plays a significant role in the acceptance of GenAI and that younger academics are more likely to adopt and use AI technologies.

Keywords

AI literacy, Generative artificial intelligence, Higher education, Academics, Türkiye

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Introduction

The increasing number of smart devices, together with the emergence of AI technologies and the growing compatibility of applications with AI, has significantly transformed every day. This transformation requires individuals to acquire new skills and embrace technological change to participate effectively in digital transformation and use these technologies proficiently. In this regard, many researchers (Bozkurt, 2023, 2024; Ivanov et al., 2024; Schiavo et al., 2024; Tlili, Shehata, Adarkwah et al., 2023; Wang, Wang, Li, Dai, Gu, & Yu, 2025) have emphasized the need to develop individuals' ability to use AI and have argued that the acceptance of GenAI applications is essential for developing competence in AI tools.

In literature, competencies related to the use of AI technologies have been associated with previously established forms of literacy, such as digital literacy, computational literacy, scientific literacy, and data literacy (Long & Magerko, 2020). However, Wang, Rau and Yuan (2023) proposed the concept of AI literacy to define individuals' competence in using related

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technologies. AI literacy refers to the ability to understand, use, and evaluate AI tools within an ethical framework (Wang et al., 2023). Individuals with higher AI literacy levels are better able to evaluate, understand, and operate emerging AI technologies (Long & Magerko, 2020). Considering GenAI as a practical application of AI, AI literacy is particularly well suited to evaluating the competencies required to use these tools effectively.

The integration of GenAI technologies into everyday life, together with the increasing frequency and intensity of their use, demonstrates the growing importance of AI literacy (Bozkurt, 2023; Wang et al., 2023). Strong AI literacy enables users to integrate GenAI tools into their daily activities while promoting their informed and ethical use. Owing to its substantial technological advances, GenAI has considerable potential to meet the future needs of education (Wang et al., 2025). The transformative impact of GenAI, particularly through interactions with GenAI-supported chatbots, has become increasingly evident in teaching and learning. In this context, promoting AI literacy offers a pathway to expanding future educational opportunities. Likewise, the use of GenAI to enhance academic capabilities demonstrates the potential of AI technologies to reshape academia (Bozkurt, 2023).

International organizations have also become actively engaged in discussions on AI-supported education and the appropriate use of GenAI in teaching and learning. In its 2021 report, UNESCO emphasized the importance of protecting human rights and dignity by upholding fundamental principles such as transparency and justice and ensuring that AI systems remain under human supervision (UNESCO, 2021). In a subsequent report published in 2023, UNESCO advocated a human-centered approach to AI that emphasizes human autonomy, inclusivity, equality, gender equality, cultural and linguistic diversity, diverse perspectives, and pluralistic expressions. The report also proposed measures for developing consistent and comprehensive policy frameworks to regulate the use of GenAI in education and research (UNESCO, 2023).

The European Union, which has taken the first major step toward regulating AI, adopted the AI Act, the world's first comprehensive and legally binding framework governing AI. Approved by the European Parliament in 2024, the Act establishes consistent rules for AI, addresses potential risks, and positions Europe to play a leading role in global AI governance (Regulation No. 2024/1689). Its primary objective is to promote the safe development and use of AI across Europe. The Act also requires AI technologies used in education to comply with standards related to data quality, discrimination risk, and human oversight (see AI Act). Consistent with these global developments, Türkiye published its *National Artificial Intelligence Strategy* in 2021 under the coordination of the Presidential Digital Transformation Office. As Türkiye's first national strategy document dedicated to AI, it placed the country among those with formal AI strategies (National Artificial Intelligence Strategy, 2021). The strategy was developed in accordance with national priorities, policy needs, and recommendations from international organizations. Its preparation followed a participatory approach, and a comprehensive study was conducted involving numerous stakeholders, including public institutions, universities, private sector organizations, non-governmental organizations, professional associations, and international organizations.

Education is one of the fields in which innovative AI applications are being widely adopted. Within higher education, universities are often among the first institutions to embrace emerging technologies (Wang et al., 2025). Stanford Human-Centered Artificial Intelligence (2024), one of the world's most comprehensive annual reports on AI, documents global progress in AI using extensive data. The report indicates that society is entering a period in which AI is having an increasingly visible impact, investments in GenAI are expanding rapidly, and educational applications of AI are advancing. The report also suggests that Türkiye is globally competitive across several AI-related indicators. Keeping pace with technological developments in education is important not only for students but also for academics. According to the Digital Education Council (DEC) Global AI Faculty Survey, which included 1,681 academics from 52 higher education institutions across 52 countries, most respondents viewed AI as an opportunity. However, many reported being unaware of institutional AI policies and believed that their institutions did not provide sufficient resources to support AI literacy development. These shortcomings were found to hinder the use and integration of AI into teaching (see DEC Global AI Faculty Survey, 2025a).

Against this background, this study examines the effect of academics' AI literacy on the acceptance of GenAI technologies within the framework of the UTAUT. In addition, it investigates whether AI literacy and GenAI acceptance differ according to academics' demographic characteristics. By doing so, the study extends the applicability of the proposed model beyond its immediate context and provides a deeper understanding of academics' attitudes toward and acceptance of GenAI technologies. This distinguishes the study from previous research and highlights its unique contribution. Furthermore, the study makes a practical contribution by examining the nature and extent of Turkish academics' adoption of AI technologies, an area that has received limited attention in the existing literature. Accordingly, the research addresses the following questions:

To what extent does academics' AI literacy in Türkiye affect their acceptance of GenAI?
Are there significant differences in AI literacy and the acceptance of GenAI based on academics' demographic characteristics?

The remainder of this paper is organized as follows. First, the relevant literature is reviewed, and the theoretical framework is presented. Next, the research methodology is described in detail. The findings are then presented, followed by a discussion of the results and the study's conclusions.

A Conceptual Framework for AI Literacy and GenAI Acceptance

Literacy refers to the ability to express oneself and communicate using written language. This concept has also been applied to encompass skill sets in various disciplines (Long & Magerko, 2020). These forms of literacy include digital literacy (Gilster, 1997), data literacy (Borne et al., 2009), financial literacy (Remund, 2010), health literacy (Sørensen et al., 2012), technological literacy (Dakers, 2006), media literacy (Koltay, 2011), visual literacy (Felten, 2008), AI literacy (Kandlhofer et al., 2016), and GenAI literacy (Bozkurt, 2023).

