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Research Article

Understanding the nature of the relationship between technology use to AI literacy among university students: The mediating role of ethical awareness

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ABSTRACT

This study aims to examine the relationships among university students' artificial intelligence (AI) literacy, AI ethical awareness, and technology use, and to determine the mediating role of AI ethical awareness in this relationship. The sample of the study consisted of 438 university students in Kazakhstan (233 female, 205 male). Data were collected using the AI literacy scale, AI ethical awareness scale, and technology use scale. Pearson correlation analysis, *independent samples t-test, one-way analysis of variance,* and mediation analysis with *PROCESS macro (version 4.2)* were employed for data analysis. The findings revealed that male students scored significantly higher than female students in AI ethical awareness and technology use according to the gender variable. Significant differences were found among age groups in terms of AI ethical awareness and technology use, with students aged 27 and above obtaining the highest scores. Regarding the field of study variable, social sciences students had the highest means in AI ethical awareness and technology use, whereas health sciences students demonstrated the lowest scores. The results indicated positive and significant relationships among AI literacy, AI ethical awareness, and technology use. Mediation analysis results revealed that AI ethical awareness played a partial mediating role in the effect of technology use on AI literacy. Technology use had both direct and indirect effects on AI literacy through AI ethical awareness. In conclusion, this study demonstrated that technology use influences AI literacy both directly and indirectly through the development of ethical awareness. The findings suggest that AI literacy education in higher education institutions should be designed with holistic approaches that incorporate ethical dimensions alongside technical content.

Keywords: artificial intelligence literacy, AI ethical awareness, technology use, mediation analysis, university students

INTRODUCTION

Artificial intelligence (AI) technologies are currently exerting a transformative impact across a broad spectrum, ranging from individual life practices to societal structures, from economic systems to educational institutions. Particularly in the context of higher education, the integration of AI applications into learning processes necessitates the restructuring of teaching methods and the redefinition of academic competencies (Chen & Zhang, 2025). University students, as both users and future developers of these technologies, must adapt to the dynamics of the AI era. However, upon examining the current situation, it is observed that although students frequently utilize AI tools, they fail to adequately comprehend the mechanisms underlying these technologies, their societal impacts, and their ethical dimensions (Hornberger et al., 2023). This situation reveals that technology use alone does not translate into AI literacy and that the structural and individual factors supporting this transition require investigation.

The conceptual distinction between technology use and AI literacy constitutes the fundamental starting point of this research. Technology use is generally defined as an instrumental competency and refers to how frequently and for what purposes individuals employ digital tools for specific functions (C. Wang et al., 2025). Lumandas and Taja-on (2026) state that university students show a strong interaction with technology use and AI-based tools. AI literacy requires higher-order cognitive competencies such as understanding how these tools operate, evaluating the consequences of algorithmic decisions, and questioning AI systems from a critical perspective (Chiu et al., 2024). In other words, a student may regularly use generative AI tools such as ChatGPT; however, this use does not necessitate awareness regarding how the model is trained, which data it relies upon, or the reliability of the content it generates (Young et al., 2024). Therefore, the transition from technology use to AI literacy is associated not only with technical skills but also with conceptual understanding and critical thinking capacity.

Upon examining the current literature, the importance of being a conscious and competent AI literate individual rather than merely a user is increasingly emphasized. Kong et al. (2021) indicate that AI literacy encompasses not only technical knowledge but also the ability to understand societal impacts and engage in ethical decision-making. At this juncture, ethical awareness emerges as a critical mediating variable in the transition from technology use to AI literacy. Ethical awareness can be defined as individuals' capacity to recognize and evaluate the potential harms, biases, and societal impacts of AI systems (Saklaki & Gardikiotis, 2024). With the proliferation of AI technologies, issues such as the transparency of algorithmic decision-making processes, data privacy, AI's potential to reproduce societal inequalities, and automation ethics require technology users to ask not only "how to use" but also "when, where, and under what conditions should it be used" (Canales-Morales, 2025). Ethical awareness functions as a bridge enabling students to consciously evaluate AI tools by understanding their social and ethical consequences, beyond merely using them.

Although studies examining the relationship between technology use and AI literacy exist in the literature, research systematically addressing the mediating role of ethical awareness in this relationship remains quite limited. Numerous studies have defined the components of AI literacy (Chiu et al., 2024; Kong et al., 2021) or measured university students' AI literacy levels (Hornberger et al., 2023; Lee et al., 2024; Mansoor et al., 2024). However, these studies do not explain what kind of mechanism ethical awareness constitutes in the transition process from technology use to AI literacy. Particularly, Akca Sumengen et al. (2025) and El-Sayed et al. (2025) emphasized the importance of AI attitudes and literacy in specific disciplines, yet the mediating role of ethical awareness in this relationship has not been sufficiently investigated. This gap creates significant uncertainty regarding how AI education and curriculum should be designed and constitutes the primary motivation for this research. This study aims to examine the mediating role of ethical awareness in the relationship between university students' technology use and AI literacy.

THEORETICAL FRAMEWORK AND LITERATURE REVIEW

Technology Use and Digital Competence

Technology use is a concept that refers to how frequently, for what purposes, and to what extent functionally individuals employ digital tools and platforms. Technology use is a dynamic process emerging from the interaction of motivation, attitude, and social context, rather than simple tool acquisition (Aguilos & Fuchs, 2024; Ay et al., 2015). Therefore, understanding technology use requires focusing not only on usage frequency but also on what purposes this use serves and what types of functional gains it provides to the individual (Tatli et al., 2024).

Although technology usage frequency is closely related to digital competence and digital literacy, it does not completely overlap with these concepts. Salleh (2022), while examining student perceptions regarding the use of online technologies in flipped classrooms, revealed that usage frequency alone is not a strong indicator of learning outcomes; the determining factor is how technology is used in alignment with learning objectives. Gil-Garcia et al. (2023) investigated university students' access to, use of, and attitudes toward digital technology and determined significant differences between access and competence. Huang et al. (2025) addressed the integration of AI and data mining technologies into university-level English teaching, highlighting the importance of use aligned with pedagogical goals beyond merely using technology. These studies demonstrate that technology use is a component of digital competence but is insufficient by itself.

Digital competence can be defined as individuals' capacity to use digital tools safely, effectively, and critically (Saiz-Manzanares et al., 2024). Digital competence should be considered as a superordinate concept encompassing higher-order cognitive skills such as problem-solving, attention management, collaboration, and critical thinking (Sanchez-Rivas et al., 2023). Digital literacy refers to a structure encompassing the broader social and ethical dimensions of digital competence (Atenas et al., 2024). Sumardi et al. (2022) also revealed that digital literacy is shaped through interaction with factors such as trust, perceived usefulness, and social impact. In this context, while technology use constitutes a fundamental component of digital competence and digital literacy, there exists a hierarchical and reciprocal relationship among these concepts. The studies by Aktan and Gökçearslan (2022) and Tutar and Mutlu (2024) reveal that intensive technology use does not always yield positive outcomes and emphasize the importance of conscious, balanced use. Accordingly, technology use must be supported by digital competence and digital literacy.

AI Literacy

AI literacy can be defined as individuals' capacity to understand, evaluate, and use AI technologies, as well as critically question the societal impacts of these technologies (Chiu et al., 2024). AI literacy consists of components such as technical knowledge, algorithmic thinking, ethical evaluation, and application awareness (C. Wang et al., 2025). Kong and Zhang (2021) indicate that AI literacy is not a competency limited to computer science and should be considered as one of the fundamental components of 21st century education for students across all disciplines.

