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THE EFFECT OF PRE-SERVICE SCIENCE AND MATHEMATICS TEACHERS' AI LITERACY AND ETHICAL USE OF INFORMATION TECHNOLOGIES ON THEIR ETHICAL REFLECTIONS ON AI

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Abstract. *The growing presence of artificial intelligence (AI) in education raises critical questions about teachers' AI literacy and ethical reflection. This study aims to examine the effects of pre-service science and mathematics teachers' AI literacy and their ethical use of information technologies on their ethical reflections on AI. The study, designed as a correlational survey, included 219 pre-service science and mathematics teachers from a university in Eastern Türkiye. Data were collected using three instruments: the Artificial Intelligence Literacy Scale, the Information Technologies Ethical Use Scale, and the Artificial Intelligence Ethical Reflection Scale. The findings indicate that, although pre-service teachers demonstrate high levels of knowledge in the technical and critical dimensions of AI, they remain at a moderate level in translating this knowledge into practical application and in engaging in ethical reasoning. Structural equation modelling results indicate that AI literacy significantly and directly influences ethical reflection on AI, whereas the ethical use of information technologies constitutes a weaker predictor. The mediation analysis further reveals that general ethical use of information technologies does not play a significant mediating role in the relationship between AI literacy and ethical reflection on AI.*

Keywords: *artificial intelligence (AI) ethics, artificial intelligence (AI) literacy, information technology (IT), mathematics education, science education*

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Introduction

Artificial intelligence (AI) has pervaded nearly all domains of modern life in the 21st century-often characterized as the age of technology-positioning itself at the center of the technological revolution. Designed by modelling human thought systems and neurological activity, contemporary AI systems are now capable of producing professional outputs more rapidly and efficiently across many critical sectors, including the economy, health, transportation, and industry. Research in AI is advancing rapidly, and applications tailored for specific domains are being developed apace. In recent years, AI has also begun to be widely used in educational processes, signaling that a comprehensive transformation in teaching and learning is imminent (Deniz & Bagceci, 2025). With its potential to offer personalized learning experiences (Bulus & Elmas, 2024; Chen et al., 2020; Deniz & Bagceci, 2025; Incemen & Ozturk, 2024; Timms, 2016), enrich instructional materials (Bulus & Elmas, 2024), automate assessment and evaluation processes (Coskun & Gulleroglu, 2021; Su et al., 2023), and streamline administrative tasks (Filgueiras, 2023; Yesilbas Ozenc, 2025; Zawacki-Richter et al., 2019), AI is becoming an indispensable tool for education systems. Especially in the aftermath of the COVID-19 pandemic, the heightened need for digital learning has further accelerated the integration of AI technologies into teaching and learning activities (Temur, 2025b; Yesilbas Ozenc & Basaran, 2024; Yesilyurt et al., 2024; Zhai et al., 2021).

This rapid digital transformation necessitates new domains of competence for educational stakeholders, particularly teachers, who shoulder the responsibility of educating future generations (Coskun & Gulleroglu, 2021; Laupichler et al., 2022). As underscored by the Council of Europe, given AI's societal implications and potential effects on individuals, enhancing AI literacy among the general public-and especially among individuals in schools-is a democratic imperative (Sperling et al., 2024). This imperative requires that teachers reshape their professional knowledge and skills around the axis of AI literacy (Chiu et al., 2021; Sperling et al., 2022). In its broadest sense, AI literacy refers to a collection of competencies that enable individuals to critically appraise AI technologies and to engage in effective communication

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and collaboration with AI systems, and use these technologies ethically as tools in online environments, at home, and in the workplace (Sperling et al., 2024). These competencies encompass understanding core AI concepts, assessing AI's potential societal impacts, and using AI-enabled tools in an informed manner (Bulus & Elmas, 2024; Laupichler et al., 2022).