AI literacy is necessary not only for computer scientists and information technology specialists but also for the public. Kandlhofer et al. (2016) stated that many aspects of life are closely associated with AI and that, in this context, AI literacy will eventually become as important as traditional literacy (reading/writing). AI is now integrated into many of the tools used in everyday life, often without users realizing it. Search engines (e.g., Google, Yandex, and Yahoo), virtual assistants (e.g., Alexa, Siri, and Google Assistant), and personalized recommendations on streaming platforms (e.g., Netflix, Spotify, and Amazon Prime Video) are examples of such tools.

AI literacy does not require individuals to possess expertise in the theory underlying AI or related developments. Rather, an individual is considered AI-literate if they can use AI technologies competently and appropriately (Wang et al., 2023). Long and Magerko (2020, p. 2) defined AI literacy as "a set of skills that enables individuals to critically evaluate AI technologies, facilitate effective communication and collaboration with AI, and allow them to use it as a tool online, at home, and at work." Bozkurt (2024, p. 285) stated that "AI literacy is a comprehensive set of competencies, skills, and fluency needed to understand, apply, and critically evaluate AI technologies, and includes individuals to interact with AI technologies in a responsible, knowledgeable, ethical, and effective manner." Wang et al. (2023) defined AI literacy as the ability to understand AI technology in practical applications, apply AI technology efficiently to perform tasks, analyze, select, and critically evaluate AI-generated data and information, and to develop an awareness of personal responsibilities while respecting mutual rights and obligations. Based on this definition, four dimensions of AI literacy were defined: awareness, usage, evaluation, and ethics. Drawing on these definitions, Calvani et al. (2009) suggested that the three fundamental dimensions of digital literacy—technological, cognitive, and ethical competencies—can also provide a general framework for AI literacy.

For AI literacy, users should possess not only technical knowledge and skills but also emotional, behavioral, and ethical competencies (Ng et al., 2024). In its report titled *Digital Education Council AI Literacy Framework*, the Digital Education Council (2025b) emphasizes the importance of human skills, such as critical thinking, creativity, and emotional intelligence, and introduces a human-centered approach to AI literacy. Social responsibility and ethical consciousness must also be fostered when using AI for social benefits (Ng et al., 2021). Through the development of AI literacy, users can better understand how these systems operate, what data they collect, and how they influence behavior, thereby enabling them to engage critically with these technologies (Wang et al., 2023). In this context, utilizing GenAI to improve social and cognitive learning processes, enhance academic abilities, and promote AI literacy is essential for future opportunities (Bozkurt, 2023).

GenAI refers to AI tools or technologies that generate content such as text, audio, and video by creating new, unique, and creative outputs using the data on which it was trained (Aydın & Karaarslan, 2023; Ivanov et al., 2024; Lund & Wang, 2023). Compared with speech-based AI, GenAI systems have a unique ability not only to generate answers but also to generate the content of those answers (Mannuru et al., 2025). The benefits of GenAI include improving efficiency by saving time and resources, enabling users to focus on more creative and higher-level responsibilities by automating repetitive tasks, enabling more informed decision-making, and facilitating innovation (Tacheva & Ramasubramanian, 2023). GenAI software can generate text-, audio-, or image-based responses to questions, including relatively complex tasks such as outlining a research paper, translating text, and generating creative content (O'Dea, 2024). For instance, ChatGPT is a GenAI tool that can automatically generate coherent text based on user input and simulate real speech (Wang et al., 2025). However, AI models are not limited to ChatGPT; the number of AI tools and models continues to increase daily (Maral, 2024).

As a human-made technology, GenAI is shaped not only by its own characteristics and nature but also by users' ability to use it effectively (Bozkurt, 2024). By storing and utilizing user-provided information, GenAI can assist with various tasks in higher education, including writing, communication, curriculum development, and administrative duties (Mannuru et al., 2025). Human-AI interaction (i.e., AI, chatbots, and ChatGPT) enriches educational experiences, reflects significant changes in educational technologies, and demonstrates that this new form of interaction presents a remarkable opportunity for educational environment (Bozkurt, 2023). GenAI can be used to improve pedagogical practices in higher education through various approaches, including personalized learning, automated assessment and feedback generation, knowledge and skill

development, interactions with virtual assistants and chatbots, content generation, resource recommendations, time management, language translation and support, simulations, laboratories, and virtual media (Karaoglan-Yilmaz, et al., 2024; Nikolopoulou, 2024). As AI models have become increasingly widespread, raising academics and students' awareness of their use has become increasingly important.

AI literacy helps define the competencies and skills expected of individuals within a specific technological field. However, GenAI is a rapidly evolving technology (Bozkurt, 2024). Despite the optimistic outlook for the use of GenAI tools in education because of their innovative impact, concerns remain regarding the use of these technologies in education (Tlili et al., 2023). Kasneci et al. (2023) summarized several ethical concerns associated with GenAI, including data privacy and security, copyright and intellectual property violations, unequal access, and technological inadequacy. However, Ivanov et al. (2024) reported that academics and students did not consider these risks to be important. This may be because the perceived strengths and benefits of using GenAI in teaching and research outweigh its weaknesses and risks. However, future studies should provide more definitive answers to this question.

Developing countries have the potential to become global leaders and experience rapid economic growth by developing and adopting GenAI technologies (Mannuru et al., 2025). Previous studies on the acceptive of GenAI have focused on attitudes, subjective norms, and perceived behavioral control (Ivanov et al., 2024), concern (Budhathoki et al., 2024; Kasneci et al., 2023; Schiavo et al., 2024), individual abilities (Qi et al., 2025), motivational factors (Kang, et al., 2024), and individual innovation and self-efficacy (Hsiao & Tang, 2025). Qi et al. (2025) examined how individual abilities, such as critical thinking and self-guided learning, affect knowledge quality and student satisfaction and investigated their relationship with the intention to continue using GenAI tools in higher education. Kang et al. (2024) reported that individual, social, and technical motivational factors all have a positive effect on attitudes toward accepting GenAI services. Hsiao and Tang (2025) found that technological, ethical, social, and individual determinants, including innovation and self-efficacy, are significant factors influencing GenAI acceptance. These studies have examined users' acceptance of GenAI technologies. However, given the significant advances in GenAI technology in recent years, further research is needed on academics' acceptance of GenAI tools and applications in higher education.