The knowledge dimension of AI literacy refers to students' level of understanding the fundamental concepts, operational principles, and application domains of AI (Chen & Zhang, 2025). Critical evaluation capacity is another fundamental component of AI literacy (Young et al., 2024). Lu et al. (2025) examined the relationship between AI literacy and higher-order thinking skills and demonstrated that behavioral engagement and peer interaction play mediating roles in this process. These studies indicate that AI literacy is directly related to higher-order cognitive skills such as critical thinking, problem-solving, and reflective thinking. Ethical sensitivity, as an indispensable component of AI literacy, refers to individuals' capacity to recognize and evaluate the potential risks, biases, and societal impacts of AI technologies (Akca Sumengen et al., 2025; Saklaki & Gardikiotis, 2024; K. Wang et al., 2025). Application awareness refers to students' level of comprehension regarding how they can use AI technologies in their own disciplines and daily lives, as well as the limitations of such use (Lee et al., 2024). Kong et al. (2021) indicated that interdisciplinary AI literacy courses facilitate students' transfer of AI to their own fields. Higher AI literacy has been associated with more positive attitudes toward AI (Akhmadieva et al., 2026).

In the context of higher education, AI literacy is becoming increasingly critical due to the responsibility of preparing students for an AI-driven workforce. Ma and Chen (2024) emphasized the multidimensional structure of this competency and students' professional and academic benefits, while Mansoor et al. (2024) identified the positive outcomes of AI literacy levels among university students in different countries in academic and everyday tasks. Cengiz and Peker (2025) demonstrated that AI literacy assumes a sequential mediating role in the relationship between AI use and AI anxiety. In this context, it is evident that higher education institutions need to integrate AI literacy into their curricula with a holistic and critical approach.

Ethical Awareness in the Context of AI

Ethical awareness in the context of AI can be defined as individuals' capacity to recognize and understand ethical issues arising in the design, development, and implementation processes of AI systems, and to make conscious evaluations regarding these issues (Canales-Morales, 2025). Algorithmic bias constitutes one of the most critical dimensions of ethical awareness in the AI context. Algorithmic bias refers to the situation where AI systems reproduce or reinforce existing societal biases present in training data (Atenas et al., 2024). Xie et al. (2025) demonstrated that ethical governance mechanisms play an important role in reducing algorithmic biases. Sparrow (2023) emphasized that ethical evaluations are a political process reflecting power relations and societal values, beyond being merely a technical process. These studies reveal that algorithmic bias is an ethical issue directly related to social justice and equality, beyond being a technical problem.

Data privacy and security constitute another fundamental dimension of AI ethics. AI systems typically operate on large amounts of personal data, and serious privacy risks emerge in the processes of collecting, processing, and storing these data (Mata et al., 2022; Wang, 2023). Weckert and Bayod (2023) indicated that concepts such as data sovereignty are influenced by different cultural perspectives. Hongladarom and Bandasak (2024) discussed the cross-cultural dimensions of technology ethics and emphasized that local values should be considered alongside universal ethical principles. This approach demonstrates that ethical awareness must be sensitive not only to universal ethical principles but also to cultural and contextual factors. Therefore, AI ethics should be evaluated as a dynamic field encompassing different social and cultural perspectives rather than a monolithic concept.

Transparency constitutes a critical ethical requirement in the evaluation of AI systems, with explainability considered an integral component of transparency. While transparency concerns the understandability of how AI systems function and make decisions, explainability refers to the ability to provide understandable reasons for specific decisions or outputs (De Bie et al., 2023; Saklaki & Gardikiotis, 2024). As AI systems become increasingly autonomous, important ethical questions emerge regarding who is responsible for the decisions these systems make and who will be held accountable when systems make errors or cause harm. Responsibility and accountability constitute the final fundamental component of AI ethics (Lee et al., 2023; Xie et al., 2025).

Relationships Among Technology Use, Ethical Awareness, and AI Literacy

The hypothesized mediating role of AI ethical awareness is grounded in theoretical perspectives suggesting that the relationship between technology use and higher-order competencies, such as AI literacy, operates through intermediate cognitive and reflective processes rather than as a direct or conditional effect. From the perspective of Social Cognitive Theory, individuals develop knowledge and competencies through the interaction of behavioral engagement and internal cognitive factors (Bandura, 1986). In this context, engagement with technology is likely to increase exposure to ethical issues related to AI, thereby fostering ethical awareness, which in turn supports a deeper and more critical understanding of AI systems. Similarly, research in Digital Literacy emphasizes that technical skills alone are insufficient; critical and ethical competencies play a central role in transforming usage into meaningful literacy (Eshet, 2004; Hargittai, 2010). Moreover, contemporary AI literacy frameworks highlight ethical awareness as a core component that enables individuals to evaluate and interpret AI systems responsibly (Long & Magerko, 2020). Accordingly, mediation is theoretically more appropriate than moderation, as ethical awareness is conceptualized not as a boundary condition that alters the strength of the relationship, but as an explanatory mechanism through which technology use is associated with AI literacy. This reasoning aligns with prior studies suggesting that reflective and ethical competencies function as intervening variables in technology-supported learning processes (Mayer, 2005).

Although the relationship between technology use and AI literacy has been addressed through various theoretical and empirical studies in the current literature, it is increasingly recognized that this relationship is neither direct nor linear. C. Wang et al. (2025) integrated the theory of planned behavior and AI literacy to examine factors affecting university students’ behavioral intentions to use generative AI and found that AI literacy directly affects technology use intention. Similarly, Aguilos and Fuchs (2024) determined university students’ behavioral intentions regarding ChatGPT using the extended technology acceptance model and demonstrated that perceived benefit and ease increase technology use. However, these studies imply that technology use alone does not guarantee AI literacy; rather, usage frequency is a necessary but insufficient condition for literacy development.

Some indirect evidence exists regarding ethical awareness playing a mediating role in the relationship between technology use and AI literacy. Cengiz and Peker (2025) examined generative AI acceptance and AI anxiety among university students and demonstrated the sequential mediating role of attitudes toward AI and literacy. This finding reveals that attitudinal and cognitive factors are critical in transforming technology use into literacy. Saklaki and Gardikiotis (2024) examined Greek students’ attitudes toward AI in relation to AI ethics, media, and digital literacy, and found that ethical awareness is an important factor in shaping AI attitudes. Young et al. (2024) analyzed chemistry students' critical reflections on chatbot responses, demonstrating that ethical evaluation skills play a central role in the development of AI literacy. These studies indicate that ethical awareness may be a mechanism that transforms technology use into more conscious and critical literacy, beyond being merely a component of AI literacy.

The relationship between technology use and ethical awareness can be evaluated bidirectionally. On one hand, intensive technology use may increase ethical awareness by enabling students to experience the potential risks and ethical issues of AI systems. Mata et al. (2022), while addressing current issues regarding the ethical use of information technology, indicated that instructors' technology experiences shape their ethical sensitivities. On the other hand, high levels of ethical awareness may encourage students to use technology more responsibly and critically. Xie et al. (2025) examined the impact of technology ethical governance on organizational AI development and demonstrated that ethical awareness transforms technology use practices. This reciprocal relationship indicates a dynamic interaction between technology use and ethical awareness, and that this interaction plays a critical role in the development of AI literacy.

The direct relationship between ethical awareness and AI literacy has been emphasized by numerous studies. Akca Sumengen et al. (2025) examined nursing students' attitudes toward AI and their literacy, demonstrating that ethical sensitivity is a fundamental component of AI literacy. El-Sayed et al. (2025) investigated the role of AI literacy and innovative mindset in shaping nursing students' career and competence self-efficacy, finding that ethical awareness is critical for the development of professional competencies. Atenas et al. (2024) addressed critical and creative pedagogies for AI and data literacy, emphasizing that ethical awareness should be at the center of AI literacy education. These studies demonstrate that ethical awareness is both a component and a precursor of AI literacy.

Although the current literature has partially addressed the relationships among technology use, ethical awareness, and AI literacy, studies systematically examining how these variables interact and the mediating role of ethical awareness remain limited. Kong et al. (2021) evaluated an AI literacy course for students with different study backgrounds but did not focus on the mediating role of the ethical dimension. Hornberger et al. (2023) developed and validated an AI literacy test but did not examine the role of ethical awareness in the relationship between technology use and literacy. Lu et al. (2025), while addressing the relationship between AI literacy and higher-order thinking skills, demonstrated the mediating roles of behavioral engagement and peer interaction but did not directly test ethical awareness as a mediating variable. This situation indicates that the mediating role of ethical awareness has not been systematically examined in the current literature and that empirical research is needed in this area.