At the same time, the proliferation of AI and other information technologies brings significant ethical concerns to the fore (Bulus & Elmas, 2024; Temur, 2025a, 2025b). As a set of norms that delineate rules to be followed when using information technologies, information ethics aims to ensure that users obtain maximum benefit with minimal harm (Arikan & Duymaz, 2014). Issues such as information privacy, data security, intellectual property, network integrity, and societal impact constitute core foci of information ethics (Ozbay et al., 2021; Zeybek & Beyhan, 2014). Problems, including potential biases in decision-making, discrimination, lack of transparency and accountability in AI systems, stand at the center of debates on AI ethics (Borenstein & Howard, 2021; Cerratto Pargman & McGrath, 2021; Sperling et al., 2024). For instance, if AI algorithms inherit existing social biases embedded in the data on which they are trained and produce discriminatory outcomes, this poses a serious risk to the principle of equal opportunity in education (Temur, 2025b; Wang et al., 2024). Therefore, AI literacy should be approached not merely as a technical skill set but also as a critical perspective that encompasses the ethical and responsible use of these technologies (Murtezaoglu & Birol, 2025; Sperling et al., 2024; Temur, 2025b).

Teachers play a key role in cultivating students' digital citizenship skills and serving as role models for the proper and ethical use of information technologies (Coskun & Gulleroglu, 2021; Temur, 2025a). This responsibility has become even more critical in the age of AI. Teachers are expected to understand both the potential benefits and ethical risks of AI, to use these technologies pedagogically in effective and responsible ways, and to guide their students accordingly (Li, 2025; Sperling et al., 2024; Temur, 2025b; Wang et al., 2023). Consequently, it is of great importance that pre-service teachers be equipped during their undergraduate education with knowledge and skills related to AI literacy, the ethical use of information technologies, and AI ethics (Bond et al., 2024; Cetindamar et al., 2022; Laupichler et al., 2022; Ng et al., 2021).

In recent years, AI literacy has emerged as a rapidly expanding research topic in both national and international literature (Celebi et al., 2023; Laupichler et al., 2022; Li, 2025; Sperling et al., 2024). Literature reviews reveal a sharp rise in interest in AI literacy, particularly after 2020 (Ng et al., 2024). Studies in this area generally focus on defining the concept of AI literacy, identifying its components and frameworks, developing curricula for different educational levels, and measuring teachers' or students' attitudes, readiness, and perceptions toward AI (Laupichler et al., 2022; Su et al., 2023; Yim, 2024a).

Comprehensive review studies by Sperling et al. (2024) demonstrate that while AI literacy is an ascending global research area, research in the field of teacher education is still rather limited. Their study concluded that most research on AI literacy has been influenced by computer science and exploratory instructional approaches, and that teachers' professional knowledge (theoretical, practical, and ethical) has not been examined or has been largely overlooked. Much of the literature centers on students' AI literacy, while the question of what kinds of knowledge teachers should possess has been largely neglected (Nazaretsky et al., 2022; Ng et al., 2021; van Vaerenbergh & Pérez-Suay, 2022). Similarly, another review by Laupichler et al. (2022) identified that research on AI literacy in higher and adult education remains at an early stage, with a lack of clarity about how AI literacy should be defined and what content should be taught to non-experts. Collectively, these studies indicate that AI literacy research has mostly been a computer-science-centered endeavor and does not sufficiently reflect the perspectives of the educational sciences.

Within the literature focusing on teachers' AI literacy, studies have typically examined teachers' attitudes, (mis)perceptions, and willingness to adopt AI. For example, Antonenko and Abramowitz (2023) investigated in-service science teachers' misconceptions about AI. Celik (2023) examined teachers' professional knowledge in the context of ethically integrating AI-based tools. However, these studies lack experimental research that models the relationships among different components of AI literacy (e.g., knowledge, skills, ethical awareness) and how these components influence pre-service teachers' ethical decision-making processes.

Regarding the ethical use of information technologies, the literature is comparatively richer. Using scenario-based scales in particular, researchers have investigated individuals' attitudes and behaviors in the face of various ethical dilemmas. Loch and Conger (1996) examined user attitudes on topics such as privacy and ownership of resources, while Saghafi and Angelopoulos (2025) investigated how moral philosophies such as consequentialism and deontology influence ethical decision-making in virtual governance contexts. In Türkiye, studies have examined pre-service teachers' levels of ethical use of information technologies across various variables. For instance, Beyhan and Tunc (2012) found that pre-service teachers who rated their computer and internet use as "very good"

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tended to use information technologies less ethically, while those at a "moderate" level were the most ethical users. Ozbay et al. (2021) determined that pre-service teachers who had received education in information ethics displayed higher levels of ethical use than those who had not. These studies demonstrate that the ethical use of information technologies is affected by various demographic and experiential factors. However, the relationship between ethical use habits in information technologies and ethical reflections on AI-a newer and more complex domain-has yet to be investigated.