Along with the technological advances, AI literacy continues to develop, change, and evolve. Therefore, it is crucial for academics to keep pace with these changes and use GenAI technologies in ways that meet their needs. Furthermore, students who integrate technology into education, use a common technological language at the international level, and aspire to be part of a developing society supporting an appropriate technological infrastructure must also be equipped accordingly. The competence of academics in preparing students for this technological transformation may enable them to guide and support their students more effectively as they prepare for the future.

In summary, the integration of GenAI into daily life highlights the critical need for the effective use and understanding of these technologies. As GenAI has become increasingly widespread, its role in promoting AI literacy has gained significant importance, necessitating the development of educational frameworks that not only explain AI functions but also encourage critical engagement with the social impacts of these technologies. Given the increasing prevalence of GenAI technologies in everyday life, prioritizing AI literacy is crucial for preparing individuals to interact with and shape the evolving technological and educational environment (Bozkurt, 2024).

Theoretical Framework and Hypotheses

GenAI applications are increasingly being adopted in education alongside the growing use of technology. Numerous tools have been developed in literature to assess AI literacy by measuring the various competencies required for the use of AI technologies. Most existing tools assess general AI literacy by focusing on technical knowledge, awareness, and ethical issues; however, they do not adequately capture the competencies required for GenAI (Zhao, et al., 2024). The benefits offered by AI across many fields, together with its human-like cognitive capabilities, are closely related to users' acceptance of GenAI. Because acceptance reflects an individual's decision to adopt AI technologies through personal choices such as purchasing subscriptions to AI, it is considered a key factor influencing their use and acceptance (Batuk et al., 2025). In this regard, the integration of GenAI into higher education is closely associated with academics' acceptance of technology. Researchers have long sought to understand why individuals accept or reject new technologies, leading to the development of numerous theories and models (Marangunić & Granić, 2015; Ustun, Karaoglan-Yilmaz, Yılmaz, Ceylan & Uzun, 2024).

UTAUT, which closely resembles the Technology Acceptance Model (TAM), was developed to consolidate the literature on the acceptance of information technologies (Venkatesh, Morris, Davis & Davis, 2003). Known for its comprehensive structure, the UTAUT model is a theoretical model that examines the factors influencing technology acceptance and use (Venkatesh et al., 2012). Compared with other technology acceptance models, UTAUT provides an empirical explanation of technology acceptance and accounts for 70% of the variance in behavioral intention to use technology (Venkatesh et al., 2003). The model proposed by Venkatesh et al. (2003) consists of four main dimensions: performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), and social influence (SI), which serve as the direct determinants of users'

technology acceptance and use (Venkatesh et al., 2003, 2012). *Performance expectancy* refers to users' expectations regarding technology use and what they intend to accomplish through its use. *Effort expectancy* refers to users' perceptions of the effort required to use technology. *Facilitating conditions* refer to organizational and technical infrastructures that support the use of technology. *Social influence* reflects the impact of other individuals' attitudes and social pressures on the use of technology (Venkatesh et al., 2003, 2012). However, this approach is still evolving and requires further investigation. Accordingly, the present study proposes that the four components of the UTAUT model—performance expectancy, effort expectancy, facilitating conditions, and social influence—are impacted by academics' AI literacy in relation to the acceptance of GenAI tools (Figure 1).

Accordingly, the following hypotheses were developed:

H1: AI literacy positively affects the level of GenAI acceptance.
H2a: Academics' AI literacy differs significantly according to their demographic characteristics.
H2b: Academics' GenAI acceptance differs significantly according to their demographic characteristics.

Methods

Procedure

This study was conducted using an online survey administered between October 15, 2024, and January 30, 2025, through self-selection sampling, a nonprobability sampling method. Ethics approval was obtained from the local institutional review committee, and the study was conducted in accordance with the ethical principles of the Declaration of Helsinki. Following ethics approval, information about the study and the survey link were sent to all state and private universities in Türkiye via official correspondence through the Rectorate of Uşak University. The survey link was subsequently shared with academic staff at these institutions. The research protocol was approved before data collection, and all responses were collected anonymously. Before completing the survey, participants reviewed an informed consent form describing the purpose of the study and the security storage of their data. The survey began only after participants provided their consent. According to data from the Higher Education Council in Türkiye, there were approximately 180,000 academics employed across 208 universities during the 2024–2025 academic year. A total of 430 valid responses were obtained from academic staff working at 77 universities in Türkiye. This sample size is consistent with the acceptable sample sizes recommended for populations of this size (Sekaran, 1992, as cited in Altunışık et al., 2004).

Participants

The participants were academics employed in higher education, including professors, associate professors, assistant professors, research assistants, and lecturers. Among the 430 valid responses, 51.40% of the participants were female and 48.60% were male. In terms of academic rank, 13% were professors, 13.3% were associate professors, 27.9% were assistant professors, 28.8% were lecturers, and 17% were research assistants. Regarding disciplinary affiliation, 41.1% worked in the social and humanities sciences, 25.2% in the health sciences, 18.6% in engineering and natural sciences, and 15.1% in education sciences. Detailed demographic information is presented in Table 1.

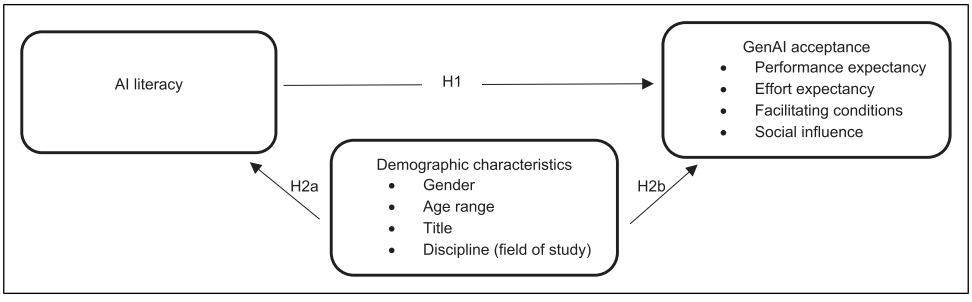

Figure 1. Research Model

Table 1. Demographic Characteristics of Participants (N=430)

Gender	N	Valid (%)
Male	209	48.6
Female	221	51.4
Age range		
21-30	48	11.2
31-40	172	40.0
41-50	119	27.7
51+	91	21.2
Title		
Res.Asst.	73	17.0
Lecturer	124	28.8
Asst. Prof.	120	27.9
Assoc. Prof.	57	13.3
Prof.	56	13.0
Discipline (Field of Study)		
Education Sciences	65	15.1
Eng. and Natural Sci.	80	18.6
Health Sciences	108	25.2
Social and Hum. Sci.	177	41.1

Measures

This study employed the AI Literacy Scale developed by Wang et al. (2023), which was adapted into Turkish by Celebi et al. (2023), who also established its reliability and validity. The instrument is a seven-point Likert scale consisting of 12 items organized into four dimensions: awareness, usage, evaluation, and Ethics. Each dimension comprises three items. The study also employed the GenAI Acceptance Scale developed by Karaoglan-Yilmaz et al. (2024) based on the UTAUT model. The scale consists of four subdimensions—performance expectancy, effort expectancy, facilitating conditions, and social influence—and includes 20 items rated on a five-point Likert scale.