The contribution of this research is to test the mediating role of ethical awareness in the relationship between technology use and AI literacy, thereby clarifying the complex interaction among these variables. Previous studies have generally examined these variables in isolation or within the framework of bilateral relationships, but have not holistically addressed the mechanism formed by the three variables together. This research aims to demonstrate how ethical awareness facilitates or hinders the transition from technology use to AI literacy. Thus, the research aims both to theoretically deepen the relationship between technology use and AI literacy and to provide concrete recommendations to higher education institutions in practice for designing ethical awareness-based educational programs to develop students' AI competencies.

In this context, the following research questions (RQs) were tested:

1. **RQ1.** What are the current levels of AI literacy, AI ethical awareness, and technology use among university students?
2. **RQ2.** Do AI literacy, AI ethical awareness, and technology use differ significantly based on demographic variables (gender, academic discipline, age)?
3. **RQ3.** Is there a significant relationship between technology use and AI literacy among university students?
4. **RQ4.** Does ethical awareness regarding AI mediate the relationship between technology use and AI literacy?

The hypothesis are as follows:

1. **H1.** Technology use positively and significantly affects AI ethical awareness.

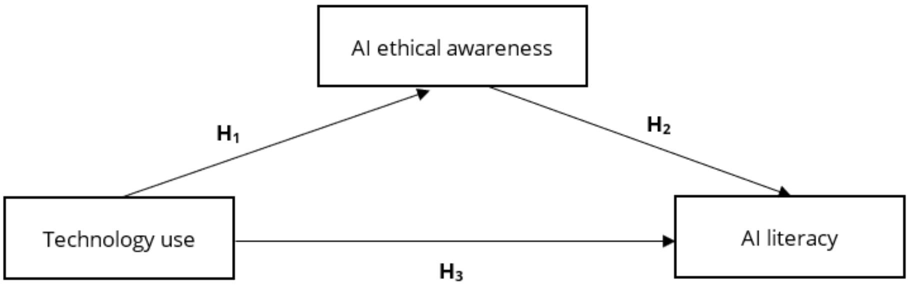

Figure 1. Research variables and model (Source: By authors based on data)

Table 1. Demographic information of the sample

Variable	Category	Frequency (f)	Percentage (%)
Age	18-20 years	133	30.4
	21-23 years	95	21.7
	24-26 years	103	23.5
	27 years and above	107	24.4
Gender	Female	233	53.2
	Male	205	46.8
Field of study	Natural sciences	76	17.4
	Social sciences	84	19.2
	Health sciences	102	23.3
	Engineering sciences	84	19.2
	Other sciences	92	21.0
AI usage frequency	Once a week	99	22.6
	More than once a week	124	28.3
	Almost every day	215	49.1
Device used for AI	Smartphone	383	87.4
	Smartphone, computer	15	3.4
	Smartphone, tablet	33	7.5
	Smartphone, tablet, computer	5	1.1
	Computer	2	0.5

2. **H2.** AI ethical awareness positively and significantly affects AI literacy.
3. **H3.** Technology use positively and significantly affects AI literacy.
4. **H4.** AI ethical awareness mediates the relationship between technology use and AI literacy among university students.

METHOD

Research Design

This study was designed as quantitative research employing both descriptive and correlational survey models. The descriptive survey model is one of the quantitative research approaches that aims to reveal an existing situation as it is, without the researcher intervening in any variable. The purpose of this model is to systematically describe specific characteristics, attitudes, views, or behaviors of individuals, groups, or phenomena and to explain the existing situation (Fraenkel et al., 2019). The correlational research design is used to determine relationships between two or more variables without any intervention (Creswell, 2012) (**Figure 1**).

Population and Sample

The population of the study consists of students enrolled in university education in Kazakhstan during the 2025-2026 academic year. In this context, a sampling methodology was employed: 438 undergraduate and graduate students from four different universities, selected via convenience sampling, were included in the research and completed online forms. Demographic information pertaining to the students is presented in **Table 1**.

According to **Table 1**, when examining the age distribution of the 438 university students participating in the research, it was determined that 30.4% of the participants were in the 18-20 age range, 21.7% in the 21-23 age range, 23.5% in the 24-26 age range, and 24.4% were 27 years of age and above. According to the gender variable, 53.2% of the participants were female, and 46.8% were male. When examining the distribution regarding the fields in which participants receive education, it is observed that 17.4% study in natural sciences, 19.2% in social sciences, 23.3% in health sciences, 19.2% in engineering sciences, and 21.0% in other scientific fields. When evaluated in terms of AI usage frequency, it was determined that 22.6% of the participants use AI tools once a week, 28.3% more than once a week, and 49.1% almost every day. Regarding the devices used to access AI tools, it is observed that the vast majority of participants (87.4%) use only smartphones; 7.5% use smartphones and tablets, 3.4% use smartphones and computers, 1.1% use smartphones, tablets, and computers together, and 0.5% access AI tools only through computers.

Data Collection Tools

Data collection was conducted through a comprehensive online survey consisting of four main sections.

Demographic information form

This form was developed by the researchers and collects basic demographic and background information, including academic discipline, grade level, gender, age, frequency of AI technology use, and purposes of AI technology use.

AI literacy scale

The AI literacy scale (AILS), originally developed by Wang et al. (2023), is a multidimensional measurement tool composed of 12 items organized under four distinct factors. The awareness dimension captures individuals' capacity to identify the presence of AI technologies and comprehend their potential capabilities, whereas the usage dimension reflects proficiency in employing AI tools effectively. The evaluation dimension focuses on the ability to critically examine and judge AI systems, while the ethics dimension addresses understanding ethical considerations, societal implications, and principles of responsible AI use. Each dimension is represented by three items.

AILS is structured as a 7-point Likert-type scale, with response options ranging from 1 to 7. Items 2, 5, and 11 are reverse-scored. Higher total scores indicate a higher level of AI literacy. The total score obtainable from the scale ranges from 12 to 84. Regarding reliability, Wang et al. (2023) reported a Cronbach's alpha coefficient of 0.83 for the original scale, while the internal consistency coefficient calculated in the present study was found to be 0.862.

AI ethical awareness scale

The AI ethical awareness scale (AIEAS) is a 12-item scale developed by Bayram (2025) that measures participants' awareness and attitudes regarding ethical considerations in AI development and implementation. The scale consists of 4 dimensions and is of a five-point Likert type. The sub-dimensions are determined as "bias" (3 items), "transparency" (3 items), "accountability" (3 items), and "data privacy" (3 items), respectively. The Cronbach's alpha reliability coefficient calculated for the entire scale is 0.84. The Cronbach's alpha coefficients for the sub-dimensions were found to be 0.76, 0.87, 0.82, and 0.78, respectively.

Technology use scale

The technology use scale (TUS) (Zincirkıran & Tiftik, 2014) is a 5-point Likert-type scale with 13 items and three factors. These factors are perception of innovation, technology monitoring, and technology enthusiasm. The scale utilizes a 5-point Likert scale ranging from 1 (strongly agree) to 5 (strongly disagree). The total Cronbach's alpha reliability coefficient of the scale is 0.91, with sub-dimensions ranging between 0.86 and 0.93.

Data Collection Process

Data were disseminated to students online through various channels, including student email lists and social media platforms. The survey begins with an informed consent statement explaining the purpose of the study, the voluntary nature of participation, privacy protections, and participants' right to withdraw at any time. Only consenting participants proceeded to complete the survey instruments. The average completion time was 15-20 minutes. All data were collected anonymously to ensure participant confidentiality.

Data Analysis

In this research, the *PROCESS macro (version 4.2)*, developed by Hayes (2022) and integrated into *SPSS for Windows 27.0 software,* was used to examine the direct and indirect effects among variables. Before proceeding to multivariate analyses, basic statistical assumptions were systematically evaluated to determine the suitability of the dataset for analysis.