AI ethics has garnered increasing attention in the literature, with studies highlighting issues such as bias, discrimination, privacy violations, and accountability that may arise from AI systems. According to Sperling et al. (2024), discussions of AI ethics in education are often framed as a matter of understanding the technical configurations of data-driven AI technologies; ethics is thereby conceptualized as a set of facts (episteme) that teachers should know, rather than as a mode of moral and adaptive thinking and action. This approach overlooks how teachers should exercise professional judgement (phronesis) when faced with complex, context-specific ethical dilemmas. Yim (2024a) similarly argues that existing AI literacy frameworks tend to concentrate on technical knowledge and do not sufficiently empower students to develop critical thinking and a creative mindset.

Taken together, the literature indicates that AI literacy has not been sufficiently studied in the context of teacher education and that the role of teachers' professional knowledge and skills in this area has been largely neglected. Moreover, the topics of AI literacy, the ethical use of information technologies, and AI ethics are often examined separately; there is a notable scarcity of empirical studies that investigate the relationships among these three foundational constructs within an integrated model. In particular, it remains insufficiently understood how individuals' general habits of ethical use of information technologies shape their ethical reflections on AI, a more specific and novel domain. Additionally, AI ethics is frequently treated solely as technical knowledge (episteme), and studies focusing on cultivating pre-service teachers' practical and moral reasoning (phronesis) skills remain inadequate.

Research Aim and Research Questions

Given AI's intrinsic links to computer science, statistics, and mathematics, the status of pre-service science and mathematics teachers, whose analytical thinking skills are typically strong regarding AI literacy and ethics, is of special interest; nonetheless, comprehensive studies focusing on this specific group are scarce. By determining how pre-service science and mathematics teachers' AI literacy and ethical use of information technologies affect their ethical reflections on AI, the present study aims to address these gaps and make an original contribution to the literature (Figure 1). The purpose of this study is to examine the mediating role of ethical use of information technologies between AI literacy and ethical reflection on AI. In line with this aim, the following research questions were posed:

a) How does AI literacy predict ethical reflection on AI?
b) How does the ethical use of information technologies predict ethical reflection on AI?
c) How does AI literacy predict the ethical use of information technologies?
d) Does ethical use of information technologies mediate the relationship between AI literacy and ethical reflection on AI?

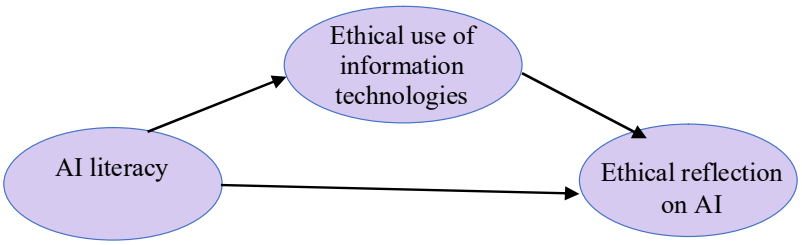
The study hypotheses are followed for clarity:

H1. AI literacy has a direct effect on ethical reflection on AI.
H2. Ethical use of information technologies has a direct effect on ethical reflection on AI.
H3. AI literacy has a direct effect on the ethical use of information technologies.
H4. Ethical use of information technologies mediates the relationship between AI literacy and ethical reflection on AI.