Data Analysis

First, first-order confirmatory factor analyses (CFA) were conducted separately for each scale using IBM SPSS AMOS 24 to examine their validity. Maximum likelihood estimation was employed because the data met the assumption of normality. Subsequently, multiple regression analysis was performed using structural equation modeling in AMOS 24. Statistical significance was established at $p < .05$. Finally, independent-samples t-tests and analysis of variance (ANOVA) were

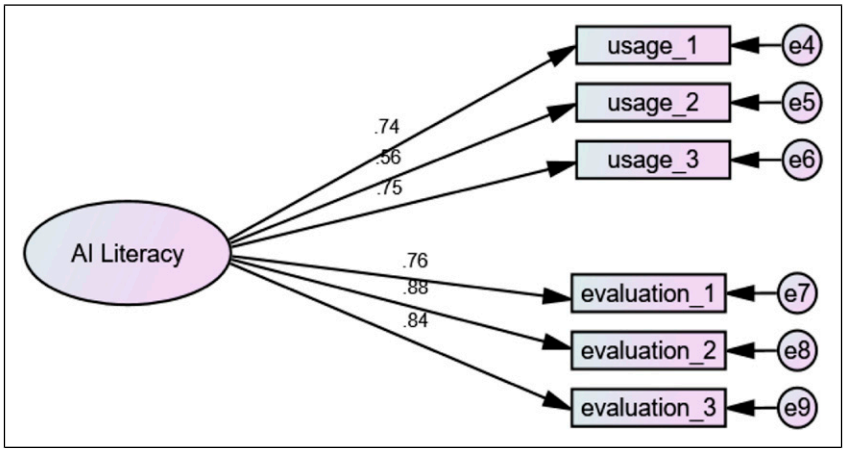

Figure 2. CFA Results for the AI Literacy Scale

Table 2. Expected and Observed Fit Indices for the AI literacy Scale

Fit Index	Acceptable Fit	Good Fit	Observed Value
χ^2 (CMIN)	$p > .05$	$p > .05$	$p < .001$
χ^2/df	< 5	< 3	3.776
CFI	$> .90$	$> .95$	.982
NFI	$> .90$	$> .95$	.975
RFI	$> .90$	$> .95$	.959
IFI	$> .90$	$> .95$	.982
TLI	$> .90$	$> .95$	.970
RMSEA	$< .08$	$< .05$	.080
SRMR	$< .09$	$< .05$	.025

Reference: Collier (2020).

conducted using IBM SPSS Statistics 23 to examine whether academics' AI literacy and GenAI acceptance differed significantly according to their demographic characteristics.

Confirmatory Factor Analyses

AI Literacy Scale

The CFA results for AI Literacy Scale did not demonstrate an adequate model fit in the initial analysis. The items in the Awareness and Ethics factors had very low factor loadings (below .40); therefore, these factors were removed, and the analysis was repeated using the remaining two factors (Usage and Evaluation). Although the revised model demonstrated an acceptable fit, the two factors were found to be highly correlated (r = .94), indicating insufficient discriminant validity. Consequently, the Usage and Evaluation factors were combined into a single factor, resulting in a final six-item, single-factor

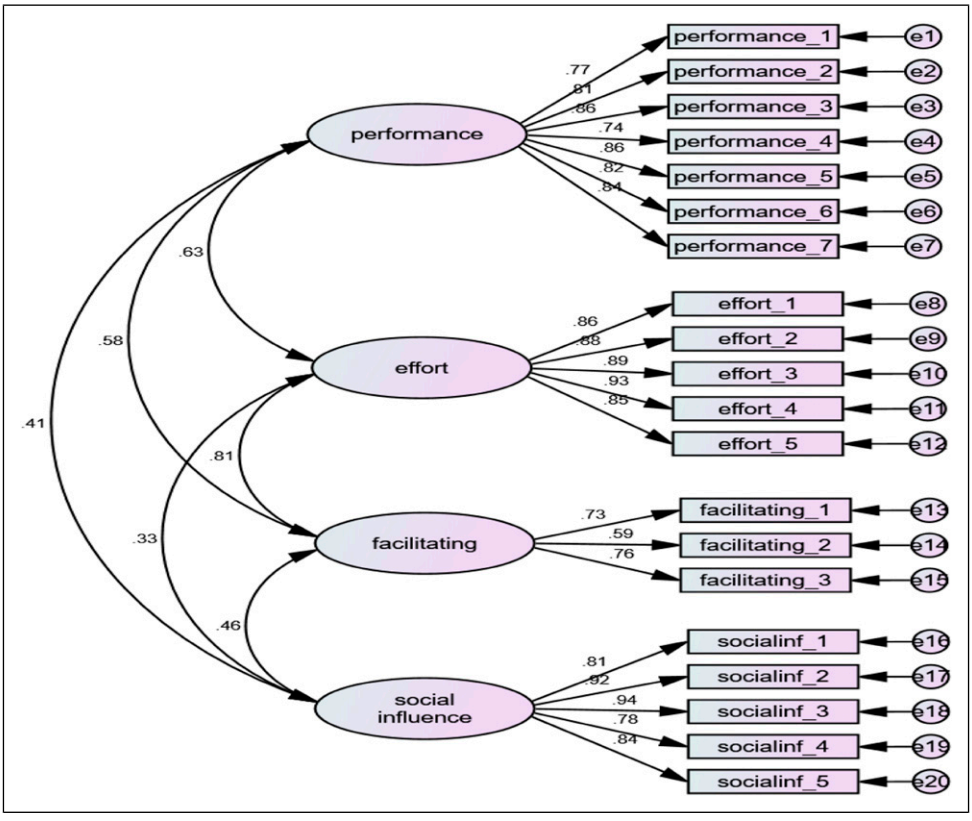

Figure 3. CFA Results for GenAI Acceptance Scale

Table 3. Expected and Observed Fit Indices for GenAI Acceptance Scale

Fit Index	Acceptable Fit	Good Fit	Observed Value
χ^2 (CMIN)	$p > .05$	$p > .05$	$p < .001$
χ^2/df	< 5	< 3	3.662
CFI	> .90	> .95	.940
NFI	> .90	> .95	.920
RFI	> .90	> .95	.907
IFI	> .90	> .95	.907
TLI	> .90	> .95	.931
RMSEA	< .08	< .05	.079
SRMR	< .09	< .05	.055

Reference: Collier (2020).

model. As shown in Figure 2, all standardized factor loadings exceeded .50, with most exceeding .70, indicating that the final version of the AI Literacy Scale has a well-fitting measurement model.