The reliability of the measurement instruments used in the research was primarily examined through Cronbach's alpha coefficient, and it was determined that the coefficients obtained for all scales were above 0.70, concluding that the reliability levels were adequate (George & Mallery, 2003). Descriptive statistics were presented through the arithmetic mean (M) and standard deviation (SD) values. For ease of interpretation, descriptive statistics were reported as item-level mean scores based on the 7-point Likert scale, whereas group comparison analyses were conducted using raw total scale scores. Differences in scale scores according to the demographic characteristics of university students were analyzed using independent samples t-test and one-way analysis of variance (ANOVA) due to the satisfaction of parametric test assumptions; post hoc comparisons were conducted using the Tukey test to determine the source of significant differences. The direction and strength of relationships among variables were examined through Pearson correlation analysis.

Prior to regression-based analyses, the multicollinearity assumption was checked; it was determined that bivariate correlations among independent variables were below 0.80. Additionally, it was found that variance inflation factor values were at a maximum level of 2.22 and all values remained below 3, concluding that there was no multicollinearity problem (Cheng et al., 2022). The normality assumption was evaluated through skewness and kurtosis coefficients, and these values were observed to fall within acceptable ranges between -2 and +2 (Hahs-Vaughn & Lomax, 2020). These findings indicate that the data satisfied the normal distribution assumption. The statistical significance of indirect effects was tested with 5,000 resampling within the bootstrap technique, and all estimates were reported based on a 95% confidence interval (CI). Given that all variables in this study were measured using self-report scales collected from the same participants at a single point in time, the potential for common method bias (CMB) was considered. To assess this issue, Harman's single-factor test was conducted. The results indicated that a single factor did not account for the majority of the variance, suggesting that CMB is unlikely to pose a serious threat to the validity of the findings (Podsakoff et al., 2003).

The linearity assumption was tested through scatter plots examining the relationships between dependent and independent variables, and it was observed that the relationships among variables possessed a linear structure. Mahalanobis distances were calculated to evaluate the potential effects of outliers, and no extreme values that could affect the analysis results were encountered. Furthermore, achieving a sample size above the minimum recommended sample size ($n \geq 200$) for mediating variable analyses supports the statistical power of model estimates and the reliability of the obtained findings (Fritz & MacKinnon, 2007). In line with all these analyses, it was determined that the dataset satisfied the necessary assumptions for the application of multivariate statistical methods. Therefore, it can be stated that the model tests conducted in the study provide valid and reliable results.

FINDINGS

This section presents the findings obtained from the analysis of the research data. In the context of the **RQ1** of the study, **Table 2** includes descriptive statistics for the research variables. **Table 2** presents descriptive statistics for the variables included in the research. When examining the AILS sub-dimensions, it is observed that participants had the highest mean in the awareness dimension (M = 4.45), followed by usage (M = 4.40), evaluation (M = 4.26), and ethics (M = 4.17) dimensions. The overall mean of AILS was calculated as 4.43, indicating that participants' AI literacy levels are above moderate. SD values reveal variability among sub-dimensions, with individual differences being particularly pronounced in the evaluation dimension.

Table 2. Descriptive statistics for research variables

Scale sub-dimension	N	Minimum	Maximum	M	SD	Skewness	Kurtosis	Skewness	Kurtosis
						Statistic	SE	Statistic	SE
Awareness	438	3.00	7.00	4.45	0.95	0.924	0.117	0.315	0.233
Usage	438	1.00	7.00	4.40	1.16	0.441	0.117	1.131	0.233
Evaluation	438	1.00	7.00	4.26	1.81	0.063	0.117	-1.129	0.233
Ethics	438	1.00	7.00	4.17	1.11	0.681	0.117	0.989	0.233
AILS	**438**	**2.75**	**6.83**	**4.43**	**1.09**	0.406	0.117	-0.833	0.233
Prejudice	438	2.00	5.00	3.12	0.40	0.563	0.117	1.432	0.233
Transparency	438	1.00	5.00	3.08	0.56	0.101	0.117	1.190	0.233
Accountability	438	2.00	5.00	3.17	0.55	0.146	0.117	-0.120	0.233
Data privacy	438	1.33	5.00	2.82	0.49	0.602	0.117	1.200	0.233
AIEAS	**438**	**2.25**	**4.58**	**3.05**	**0.38**	0.297	0.117	0.021	0.233
Innovation perception	438	1.00	5.00	3.11	0.67	0.014	0.117	0.061	0.233
Technology tracking	438	1.00	5.00	2.77	0.75	0.441	0.117	-0.527	0.233
Technology madness	438	1.00	5.00	3.35	0.62	-0.620	0.117	1.454	0.233
TUS	**438**	**1.08**	**4.92**	**3.08**	**0.61**	0.089	0.117	0.029	0.233

Note. SE: Standard error

Table 3. Independent groups t-test results for gender variable

Scale sub-dimension	Gender	N	M	SD	t	p
Awareness	Female	233	13.45	2.96	0.832	0.406
	Male	205	13.22	2.70		
Usage	Female	233	13.46	3.43	0.694	0.488
	Male	205	13.25	3.00		
Evaluation	Female	233	12.68	5.45	-0.949	0.343
	Male	205	13.18	5.51		
Ethics	Female	233	13.56	3.61	-0.266	0.790
	Male	205	13.65	3.51		
AILS total	Female	233	53.15	13.41	-0.117	0.907
	Male	205	53.30	12.88		
Prejudice	Female	233	9.07	1.16	-5.277	0.000*
	Male	205	9.67	1.20		
Transparency	Female	233	8.90	1.83	-4.726	0.000*
	Male	205	9.65	1.43		
Accountability	Female	233	9.12	1.68	-5.453	0.000*
	Male	205	9.96	1.50		
Data privacy	Female	233	8.20	1.33	-3.934	0.000*
	Male	205	8.75	1.59		
AIEAS total	Female	233	35.29	4.31	-6.567	0.000*
	Male	205	38.02	4.37		
Innovation perception	Female	233	14.68	3.23	-5.900	0.000*
	Male	205	16.49	3.17		
Technology tracking	Female	233	10.38	2.80	-5.372	0.000*
	Male	205	11.87	3.00		
Technology madness	Female	233	12.97	2.35	-3.989	0.000*
	Male	205	13.90	2.54		
TUS total	Female	233	38.03	7.48	-5.821	0.000*
	Male	205	42.26	7.72		

Note. *$p < 0.001$

When evaluating the AIEAS sub-dimensions, it is observed that the accountability dimension had the highest mean (M = 3.17), followed by prejudice (M = 3.12) and transparency (M = 3.08) dimensions. The mean of the data privacy dimension was lower at 2.82 compared to other sub-dimensions. The overall mean of the scale was determined as 3.05, indicating that participants' AI ethical awareness levels are at a moderate level.

When examining the sub-dimensions included in the TUS, it is observed that the technology madness dimension had the highest mean (M = 3.35), followed by innovation perception (M = 3.11) and technology tracking (M = 2.77) dimensions. The overall mean of the scale was calculated as 3.08, indicating that participants' technology use levels are at a moderate level. Overall, the findings demonstrate that university students' AI literacy levels are higher compared to their ethical awareness and technology use.

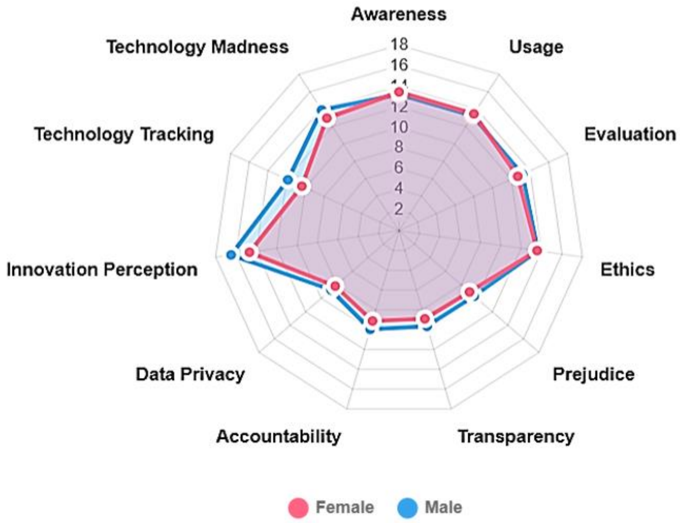

Figure 2. Gender comparison radar graph (Source: By authors based on data)

Independent samples t-test findings indicate different patterns in AILS, AIEAS, and TUS variables in terms of the gender variable (**Table 3**). No statistically significant difference was found between female and male participants regarding AILS total score ($t[436] = -0.12$, $p > .05$). Similarly, no significant difference according to gender was found in the awareness ($t[436] = 0.83$, $p > .05$), usage ($t[436] = 0.69$, $p > .05$), evaluation ($t[436] = -0.95$, $p > .05$), and ethics ($t[436] = -0.27$, $p > .05$) sub-dimensions of AILS. In contrast, statistically significant differences were determined according to the gender variable in terms of AIEAS. Male participants' AIEAS total scores were found to be significantly higher compared to female participants ($t[436] = -6.57$, $p < .001$). When examining the sub-dimensions, significant differences in favor of males were found in all dimensions: prejudice ($t[436] = -5.28$, $p < .001$), transparency ($t[436] = -4.73$, $p < .001$), accountability ($t[436] = -5.45$, $p < .001$), and data privacy ($t[436] = -3.93$, $p < .001$).