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Figure 1
Mediating Effect of Ethical Use of Information Technologies



Research Methodology

Design

In this study, a quantitative correlational research design was employed. Correlational designs examine relationships between two or more variables without any intervention and allow inferences about the possible causes and consequences of these relationships. A correlation between two variables indicates that score ranges on one vary systematically with score ranges on the other. A causal-comparative (causal-relational) approach seeks to explain intervariable patterns and to predict the values of one variable from the values of another. To this end, predictor (independent) variables were incorporated into the model with respect to their effects on the criterion (dependent) variable, and prediction accuracy was evaluated (Creswell, 2013; Fraenkel et al., 2012). Structural equation modelling (SEM) analyses were conducted using the AMOS. The study examined the structural relationships among AI literacy, ethical use of information technologies, and ethical reflection on AI within the proposed models.

Sample

In the 2024-2025 academic year, the study group comprised pre-service teachers enrolled in the Science Education and Mathematics Education programs of a Faculty of Education at a university in Eastern Türkiye. Two sampling techniques were employed: Simple random sampling in the pilot study for scale adaptation, and probabilistic two-stage cluster sampling in the main implementation. In the latter, the population was partitioned into natural clusters, clusters were selected, and representative participants were randomly drawn from each cluster (Fraenkel et al., 2012). The pilot study was conducted in the Faculty of Education of a university located in the same region with a randomly selected group of 86 pre-service teachers. Regarding sample adequacy for scale development/adaptation, the literature indicates that a sample of 300 is "good," while approximately 150 may suffice when factor loadings are high (Comrey & Lee, 1992). Another source reports that reliable results can be obtained with 200 participants, and that a sample of around 100 may be adequate when the factor structure is small and distinct (Kline, 1994). Several studies further recommend that the sample size be at least twice the number of items (Cokluk et al., 2021; Tabachnick & Fidell, 2001). In light of these findings, the sample attained in the present research is deemed adequate. The main implementation was carried out within the same faculty's science and mathematics teacher education programs. In the two-stage cluster sampling, eight subclusters were defined as the 1st, 2nd, 3rd, and 4th years of each program. Participants were randomly selected in proportion to these clusters' representation in the population. This principle of representation was adopted, given the expectation that the purpose and level of technology use might vary by field and year of study. The distributions of the 219 randomly selected pre-service teachers by field and class level are presented in Table 1.

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Table 1
Demographic Characteristics of the Study Group

Variables	Field of Study					
	Science Education		Mathematics Education		Total	
	N	%	*N*	%	*N*	%
Field	87	39.7	132	60.3	219	100.0
Level of Study						
1st year	7	8.0	21	15.9	28	12.8
2nd year	16	18.4	36	27.3	52	23.7
3rd year	29	33.3	34	25.8	63	28.8
4th year	35	40.2	41	31.1	76	34.7
Total	87	100.0	132	100.0	219	100.0
Gender						
Male	35	40.2	53	42.4	88	41.6
Female	52	59.8	79	57.6	131	58.4
Total	87	100.0	132	100.0	219	100.0

When Table 1 is examined, it is observed that 60.3% of the participants were pre-service teachers in mathematics education and 39.7% in science education; 34.7% were in the 4th year, 28.8% in the 3rd year, 23.7% in the 2nd year, and 12.8% in the 1st year; and 58.4% of the participants were female while 41.6% were male. The study received approval from the Social and Human Sciences Research Ethics Committee. Participants were informed that their involvement was entirely voluntary and that their data would remain confidential. The authors also state that they have no conflicts of interest to declare.

Instrument and Procedures

In the study, three different instruments were used as data collection tools: the Artificial Intelligence Literacy Scale, the Information Technologies Ethical Use Scale, the Information Technologies Ethical Use Scale, and the Artificial Intelligence Ethical Reflection Scale.