Table 2 presents the goodness-of-fit indices for the AI Literacy Scale. The repeated CFA demonstrated an acceptable model fit (χ^2 [9] = 33.983; p < .001; χ^2/df = 3.776; CFI = .982; NFI = .975; RFI = .959; IFI = .982; TLI = .970; RMSEA = .080; SRMR = .025). These results indicate that the six-item, single-factor model of the AI literacy Scale demonstrated excellent model fit.

GenAI Acceptance Scale

The CFA results for the GenAI Acceptance Scale demonstrated an adequate model fit without requiring any modifications to the scale (χ^2 [164] = 600.505; p < .001; χ^2/df = 3.662; CFI = .940; NFI = .920; RFI = .907, IFI = .907; TLI = .931; RMSEA = .079; SRMR = .055). As shown in Figure 3, all standardized factor loadings exceeded .50, with most exceeding .70, indicating a well-fitting measurement model for the GenAI Acceptance Scale.

Table 3 presents the goodness-of-fit indices for the GenAI Acceptance Scale. These results indicate that the 20-item, four-factor model demonstrated acceptable model fit.

Table 4 presents descriptive statistics, normality assessment, and reliability results for the scales. Cronbach's alpha (α) coefficients for the current sample exceeded 0.80, indicating good reliability (Nunnally & Bernstein, 1994).

As a result of the CFA, the Usage and Evaluation dimensions of the AI Literacy Scale were combined into a single factor. Accordingly, the AI Literacy Scale used in this study assesses users' knowledge and skills related to AI, with an overall mean score of 5.29. The GenAI Acceptance Scale measures users' attitudes toward GenAI systems, their level of acceptance, and their intention to use these systems. The overall mean score for this scale was 3.98, indicating that participants' GenAI acceptance exceeded the midpoint of the scale. The reliability of both scales was also evaluated before the data analysis. Cronbach's alpha coefficients ranged from .881 to .935, exceeding the recommended threshold of .70 (Hair et al., 2014), thereby confirming the reliability of the measures. The normality of the data was assessed using kurtosis and skewness coefficients (Kalaycı, 2010). According to Kunnan (1998, p. 313), "the normality assumption can be accepted when the kurtosis and skewness coefficients do not exceed ±2". The kurtosis and skewness values for both the AI Literacy and GenAI Acceptance scales fell within this range (Table 4), indicating that the data were normally distributed.

Table 4. Descriptive Statistics, Normality Assessment, and Reliability Results (N=430)

Scales	Number of items	Mean	Std. deviation	α	Skewness	Kurtosis
AI Literacy Scale	6	5.29	1.0801	0.881	-.540	.149
GenAI Acceptance Scale	20	3.98	0.6060	0.935	-.660	1.419

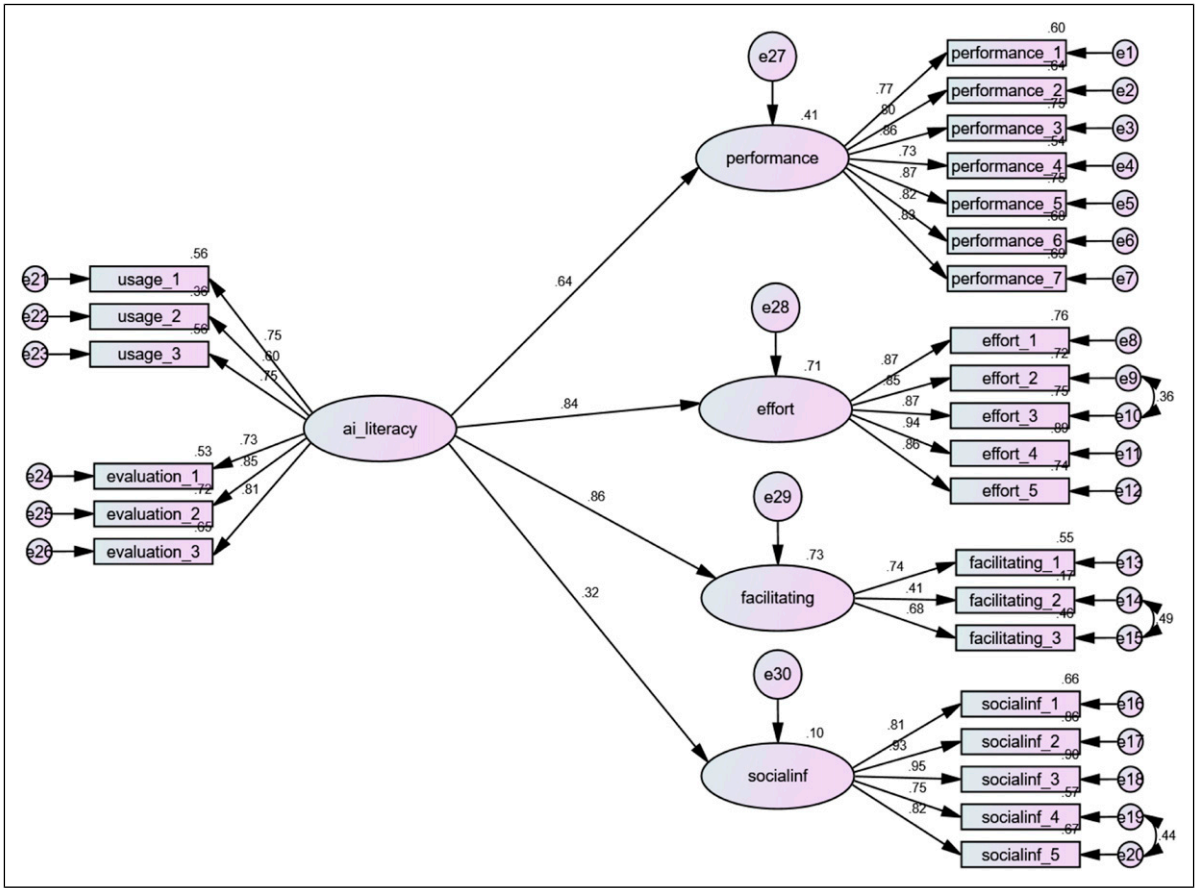

Figure 4. SEM Regression Analysis Results

Regression Analysis Results

The Effect of AI Literacy on GenAI Acceptance

To examine the effect of AI literacy on GenAI Acceptance, multiple linear regression analysis was performed using structural equation modeling (SEM) in IBM SPSS AMOS 24. Maximum likelihood estimation was used because the data were normally distributed (Collier, 2020). The structural regression model is presented in Figure 4.