Similarly, TUS scores also show significant differences according to the gender variable. Male participants' TUS total scores were determined to be significantly higher than female participants ($t[436] = -5.82$, $p < .001$). When examining the sub-dimensions of the scale, statistically significant differences in favor of male participants were observed in innovation perception ($t[436] = -5.90$, $p < .001$), technology tracking ($t[436] = -5.37$, $p < .001$), and technology madness ($t[436] = -3.99$, $p < .001$) dimensions. **Figure 2** shows the gender comparison radar graph. According to **RQ2**, **Table 4** included analysis results for age groups. The one-way ANOVA results based on age groups indicate that no statistically significant differences were found for the awareness, usage, evaluation, ethics sub-dimensions, or the AILS total score ($p > .05$).

In contrast, statistically significant age-related differences were identified in several variables. For the bias sub-dimension, a significant effect of age was observed ($F[3, 434] = 32.26$, $p < .001$), with students aged 27 years and older scoring significantly higher than those aged 24-26 years and 18-20 years. Similarly, the transparency sub-dimension showed a significant difference across age groups ($F[3, 434] = 83.44$, $p < .001$). Students aged 27 years and older, 21-23 years, and 24-26 years obtained significantly higher scores compared to the 18-20 years group. For accountability, the ANOVA results revealed a significant age effect ($F[3, 434] = 36.62$, $p < .001$), indicating that students aged 27 years and older, as well as those aged 21-23 years and 24-26 years, scored significantly higher than students aged 18-20 years. A significant difference was also found for data privacy ($F[3, 434] = 44.26$, $p < .001$), where students aged 27 years and older reported higher scores than those aged 18-20 years. Regarding the AIEAS total score, age groups differed significantly ($F[3, 434] = 103.64$, $p < .001$). The results indicate that students aged 27 years and older, 21-23 years, and 24-26 years demonstrated significantly higher ethical awareness levels than the 18-20 years group. In terms of technology-related variables, significant age effects were observed for innovation perception ($F[3, 434] = 151.18$, $p < .001$), technology tracking ($F[3, 434] = 123.56$, $p < .001$), and technology madness ($F[3, 434] = 79.13$, $p < .001$). In all three dimensions, students aged 27 years and older scored significantly higher than those aged 18-20 years, with the 21-23 years and 24-26 years groups also scoring higher than the youngest group. Finally, the TUS

Table 4. ANOVA results in terms of age variable

Scale/subscale	Student age	N	M	SD	F	p	Post-hoc
Awareness	18-20	133	13.39	3.01	1.972	0.117	-
	21-23	95	13.06	2.74			
	24-26	103	13.87	2.89			
	27+	107	13.03	2.61			
Usage	18-20	133	13.38	3.35	1.673	0.172	-
	21-23	95	13.40	3.46			
	24-26	103	13.84	3.16			
	27+	107	12.85	2.89			
Evaluation	18-20	133	12.80	5.35	1.764	0.153	-
	21-23	95	12.62	5.55			
	24-26	103	13.94	5.73			
	27+	107	12.31	5.25			
Ethics	18-20	133	13.39	3.47	0.281	0.839	-
	21-23	95	13.81	3.72			
	24-26	103	13.59	3.37			
	27+	107	13.68	3.75			
AILS total	18-20	133	52.96	13.02	1.235	0.297	-
	21-23	95	52.89	13.71			
	24-26	103	55.25	13.32			
	27+	107	51.87	12.59			
Bias	18-20	133	8.61	1.10	32.257	0.000*	D > C D > A
	21-23	95	9.68	1.04			
	24-26	103	9.43	1.01			
	27+	107	9.91	1.23			
Transparency	18-20	133	7.91	1.55	83.442	0.000*	D > A B > A C > A
	21-23	95	9.58	1.22			
	24-26	103	9.23	1.21			
	27+	107	10.64	1.33			
Accountability	18-20	133	8.53	1.72	36.621	0.000*	D > A B > A C > A
	21-23	95	9.73	1.27			
	24-26	103	9.52	1.47			
	27+	107	10.52	1.33			
Data privacy	18-20	133	7.79	1.07	44.261	0.000*	D > A
	21-23	95	8.32	1.17			
	24-26	103	8.18	1.39			
	27+	107	9.66	1.55			
AIEAS total	18-20	133	32.84	3.89	103.641	0.000*	D > A B > A C > A
	21-23	95	37.31	2.91			
	24-26	103	36.37	3.26			
	27+	107	40.74	3.60			
Innovation perception	18-20	133	12.56	2.58	151.176	0.000*	D > B > A D > C > A
	21-23	95	15.86	2.43			
	24-26	103	15.45	1.97			
	27+	107	19.00	2.24			
Technology tracking	18-20	133	8.80	2.26	123.564	0.000*	D > B > A D > C > A
	21-23	95	10.84	2.22			
	24-26	103	10.90	2.05			
	27+	107	14.28	2.25			
Technology madness	18-20	133	11.47	2.03	79.130	0.000*	D > B > A D > C > A
	21-23	95	13.55	2.22			
	24-26	103	13.65	1.83			
	27+	107	15.44	1.92			
TUS total	18-20	133	32.83	5.66	178.967	0.000*	D > B > A D > C > A
	21-23	95	40.25	5.78			
	24-26	103	40.00	4.42			
	27+	107	48.72	5.10			

Note. *p < 0.001 & Age group codes: A = 18-20 years, B = 21-23 years, C = 24-26 years, & D = 27+ years

total score differed significantly by age ($F[3, 434] = 178.97$, $p < .001$), indicating that students aged 27 years and older exhibited significantly higher overall technology use levels compared to younger age groups.

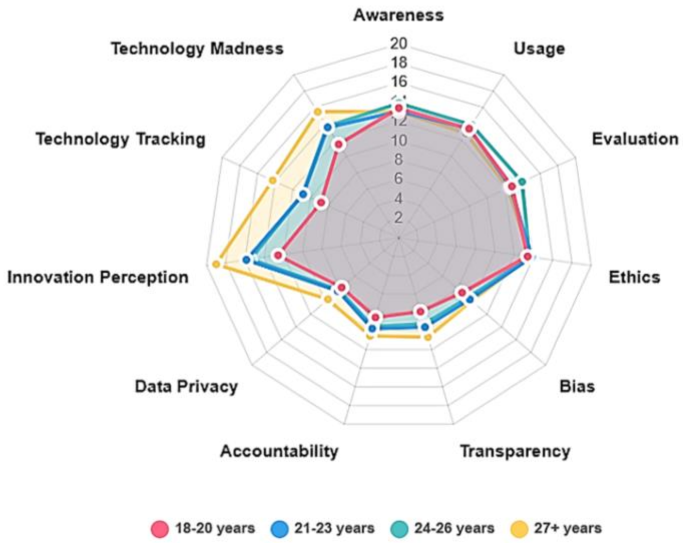

Figure 3. Age groups comparison radar graph (Source: By authors based on data)

Figure 3 shows the age groups comparison radar graph.

According to **RQ3**, **Table 5** included analysis results for the education field groups.