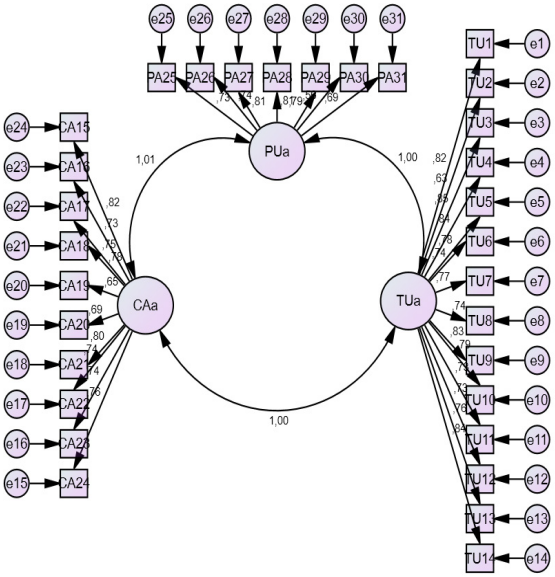
Artificial Intelligence Literacy Scale

To determine pre-service teachers' levels of AI literacy, the "Artificial Intelligence Literacy Scale (AILS)" originally developed by Laupichler et al. (2023) and adapted into Turkish by Karaoglan Yilmaz and Yilmaz (2023), was employed. The scale comprises 31 items on a 7-point Likert scale and consists of three factors: Technical understanding (TU), critical appraisal (CA), and practical application (PA). The reliability of the Turkish form was assessed using Cronbach's alpha and reported as 0.990. In this study, the Cronbach's alpha was calculated as 0.818. Confirmatory factor analysis (CFA) results indicated the following model fit indices: $\chi^2 = 472.78$, df= 431, $p > .05$, χ^2/df= 1.10, RMSEA = 0.02, IFI = 0.99, TLI = 0.99, CFI = 0.99, GFI = 0.88, AGFI = 0.86, and SRMR = 0.09. These values suggest that the scale demonstrates an overall near-excellent fit. The regression coefficients for the model are presented in Figure 2.

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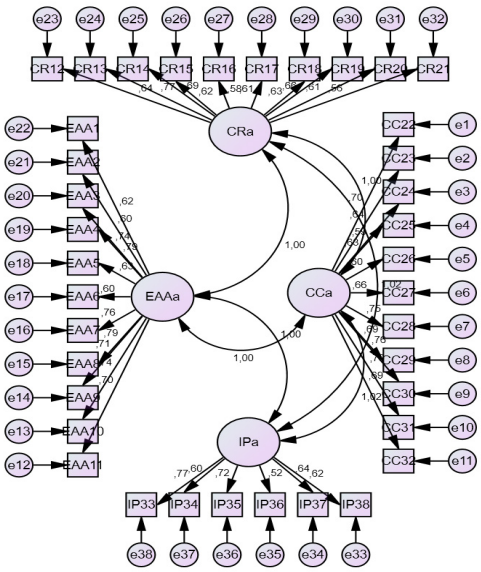
Figure 2
Regression Coefficients of the AILS



Information Technologies Ethical Use Scale

In this study, the "Information Technologies Ethical Use Scale (ITEUS)" developed by Konuk (2023) was employed to assess the extent to which pre-service science and mathematics teachers use information technologies ethically. The scale comprises 38 items on a 7-point Likert scale and includes four factors: Ethical awareness (EAA), communication and respect (CR), cybercrime (CC), and intellectual property (IP). In the original development study, internal consistency reliabilities (Cronbach's alpha) were reported as 0.90 for EAA, 0.92 for CR, 0.95 for CC, 0.72 for IP, and 0.92 for the overall scale. In the present study, the total Cronbach's alpha was calculated as 0.87. The regression coefficients for the model are presented in Figure 3.

Figure 3
Regression Coefficients of the ITEUS



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Artificial Intelligence Ethical Reflection Scale

To assess pre-service teachers' levels of ethical reflection regarding AI, the "Artificial Intelligence Ethical Reflection Scale (AIERS)" developed by Wang et al. (2025) and adapted into Turkish within the scope of this study, was employed. The scale comprises 12 items rated on a 7-point Likert scale and includes three factors: AI ethical awareness (AIEA), AI critical evaluation (AICE), and AI for social good (AISG). For linguistic adaptation, three language experts translated the scale from English into Turkish. To evaluate comprehensibility, two experts in science education and two in mathematics education reviewed the items, and the final version was produced in line with their feedback. Expert evaluations indicated that the scale was clear, comprehensible, and applicable. To obtain evidence of validity and reliability, a pilot implementation was conducted with 186 pre-service teachers. Preserving the original factor structure, a CFA was conducted to examine the structural validity of the scores obtained from the Turkish sample. CFA is a method used to test whether a theoretical construct fits a specified model and is widely employed in construct and model validation (Maruyama, 1998). Fit indices for the three-factor model were calculated, modification suggestions were considered, and, following the necessary adjustments, the resulting fit indices, together with their recommended ranges, are presented in Table 2.