The structural model, consisting of the AI Literacy and GenAI Acceptance factors, demonstrated acceptable model fit (CMIN [292, N = 430] = 923.202; $p < .001$; $\chi^2/df = 3.162$; CFI = .931; SRMR = .089; RMSEA = .071). The analysis showed that AI literacy had a statistically significant, positive, and very strong effect on the Effort Expectancy ($\beta = .841$, $p < .001$) and the Facilitating Conditions ($\beta = .855$, $p < .001$) dimensions of GenAI acceptance. AI literacy also had a statistically significant, positive, and strong effect on Performance Expectancy ($\beta = .644$, $p < .001$). Moreover, AI literacy had a statistically significant, positive, and moderate effect on Social Influence ($\beta = .317$, $p < .001$). The analysis further indicated that AI literacy explained 41.4% of the variance in Performance Expectancy, 70.7% of the variance in Effort Expectancy,

Table 5. SEM Regression Analysis Results

Predictor Variable		Outcome Variable	β	B	SE	t	p
AI Literacy	→	Performance Expectancy	.644	0.403	0.035	11.543	< .001
AI Literacy	→	Effort Expectancy	.841	0.747	0.047	15.971	< .001
AI Literacy	→	Facilitating Conditions	.855	0.611	0.047	13.116	< .001
AI Literacy	→	Social Influence	.317	0.298	0.049	6.085	< .001

CMIN [292, N = 430] = 923.202; $p < .001$; $\chi^2/df = 3.162$; CFI = .931; SRMR = .089; RMSEA = .071.

Table 6. Results by Gender

Scale	Gender	N	Mean	Std. Deviation	t	p
AI Literacy	Male	209	5,32	1,161	,514	.607
	Female	221	5,26	,999		
GenAI Acceptance	Male	209	3,99	,595	,321	,749
	Female	221	3,97	,616		

73.1% of the variance in Facilitating Conditions, and 10.1% of the variance in Social Influence. Therefore, the proposed model was statistically significant at the 0.05 level, providing support for H1 (Table 5).

t-test and ANOVA results

This section presents the results of the analyses examining whether academics' AI literacy and GenAI acceptance differ according to their demographic qualifications.

As shown in Table 6, an independent-samples t-test was conducted to determine whether academics' AI literacy and GenAI acceptance levels differed by gender. The results indicated no statistically significant differences in either AI literacy or GenAI acceptance between male and female academics ($p>0.05$). These findings suggest that AI literacy and GenAI acceptance levels were comparable across genders.

Table 7 presents the ANOVA results examining whether AI literacy and GenAI acceptance levels differ according to academic title. No statistically significant differences were found in AI literacy across academic titles. However, GenAI acceptance differed significantly according to academic title. To identify the source of these differences, post hoc (Bonferroni) tests were conducted. As shown in Table 8, statistically significant differences were observed between the groups marked with an asterisk (*).

The results indicate that GenAI acceptance varies according to academic title. Research assistants had the highest mean GenAI acceptance score, whereas professors had the lowest. This difference may be attributable to the greater professional experience of professors, which may be associated with more established work practices. In contrast, research assistants may adapt more readily to technological innovations and may have received more recent training in emerging technologies during the later stages of their education. Consequently, academics in the early stages of their careers may be more inclined to adopt and apply new technologies, which may contribute to their higher levels of GenAI acceptance.

Table 9 presents the ANOVA results examining whether AI literacy and GenAI acceptance differ according to age group. The results indicated statistically significant differences in both AI literacy and GenAI acceptance across age groups ($p < .05$). Post hoc (Bonferroni) tests were conducted to determine which age groups differed significantly. As shown in Table 10, statistically significant differences were found between the groups marked with an asterisk (*).

The results indicate that both AI literacy and GenAI acceptance varied according to age group. Academics aged 21–30 had higher AI literacy and GenAI acceptance scores than those aged 41–50 and over. These findings are consistent with the differences observed across academic titles. One possible explanation is that younger academics may adapt more readily to technological innovations and demonstrate greater interest in emerging technological, which may contribute to their higher levels of AI literacy and GenAI acceptance.

Table 11 presents the ANOVA results examining whether AI literacy and GenAI acceptance differ according to discipline (field of study). The results indicated no statistically significant difference in either AI literacy or GenAI acceptance across disciplines ($p > 0.05$). Table 12 presents the descriptive statistics and the results of the multiple comparisons by discipline. Overall, the findings indicate that AI literacy and GenAI acceptance did not differ significantly across disciplines.

Table 7. ANOVA Results by Academic Title

		Sum of Squares	SD	Mean Square	F	p
AI Literacy	Between groups	8.929	4	2.232	1.930	.105
	Within groups	491.621	425	1.157		
	Total	500.550	429			
GenAI Acceptance	Between groups	4.293	4	1.073	2.976	.019*
	Within groups	153.252	425	.361		
	Total	157.546	429			

Table 8. Descriptive Statistics and Multiple Comparisons

Dependent Variable	Descriptive Statistics			Multiple Comparisons			
	Independent Variable (Title)	N	Mean	Title I	Title J	Mean Difference (I-J)	Sig
GenAI Acceptance	Res. Asst.	73	4.14	Res. Asst.	Lecturer	.12670	1.000
	Lecturer	124	4.01		Asst. Prof.	.19124	.325
	Asst. Prof.	120	3.95		Assoc. Prof.	.20357	.558
	Assoc. Prof.	57	3.94		Prof.	.35202*	.010*
	Prof.	56	3.79				

According to the results of the t-tests and ANOVA, significant differences in AI literacy and GenAI acceptance were observed only with respect to academic title and age group. No significant differences were found with respect to gender and discipline. Therefore, H2a and H2b were partially supported.