Table 5. ANOVA results according to education field variable

Scale/subscale	Education field	N	M	SD	F	p	Post-hoc
Awareness	Natural sciences	76	14.65	2.96	2.944	0.038*	D > E A > D
	Social sciences	84	13.79	2.88			
	Health sciences	102	13.37	2.65			
	Engineering	84	14.84	3.33			
	Other	92	11.03	2.38			
Usage	Natural sciences	76	14.97	3.76	2.823	0.041*	D > E A > D
	Social sciences	84	13.73	3.37			
	Health sciences	102	13.29	3.06			
	Engineering	84	14.27	3.41			
	Other	92	12.68	2.50			
Evaluation	Natural sciences	76	12.47	5.65	0.575	0.681	-
	Social sciences	84	13.64	5.27			
	Health sciences	102	13.00	5.81			
	Engineering	84	12.77	5.26			
	Other	92	12.63	5.37			
Ethics	Natural sciences	76	14.32	3.83	2.691	0.040*	B > D
	Social sciences	84	14.96	3.65			
	Health sciences	102	13.22	3.20			
	Engineering	84	13.85	3.55			
	Other	92	12.98	3.57			
AILS total	Natural sciences	76	54.21	14.05	0.997	0.409	-
	Social sciences	84	55.01	13.29			
	Health sciences	102	52.88	13.05			
	Engineering	84	53.01	13.57			
	Other	92	51.33	11.94			
Bias	Natural sciences	76	9.66	1.17	7.296	0.000**	-
	Social sciences	84	9.77	1.09			
	Health sciences	102	8.95	1.19			
	Engineering	84	9.20	1.20			
	Other	92	9.29	1.24			
Transparency	Natural sciences	76	9.14	1.16	23.719	0.000**	B > C D > C
	Social sciences	84	10.48	1.63			
	Health sciences	102	8.32	1.32			
	Engineering	84	9.00	1.71			
	Other	92	9.48	1.76			

Table 5 (Continued).

Scale/subscale	Education field	N	M	SD	F	p	Post-hoc
Accountability	Natural sciences	76	9.45	1.48	7.110	0.000**	B > C
	Social sciences	84	10.33	1.48			
	Health sciences	102	9.23	1.45			
	Engineering	84	9.23	2.07			
	Other	92	9.39	1.50			
Data privacy	Natural sciences	76	8.14	1.22	17.174	0.000**	B > D
	Social sciences	84	9.56	1.62			
	Health sciences	102	8.06	1.03			
	Engineering	84	8.23	1.28			
	Other	92	8.35	1.67			
AIEAS total	Natural sciences	76	36.39	3.48	22.613	0.000**	B > D B > C
	Social sciences	84	40.14	3.70			
	Health sciences	102	34.56	3.92			
	Engineering	84	35.65	4.97			
	Other	92	36.51	4.47			
Innovation perception	Natural sciences	76	14.93	2.65	40.616	0.000**	B > C B > D
	Social sciences	84	18.94	2.50			
	Health sciences	102	13.94	2.54			
	Engineering	84	14.71	3.32			
	Other	92	15.41	3.15			
Technology tracking	Natural sciences	76	9.93	1.81	54.583	0.000**	B > D
	Social sciences	84	14.33	2.05			
	Health sciences	102	9.40	2.17			
	Engineering	84	10.55	2.81			
	Other	92	11.38	3.09			
Technology madness	Natural sciences	76	12.70	2.35	32.894	0.000**	B > A B > C
	Social sciences	84	15.56	1.90			
	Health sciences	102	12.05	2.02			
	Engineering	84	13.20	2.38			
	Other	92	13.70	2.26			
TUS total	Natural sciences	76	37.57	5.58	57.409	0.000**	B > E > D
	Social sciences	84	48.83	5.30			
	Health sciences	102	35.39	5.69			
	Engineering	84	38.46	7.46			
	Other	92	40.49	7.53			

Note. *p < 0.05; **p < 0.001; & Education field codes: A = Natural sciences, B = Social sciences, C = Health sciences, D = Engineering, & E = Other

ANOVA results conducted according to the education field variable indicate statistically significant differences in some scales and sub-dimensions. A significant difference was found in the awareness sub-dimension of AI literacy according to field of study (F[4, 433] = 2.94, p < .05), and it was determined that engineering and natural sciences students had higher means compared to students studying in other scientific fields. Similarly, a significant difference dependent on field of study was found in the usage sub-dimension (F[4, 433] = 2.82, p < .05), and it was observed that the mean scores of engineering and natural sciences students were higher than other fields. In contrast, no significant difference according to field of study was determined in terms of the evaluation sub-dimension (F[4, 433] = 0.58, p > .05) and AILS total score (F[4, 433] = 1.00, p > .05).

Analyses regarding AI ethical awareness revealed significant differences according to field of study in all sub-dimensions: prejudice (F[4, 433] = 7.30, p < .001), transparency (F[4, 433] = 23.72, p < .001), accountability (F[4, 433] = 7.11, p < .001), and data privacy (F[4, 433] = 17.17, p < .001). Additionally, the AI Ethical Awareness Scale total score also differed significantly according to field of study (F[4, 433] = 22.61, p < .001). These findings indicate that social sciences students' ethical awareness levels are higher compared to students studying in other fields. When examining the results regarding technology use, significant differences according to field of study were determined in terms of innovation perception (F[4, 433] = 40.62, p < .001), technology tracking (F[4, 433] = 54.58, p < .001), technology madness (F[4, 433] = 32.89, p < .001), and TUS total score (F[4, 433] = 57.41, p < .001). These results reveal that students studying in the social sciences field have higher levels of perception and use toward technology compared to other fields.

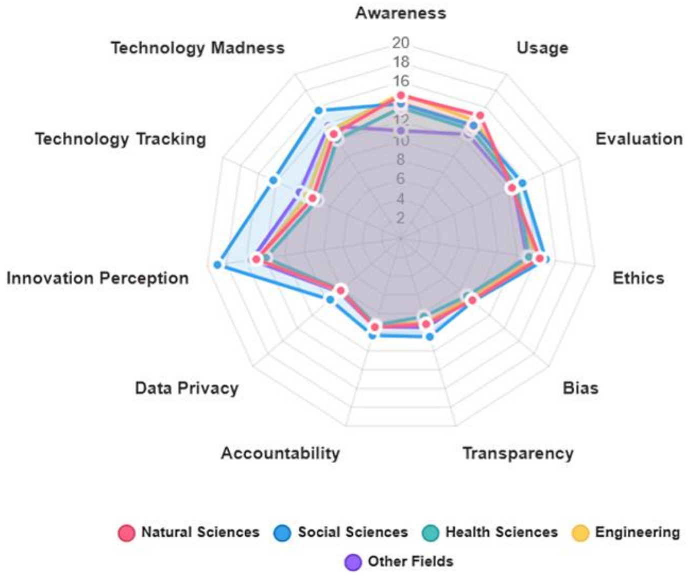

Figure 4. Field groups comparison radar graph (Source: By authors based on data)

Table 6. Correlation coefficients of relationships among research variables

Variables	AILS	AIEAS	TUS
AILS	-		
AIEAS	0.22*	-	
TUS	0.34**	0.42**	-

Note. *p < 0.05; **p < 0.01; & N = 438

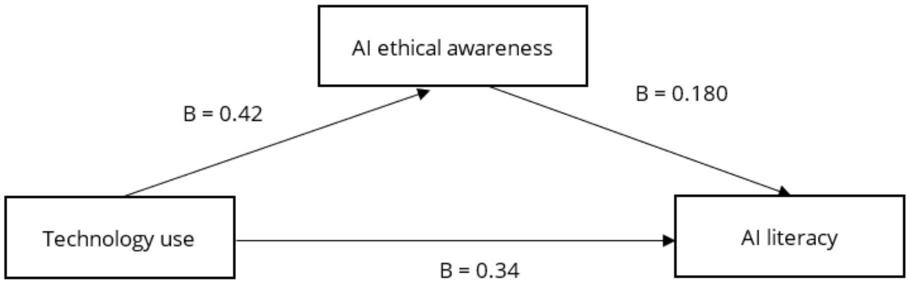

Figure 5. Mediator model (*p < 0.05; **p < 0.01; & N = 438) (Source: By authors based on data)

Figure 4 shows the field groups comparison radar graph. The Pearson correlation analysis presented in **Table 6** indicates that there are statistically significant relationships among the research variables.