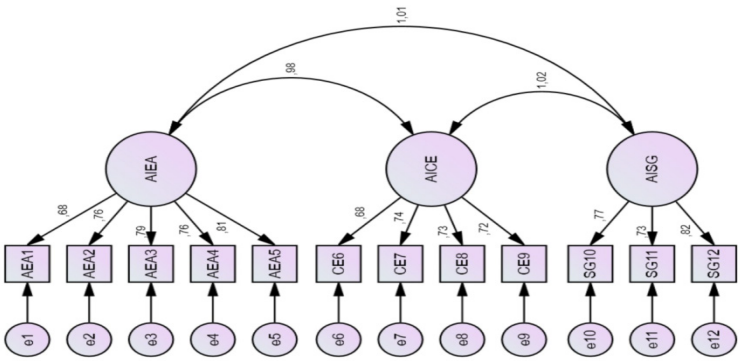
Table 2
Fit Indices for CFA and Reference Ranges

Fit Index	Excellent Fit	Acceptable Fit	Value Obtained in This Study
χ^2/df	0 ≤ CMIN/df ≤ 2	2 ≤ CMIN/df ≤ 5	0.95
RMSEA	0 < RMSEA ≤ .05	.05 < RMSEA ≤ .08	0.00
CFI	.95 ≤ CFI ≤ 1.00	.90 ≤ CFI ≤ .95	1.00
GFI	.95 ≤ GFI ≤ 1.00	.90 ≤ GFI ≤ .95	0.96
IFI	.95 ≤ IFI ≤ 1.00	.90 ≤ IFI ≤ .95	1.00
NFI	.95 ≤ NFI ≤ 1.00	.90 ≤ NFI ≤ .95	0.94
TLI	.95 ≤ TLI ≤ 1.00	.90 ≤ TLI ≤ .95	1.00
SRMR	.00 ≤ SRMR≤ .05	.05 ≤ RMSEA ≤ .10	0.00

Source: Schermelleh Engel et al., 2003

An examination of Table 2 demonstrates that the χ^2/df, RMSEA, CFI, GFI, IFI, TLI, and SRMR indices indicate an excellent fit, whereas the NFI value- although within the acceptable range- remains close to the threshold for excellent fit. Figure 4 presents the parameter estimates of the SEM with its three-factor structure.

Figure 4
CFA Diagram for the AIERS



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An examination of the factor loadings for the three-factor model obtained from the CFA is presented in Figure 4. As illustrated in Figure 4, the factor loadings range from 0.68 to 0.81 for the AIEA dimension, from 0.68 to 0.74 for the AICE dimension, and from 0.73 to 0.82 for the AISG dimension. The reliability of the developed scale was assessed using Cronbach's alpha, yielding coefficients of 0.77 for AIEA, 0.73 for AICE, and 0.81 for AISG. In this study, the Cronbach's alpha values for the subdimensions were calculated as 0.84, 0.77, and 0.79, respectively, with a reliability coefficient of 0.82 for the total scale. Given that a reliability coefficient of 0.70 or above is generally considered acceptable for measurement instruments (Fraenkel et al., 2012), the coefficients obtained in this study can be regarded as satisfactory.

Data Analysis

Prior to the commencement of the research, ethics committee approval and permission for scale administration were obtained from the host university. The implementation was conducted in the autumn semester of 2024-2025. Participation was voluntary, no personally identifiable information was collected, and participants were informed that their data would be used solely for scientific purposes in accordance with confidentiality principles. Demographic items were added to the introductory section of the AILS, and informed consent for voluntary participation was obtained from each participant at the outset. To enable matching across instruments and to check completeness, participants were asked to write their student identification numbers at the top of each form; this information was used exclusively for matching and was anonymized prior to analysis. To minimize respondent bias, administrations were scheduled outside examination weeks and completed over a three-week period at a rate of one instrument per week: Week 1 AILS (N = 239), Week 2 ITEUS (N = 241), Week 3 AIERS (N = 227). At the end of the implementation period, 219 participants were identified as having completed all three instruments without missing data, and the dataset was subsequently prepared for analysis.