Discussion

Studies on AI literacy are important because they contribute to the growing body of research on human–AI interaction. Individuals' Ai literacy may influence their behavior by fostering a way of thinking that extends beyond a purely utilitarian perspective on AI technologies (Wang et al., 2023). Learners and educators in higher education are increasingly encountering AI tools in both their professional and daily lives (Jin, Martinez-Maldonado, Gasevic & Yan, 2025) and the growing interest in the use of GenAI tools across various fields presents significant opportunities for their integration into education. However, a key prerequisite for realizing the potential benefits of this technology is users' acceptance of GenAI (Karaoglan-Yilmaz et al., 2024). Indeed, the successful implementation of new technologies is closely related to users' acceptance of those technologies (Ustun et al., 2024). The UTAUT model, recognized for its comprehensive structure, is a theoretical framework that examines the factors influencing technology acceptance and use (Venkatesh et al., 2012). Accordingly, this study adopted the UTAUT model as its conceptual framework to examine the effect of AI literacy on GenAI acceptance. To achieve this objective, the effect of academics' AI literacy on their GenAI acceptance was examined using SEM. In addition, the study investigated whether AI literacy and GenAI acceptance differed according to academics' demographic characteristics, such as gender, age, title, and discipline.

To evaluate the structural validity of the scales used in the study, first-order CFA were conducted for each scale. The CFA results for the GenAI Acceptance Scale indicated satisfactory model fit without requiring any modifications. However, the initial CFA results for the AI Literacy Scale did not demonstrate satisfactory model fit. This may indicate that some scale items did not adequately represent the underlying construct in the sampling group (Guion, 1977). Therefore, items with low factor loadings were removed, and the analysis was repeated. Because Usage and Evaluation factors were highly correlated, they were combined, resulting in a revised one-factor model consisting of six items. The repeated CFA demonstrated satisfactory model fit for the revised AI Literacy Scale. The developers of the original scale also recommended using the scale because the original dimensions demonstrated higher reliability than the individual items (Wang et al., 2023). Furthermore, according to the criteria proposed by Collier (2020), all factor loadings exceeded the recommended cutoff value of 0.50, and the model demonstrated acceptable fit indices. Internal consistency was assessed using Cronbach's alpha. Consistent with the recommendations of Hair et al. (2014) and Nunnally & Bernstein (1994), reliability coefficients of 0.70 or higher were considered acceptable. Cronbach's alpha coefficients were 0.881 for the AI Literacy Scale and 0.935 for the GenAI Acceptance Scale, indicating satisfactory reliability.

Table 9. ANOVA Results by Age Group

		Sum of Squares	SD	Mean Square	F	p
AI literacy	Between groups	19.910	3	6.637	5.882	.001*
	In-groups	480.640	426	1.128		
	Total	500.550	429			
GenAI Acceptance	Between groups	8.940	3	2.980	8.543	.000*
	Within groups	148.606	426	.349		
	Total	157.546	429			

Table 10. Descriptive Statistics and Multiple Comparisons

Dependent Variable	Descriptive Statistics			Multiple Comparisons			
	Independent Variable (Age)	N	Mean	Age I	Age J	Mean Difference (I-J)	Sig
AI literacy	21–30	48	5.79	21–30	31–40	.46124	.050
	31–40	172	5.33		41–50	.52976*	.022*
	41–50	119	5.26		51+	.78800*	.000*
	51+	91	5.00				
GenAI acceptance	21–30	48	4.29	21–30	31–40	.22414	.070
	31–40	172	4.04		41–50	.38542*	.001*
	41–50	119	3.90		51+	.48871*	.000*
	51+	91	3.80				

To examine the effect of academics' AI literacy on their GenAI acceptance, multiple linear regression analysis was conducted using SEM. The structural model consisting of the AI Literacy Scale and GenAI Acceptance Scale, demonstrated satisfactory model fit (CMIN [292, N = 430] = 923.202; $p < .001$; $\chi^2/df = 3.162$; CFI = .931; SRMR = .089; RMSEA = .071). The results showed that AI literacy had a statistically significant, positive and highly strong impact on Effort Expectancy ($\beta = .841$, $p < .001$) and Facilitating Conditions ($\beta = .855$, $p < .001$) factors. It was also determined that AI literacy had a statistically significant, positive and strong effect on Performance Expectancy ($\beta = .644$, $p < .001$), as well as a statistically significant, positive, and moderate effect on Social Influence ($\beta = .317$, $p < .001$). These findings indicate that academics' AI literacy significantly influences the performance expectancy, effort expectancy, facilitating conditions and social influence dimensions of GenAI acceptance derived from the UTAUT model. This finding is consistent with those reported by Wang et al. (2025), Ivanov et al. (2024), Choung et al. (2022), and Schiavo et al. (2024). Ivanov et al. (2024) reported that academics' and students' attitudes toward GenAI and their perceived behavioral control significantly influence their acceptance of these tools. Similarly, Choung et al. (2022) found that perceived ease of use and usefulness are key predictors of AI technology adoption. Wang et al. (2025) also reported that university students with higher levels of AI literacy exhibit more positive attitudes toward and expectations of GenAI technologies. Likewise, Schiavo et al. (2024) found that AI literacy has a significant direct effect on GenAI acceptance. Taken together, these findings suggest that AI literacy is closely associated with individuals' attitudes toward and acceptance of GenAI technology. AI literacy influences individuals' knowledge, skills, and competencies related to AI and, consequently, their ability to understand and accept AI technologies (Bozkurt, 2024; Wang et al., 2023). As individuals become more knowledgeable and skilled in AI, they may be more likely to develop favorable attitudes toward the acceptance of GenAI technologies. Accordingly, the findings provide support for H1.