Specifically, a low but significant positive correlation was found between the AILS and the AIEAS ($r = .22$, $p < .05$). In addition, AILS was moderately and positively associated with the TUS ($r = .34$, $p < .01$). A moderate and statistically significant positive relationship was also identified between AIEAS and TUS ($r = .42$, $p < .01$). Overall, these findings suggest that higher levels of AI literacy and ethical awareness are associated with increased technology use, and that the variables are meaningfully related to one another. **Figure 5** shows the mediator model.

The direct effect results presented in **Table 7** indicate that technology use has a positive and statistically significant effect on AI literacy ($B = 0.26$, $p < .001$). This finding suggests that as the level of technology use increases, the level of AI literacy also increases. Similarly, it was determined that technology use has a significant and positive effect on AI ethical awareness ($B = 0.35$, $p < .001$). When examining the predictors of AI literacy, it is observed that AI ethical awareness significantly and positively affects AI literacy ($B = 0.15$, $p < .001$). Based on these findings, it can be stated that an increase in technology use contributes to the enhancement of AI literacy both directly and through ethical awareness.

Table 7. Direct effects between dependent and independent variables

Independent variable	Dependent variable	B	SE	β	t	p	LLCI	ULCI
TUS →	AILS	0.26	0.04	0.34	6.50	0.00**	0.18	0.34
TUS →	AIEAS	0.35	0.04	0.42	8.75	0.00**	0.27	0.43
AIEAS →	AILS	0.15	0.05	0.18	3.00	0.00**	0.05	0.25

Note. **p < .001; SE: Standard error; LLCI: Lower limit of CI; & ULCI: Upper limit of CI

Table 8. Total, direct, and indirect effects of technology use on AI literacy

Effect type	B	SE	β	t/z	p	LLCI	ULCI
Total effect	0.26	0.04	0.34	6.50	0.00**	0.18	0.34
Direct effect	0.21	0.04	0.27	5.25	0.00**	0.13	0.29
Total indirect effect	0.05	0.02	0.07	-	-	0.02	0.10
Indirect effects							
TUS → AIEAS → AILS	0.05	0.02	0.07	-	-	0.02	0.10

Note. **p < .001; SE: Standard error; LLCI: Lower limit of CI; & ULCI: Upper limit of CI

The findings presented in **Table 8** reveal the total, direct, and indirect effects of technology use on AI literacy. According to the results obtained, the total effect of technology use on AI literacy is positive and statistically significant (B = 0.26, β = 0.34, $p < .001$). With the inclusion of the mediating variable in the model, it is observed that the direct effect of technology use on AI literacy decreased but maintained its significance (B = 0.21, β = 0.27, $p < .001$).

Analyses regarding indirect effects indicate that technology use significantly and positively affects AI literacy through AI ethical awareness (B = 0.05, β = 0.07, 95% CI [0.02, 0.10]). The fact that the CI does not include zero confirms that this indirect effect is statistically significant. These findings reveal that technology use primarily increases AI ethical awareness, and this increase is reflected in the level of AI literacy. The fact that the direct effect remains significant while decreasing when the mediating variable is added to the model indicates that AI ethical awareness assumes a partial mediating role in the relationship between technology use and AI literacy.

DISCUSSION

The present study examined the relationships among AI literacy, AI ethical awareness, and technology use among university students, as well as the demographic variations in these constructs. The findings revealed that university students demonstrated moderate to above-moderate levels across all three constructs, with AI literacy showing the highest mean score (M = 4.43), followed by technology use (M = 3.08) and AI ethical awareness (M = 3.05). These results align with recent research suggesting that while students possess foundational knowledge about AI, their ethical considerations and critical evaluation skills remain areas requiring further development (Chiu et al., 2024; Hornberger et al., 2023). The moderate levels of AI ethical awareness observed in this study are consistent with findings by Saklaki and Gardikiotis (2024), who similarly reported that Greek university students displayed moderate ethical concerns regarding AI technologies.

Gender-based analysis revealed significant differences in AI ethical awareness and technology use, but not in AI literacy. Male students demonstrated significantly higher scores in AI ethical awareness and all its sub-dimensions, including bias, transparency, accountability, and data privacy. Similarly, male students reported higher technology use levels across innovation perception, technology tracking, and technology madness dimensions. These findings contrast with some previous studies that reported no significant gender differences in AI literacy (Toker Gokce et al., 2025) but align with research indicating gender disparities in technology adoption and ethical awareness (Aktan & Gokcearslan, 2022). The absence of gender differences in AI literacy, despite significant differences in ethical awareness and technology use, suggests that foundational AI knowledge may be equally accessible to both genders, while attitudes and engagement patterns differ. This finding has important implications for educational interventions, suggesting that efforts to promote ethical awareness and technology engagement among female students may help bridge the gap in these dimensions without necessarily affecting their core AI literacy levels.

Age emerged as a significant factor influencing AI ethical awareness and technology use, but not AI literacy. Students aged 27 years and older consistently demonstrated higher scores in ethical awareness dimensions, including bias, transparency ($F = 83.44$, $p < .001$), accountability, and data privacy compared to younger age groups. Similarly, older students exhibited higher technology use levels across all dimensions. These findings corroborate research by Lee et al. (2024), who found that older university students in Korea displayed more sophisticated understanding of AI concepts and ethical implications. The lack of age-related differences in AI literacy suggests that while older students may have greater exposure to technology and more developed ethical reasoning capabilities, foundational AI knowledge is comparable across age groups. This pattern may reflect the fact that AI literacy, as measured in this study, captures basic awareness and understanding that are uniformly developed through contemporary educational curricula, whereas ethical awareness and technology engagement are more strongly influenced by life experience and maturity. The findings suggest that younger students may benefit from targeted interventions focusing on ethical reasoning and responsible technology use rather than basic AI literacy enhancement.

Field of study demonstrated differential effects across the three constructs examined in this study. Social sciences students consistently scored highest in AI ethical awareness and technology use, while health sciences students displayed the lowest scores across most dimensions. In contrast, no significant field differences were observed for overall AI literacy, though engineering and natural sciences students showed higher awareness and usage sub-dimensions. These results align with findings by Akca Sumengen et al. (2025), who reported that nursing students' AI literacy levels varied according to their academic exposure and disciplinary training. The higher ethical awareness among social sciences students may reflect their curriculum's emphasis on critical thinking, societal implications, and ethical reasoning, as suggested by Atenas et al. (2024), who advocated for critical and creative pedagogies in AI literacy education grounded in data justice approaches. The lower scores among health sciences students are particularly noteworthy given the increasing integration of AI in healthcare contexts (El-Sayed et al., 2025). These findings underscore the need for discipline-specific AI literacy interventions that address the unique ethical challenges and technological applications relevant to each field. Educational institutions should consider developing tailored AI literacy programs that build upon students' existing disciplinary knowledge while strengthening areas of relative weakness, particularly ethical awareness in STEM fields and technical understanding in health sciences.

The correlation analysis revealed significant positive relationships among AI literacy, AI ethical awareness, and technology use, supporting the interconnected nature of these constructs in the context of higher education. The moderate correlation between technology use and AI ethical awareness was the strongest among the examined relationships, suggesting that students who actively engage with technology are more likely to develop heightened awareness of ethical considerations surrounding AI applications. This finding aligns with C. Wang et al. (2025), who demonstrated that AI literacy significantly influences university students' behavioral intentions toward generative AI technologies by integrating the Theory of Planned Behavior. The positive correlation between AI literacy and AI ethical awareness, though relatively modest, indicates that students with greater understanding of AI concepts tend to exhibit more sophisticated ethical reasoning regarding AI systems. Similarly, Lu et al. (2025) found that AI literacy was positively associated with higher-order thinking skills through the mediating roles of behavioral engagement and peer interaction, suggesting that AI literacy development encompasses both cognitive and ethical dimensions. These correlational findings provide empirical support for the conceptual framework proposed by Chiu et al. (2024), who argued that AI literacy and competency should be understood as multidimensional constructs that integrate technical knowledge, ethical awareness, and practical engagement with technology.