Independent-samples t-tests and ANOVA were conducted to examine whether their academics' AI literacy and GenAI acceptance levels differed according to demographic characteristics such as gender, age range, title, and discipline. Although Lee et al. (2020) reported that women are more likely than men to trust and accept technological tools, Biermann et al. (2020) found that men are more willing to use technological tools and express fewer concerns about data privacy than women. In the present study, however, no statistically significant differences were found in AI literacy or GenAI acceptance according to gender ($p>0.05$). The 2024 AI Index Report published by Stanford University (see Stanford University AI Index Report, 2024) also indicates that Türkiye demonstrates greater gender equality in the field of information and communication technology. Similarly, no statistically significant differences were found in AI literacy or GenAI acceptance across academic disciplines ($p>0.05$). Although Nomura and Nakao (2010) reported disciplinary differences in attitudes toward robot technologies, with academics in science and engineering differing from those in the fine arts, no significant differences in AI literacy or GenAI acceptance across disciplines were observed in the present study. This finding may reflect the distinctive

Table 11. ANOVA Results by Discipline (Field of Study)

		Sum of Squares	SD	Mean Square	F	p
AI literacy	Between groups	7.058	3	2.353	2.031	.109
	Within groups	493.493	426	1.158		
	Total	500.550	429			
GenAI acceptance	Between groups	2.774	3	.925	2.545	.056
	Within groups	154.772	426	.363		
	Total	157.546	429			

Table 12. Descriptive Statistics and Multiple Comparisons

Descriptive Statistics				Multiple Comparison			
Dependent Variable	Independent Variable (Discipline)	N	Mean	Discipline I	Discipline J	Mean Difference (I-J)	Sig
AI literacy	Educational Sciences	65	5.39	Engineering and Natural Sciences	Educational Sciences	.13317	1.000
	Engineering and Natural Sciences	80	5.52		Health Sciences	.34390	.185
	Health Sciences	108	5.18		Soc. and Human Sci.	.29787	.243
	Soc. and Human Sci.	177	5.23				
GenAI acceptance	Educational Sciences	65	4.00	Soc. and Human Sci.	Educational Sciences	-.11530	1.000
	Engineering and Natural Sciences	80	4.09		Engineering and Natural Sciences	-.20237	.078
	Health Sciences	108	4.03		Health Sciences	-.14170	.329
	Soc. and Human Sci.	177	3.89				

characteristics of AI technologies and warrants further investigation in future research. The results also showed that that AI literacy and GenAI acceptance differed according to both academic title and age group. Research assistants demonstrated higher levels of GenAI acceptance than professors. Similarly, academics aged 21–30 reported higher levels of AI literacy and GenAI acceptance levels those aged 41–50 and those aged 51 years and older. These findings are consistent with the results for academic title. One possible explanation is that professors and older academics (41 and older) may have less confidence in their ability to learn about and use new technologies, as they are less familiar with them, whereas younger academics and those in the early stages of their careers may adapt more readily to technological innovations and show greater interest in adopting them. Previous studies have likewise reported age-related differences in attitudes and interest in technological tools. Chen (2019) found that individuals over 40 years of age place greater importance on the ease of use of technological systems and are less likely to trust new technologies. However, trust positively influences younger users' intention to use technological tools. Deb et al. (2017) reported that younger individuals are more willing to experiment with new technologies, and Bansal et al. (2016) found that younger users are more likely to accept autonomous technologies. These findings suggest that younger individuals may adapt more rapidly to technological systems, whereas older individuals may be less inclined to adopt new technologies. Overall, no significant differences in AI literacy or GenAI acceptance were found with respect to gender and discipline, whereas significant differences were observed according to age group and academic title. Therefore, H2a and H2b were partially supported.

From a practical perspective, these findings highlight the importance of improving AI competencies to promote the acceptance of AI technologies. Drawing on Bloom's taxonomy, AI literacy encompasses fundamental competencies related to recognizing, understanding, using, applying, evaluating, and generating AI. In addition, developing social responsibility and ethical awareness is essential for using AI for the benefit of society (Ng et al., 2021). The transformative potential of GenAI can be realized only through collaborative efforts that prioritize ethical considerations as well as inclusive and sustainable development in global contexts (Mannuru et al., 2025). In this regard, academics play a central role in integrating AI into education; however, institutional support is essential to realize its full potential. Higher education institutions can implement AI literacy programs to strengthen academics' competencies and foster a culture of shared learning by creating supportive environments that encourage GenAI acceptance. In addition, concerns regarding data privacy and misuse can be mitigated by providing secure, institutionally approved AI tools. Consequently, strengthening academics' AI competencies and fostering realistic expectations regarding the capabilities of AI are important steps toward promoting its acceptance.

Conclusion

The findings of this study demonstrate that AI literacy influences the acceptance of GenAI technologies. The significant relationship between AI literacy and GenAI acceptance highlights the importance of AI knowledge in fostering positive attitudes toward and intentions to use AI-based technologies. AI literacy also enhances awareness, increases the perceived benefits of AI, and facilitates interaction with these technologies, underscoring the importance of promoting AI literacy. Strengthening AI literacy may encourage the acceptance of AI by equipping individuals with the knowledge and skills needed to critically evaluate AI technologies and interact with them effectively. Consequently, improving AI literacy may facilitate

the adoption of transformative AI technologies. The findings of this study also provide valuable evidence regarding the effectiveness and applicability of AI in higher education. Future research should continue to examine the effectiveness and implementation of AI, including GenAI, in educational settings.

Although this study provides valuable insights into the role of AI literacy in academics' acceptance of GenAI technologies in higher education in Türkiye, several limitations should be acknowledged. First, the study was constrained by time and resource limitations and included 430 academics who participated in an online survey conducted between October 15, 2024, and January 30, 2025. Consequently, the sample size and its restriction to academics in Türkiye limit the generalizability of the findings. Nevertheless, the results provide an overview of academics' attitudes toward AI technologies within the Turkish higher education context. Second, because the study was conducted exclusively with academics in Türkiye, cultural homogeneity may limit the applicability of the findings to other cultural contexts. Future conducted in different countries and cultural settings would improve the generalizability of the findings. Future research could also examine students as the target population to identify the factors including university and high school students' perceptions and use of GenAI tools. Third, this study examined academics' acceptance of GenAI technologies in relation to their AI literacy. Future studies should further evaluate the dimensionality of these constructs by examining their factor structures across different time periods and independent samples (Boateng et al., 2018). Fourth, despite its many potential benefits, the integration of GenAI into higher education continues to present challenges and ethical concerns. Therefore, future research should examine how personality traits, generational differences, stress, concerns about technology and trust in AI influence the acceptance and effective use of GenAI technologies. Finally, this study relied exclusively on quantitative data. Future research incorporating qualitative interviews alongside quantitative methods may improve the reliability and accuracy of the findings.

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Ethical Considerations

All required ethical standards were adhered to in the studies involving human participants. Ethical approval was obtained from the Usak University Social and Human Sciences Committee of Scientific Research and Publication Ethics (Decision number E-89784354-050.99-237715, dated Oct 10, 2024).

Consent to Participate

Informed consent was obtained from all participants before the beginning of the online survey. Participants who consented to participate completed the survey.

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Data Availability Statement

Data will be made available on request.

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