The mediation analysis demonstrated that AI ethical awareness serves as a partial mediator in the relationship between technology use and AI literacy, indicating that technology engagement enhances AI literacy both directly and indirectly through ethical awareness development. The direct effect of technology use on AI literacy remained significant even after accounting for the mediating role of ethical awareness, suggesting that hands-on experience with technology contributes to AI understanding through multiple pathways. The significant indirect effect confirms that part of technology use's influence on AI literacy operates through heightened ethical awareness, as students who frequently engage with technology encounter ethical dilemmas and considerations that deepen their understanding of AI's societal implications. This partial mediation pattern is consistent with findings by Cengiz and Peker (2025), who identified sequential mediating roles of attitudes toward AI and literacy in the relationship between generative AI acceptance and AI anxiety among university students. The theoretical significance of this finding lies in its demonstration that

AI literacy development is not merely a technical process but involves the cultivation of ethical reasoning capabilities that emerge from active technology engagement. Kong et al. (2021) emphasized the importance of integrating ethical dimensions into AI literacy programs for educated citizens, and the current findings provide empirical evidence supporting this pedagogical approach by showing that ethical awareness naturally develops alongside technical competencies when students actively engage with technology.

The finding that technology use influences AI literacy both directly and through ethical awareness has important implications for educational practice and curriculum design in higher education contexts. First, the results suggest that providing students with abundant opportunities for hands-on technology engagement may simultaneously enhance their technical AI literacy and ethical reasoning capabilities, creating a synergistic learning effect. This is particularly relevant given the findings by Chen and Zhang (2025), who reported that a basic AI course significantly improved students' understanding of AI concepts, literacy, and empowerment, suggesting that structured educational interventions can effectively leverage the relationship between technology use and AI literacy development. Second, the partial mediation effect indicates that explicitly addressing ethical considerations in technology-enhanced learning environments may amplify the benefits of technology engagement for AI literacy development. Atenas et al. (2024) advocated critical and creative pedagogies that incorporate epistemic data justice approaches into AI and data literacy education, an approach that aligns well with the current findings by recognizing the central role of ethical awareness in comprehensive AI literacy. Third, the small effect size of the indirect path ($\beta = .07$) suggests that while ethical awareness contributes meaningfully to AI literacy development, other mechanisms also mediate the technology use-AI literacy relationship, warranting further investigation of additional mediating variables such as self-efficacy, critical thinking skills, and collaborative learning experiences that may enhance the effectiveness of technology-based AI literacy interventions (El-Sayed et al., 2025; Young et al., 2024).

IMPLICATIONS

The findings of this research indicate the necessity of multi-layered and integrated curriculum designs for the development of AI literacy in higher education institutions. Considering the direct and indirect effects of technology use on AI literacy, it is important for universities to design learning environments that offer students opportunities to interact with various technological tools and platforms. The mediating role of AI ethical awareness reveals that ethical reasoning abilities must be systematically addressed alongside technical skill development. Particularly, the high levels of ethical awareness observed in the social sciences field indicate the need to adopt interdisciplinary approaches and create learning experiences where students from different academic fields can come together to discuss the social, ethical, and technical dimensions of AI. In this context, it is recommended that AI literacy courses go beyond merely presenting technical content and address ethical issues such as data privacy, algorithmic bias, accountability, and transparency through case studies, discussions, and project-based learning activities (Atenas et al., 2024; Kong et al., 2021).

The differences observed according to gender and age groups emphasize the necessity of developing target audience-oriented and inclusive educational strategies. The fact that female students exhibit lower means compared to male students in terms of AI ethical awareness and technology use reveals the need to design special programs that support gender equality, encourage female students' participation in technology fields, and help them develop positive attitudes toward AI. In this regard, mentorship programs, increasing the visibility of female role models, and creating supportive learning environments that will strengthen self-efficacy beliefs regarding technology use are important (El-Sayed et al., 2025). The differences among age groups necessitate the development of early intervention programs, particularly targeted at young students. The low levels of ethical awareness and technology use among students in the 18-20 age group demonstrate the importance of integrating orientation programs and foundational courses focusing on AI literacy and digital ethics into the curriculum during the university entry period. The low performance of health sciences students necessitates the design of specialized educational modules that address field-specific AI applications and ethical dilemmas that may be encountered in the healthcare sector (Akca Sumengen et al., 2025; Canales-Morales, 2025).

LIMITATIONS AND RECOMMENDATIONS

While this study presents important findings regarding the relationships among AI literacy, AI ethical awareness, and technology use, it has some methodological limitations. First, the cross-sectional design of the research does not allow for the establishment of causal relationships among variables; therefore, longitudinal research designs are needed to understand the long-term and developmental characteristics of the effects of technology use on AI literacy. Second, data collected through self-report scales, and social desirability bias and response biases may have affected the results. In future studies, supporting self-report data with objective data sources such as performance-based measurements, behavioral observations, or actual technology use records will enhance the validity of the findings. Additionally, this research only examined the mediating role of AI ethical awareness, and other potential mediating and moderating variables such as critical thinking skills, self-efficacy beliefs, peer interaction, and motivational factors were disregarded.

For future research, longitudinal studies should be designed that track the development of AI literacy over time and evaluate the long-term effects of educational interventions. Such studies will help us understand how AI literacy develops, which factors accelerate or hinder this development, and the cumulative effects of changes in ethical awareness on AI literacy. Using experimental research designs, the effectiveness of different pedagogical approaches (e.g., project-based learning, case studies, and collaborative learning) in developing AI literacy and ethical awareness should be compared. Understanding students' experiences with AI technologies, ethical concerns, and learning processes should be achieved using qualitative research methods. Cross-cultural comparative studies examining how AI ethical awareness is shaped in different cultural contexts and the role of cultural values in AI literacy development can be conducted.

CONCLUSION

This research examined the relationships among university students' AI literacy, AI ethical awareness, and technology use, and revealed that AI ethical awareness plays a partial mediating role in the effect of technology use on AI literacy. The findings demonstrate that the development of AI literacy is not limited to the acquisition of technical knowledge and skills alone, but that ethical reasoning abilities, critical evaluation skills, and attitudes toward responsible technology use are also integral parts of this process. The fact that technology use affects AI literacy both directly and through ethical awareness indicates that students' active interaction with technological tools produces multidimensional learning outcomes. This situation emphasizes the importance of higher education institutions adopting pedagogical approaches that integrate technical content with ethical dimensions, offer students abundant practical experience opportunities, and develop critical thinking skills when designing AI literacy education programs. Furthermore, the systematic differences observed according to demographic variables such as gender, age, and field of study reveal that uniform educational models will be insufficient and that diversified educational strategies responding to the specific needs of different student groups need to be developed.

In an era when AI technologies are rapidly proliferating in many areas of education, healthcare, business, and daily life, it is critically important that university graduates be trained not only to use AI systems but also as individuals who can evaluate the societal impacts of these systems, recognize ethical issues, and apply principles of responsible use. The findings of this study demonstrate that developing AI ethical awareness is an important component of AI literacy and enhances the educational value of technology use. Therefore, higher education institutions should develop comprehensive and holistic AI literacy programs to ensure that students are raised as responsible, ethically sensitive, and adequately equipped citizens in the AI age.

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Ethics declaration: Data were collected through an online questionnaire. At the beginning of the form, participants were informed about the purpose of the study, voluntary participation, confidentiality, and their right to withdraw at any time. Informed consent was obtained electronically from all participants before proceeding with the survey. All sensitive and confidential personal information was anonymized and securely protected throughout the research process. The study was conducted in accordance with internationally recognized ethical principles, including the Declaration of Helsinki (2013) and relevant data protection and research ethics guidelines.

AI statement: No generative artificial intelligence (AI) or AI-based tools were used in the design, data collection, analysis, interpretation, or writing of this study.

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