Key SEM assumptions can be summarized as follows: Kline (2015) classifies sample sizes below 100 as small, between 100 and 200 as medium, and 200 or above as large, noting that a sample size of around 150 is generally considered ideal for structural equation modelling. In light of these criteria, the sample size of 219 obtained in this study can be regarded as adequate for analysis. To test the homoscedasticity and autocorrelation assumptions, the Durbin-Watson statistic was calculated. Values between 1.5 and 2.5 are considered acceptable in the literature (Kalayci, 2009), and proximity to 2 indicates the absence of autocorrelation (Field, 2017). In our dataset, DW = 1.92, indicating no autocorrelation (Tabachnick & Fidell, 2001).

Table 4
Findings from the Normality Analysis for the Measurement Instruments

Measurement Tool	*N*	*M*	*SD*	Skewness	Kurtosis
AILS	219	4.74	0.27	-0.030	-0.284
Technical Understanding (TU)	219	3.12	0.45	0.322	0.204
Critical Appraisal (CA)	219	6.09	0.41	-0.327	-0.293
Practical Application (PA)	219	6.02	0.47	-0.298	-0.167
ITEUS	219	4.57	0.69	-0.115	-0.151
Ethical Awareness (EAA)	219	5.25	1.27	-0.732	-0.234
Communication & Respect (CR)	219	5.64	1.20	-0.972	0.257
Cybercrime (CC)	219	3.06	1.45	0.507	-0.783
Intellectual Property (IP)	219	4.27	1.63	-0.188	-1.058
AIERS	219	5.93	0.91	-0.797	0.201
AI Ethical Awareness (AIE)	219	6.07	1.43	-1.734	2.515
AI Critical Evaluation (AICE)	219	5.72	1.74	-1.314	0.693
AI for Social Good (AISG)	219	5.99	1.68	-1.601	1.529

The normality assumption was examined using skewness and kurtosis coefficients (within ±3) (Buyukozturk, 2019; Kalayci, 2009; Kline, 2015). The analysis indicated that skewness values ranged from -1.734 to 0.507, while

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kurtosis values ranged from -0.284 to 2.515 (Table 4). In light of these results, the normality assumption was regarded as satisfied.

Table 5
Intercorrelations among Core Variables

Variables	AILS	ITEUS	AIERS
AILS	1		
ITEUS	0.298*	1	
AIERS	0.537*	0.563*	1

In the literature on the multicollinearity assumption, it is noted that partial correlations among variables should not be excessively high, with 0.85 (Kline, 2015) and 0.90 (Tabachnick & Fidell, 2001) commonly cited as threshold values. In the present study, the highest correlation was observed between ITEUS and AIERS at 0.563, and the lowest between AILS and ITEUS at 0.298. These values reveal that multicollinearity is not a concern in this research. Linearity is defined as the extent to which the relationships among the variables under investigation can be adequately represented by a linear function (Tabachnick & Fidell, 2001). To test this assumption-which is critical in multivariate statistical analyses-intervariable correlation coefficients were examined (Table 5). The resulting coefficients are consistent with a linear structure among the modelled relationships, thereby supporting the linearity assumption. Following the confirmation of SEM assumptions, the theoretical model was tested.

Research Results

In this study, descriptive statistics were employed to depict pre-service science and mathematics teachers' levels of AI literacy, ethical use of information technologies, and ethical reflection on AI. Accordingly, for each variable, the arithmetic mean, standard deviation, and minimum-maximum scores were calculated. Participation levels were evaluated in three tiers: low (1.00 - 2.34), moderate (2.35 - 4.70), and high (4.71 - 7.00). The findings are presented in Table 6.

Table 6
Results for the Variables

Variables	*N*	Minimum	Maximum	*M*	*SD*	*Level*
AILS	219	1.42	7.00	4.74	.26	High
TU	219	1.36	7.00	4.72	1.38	High
CA	219	1.60	7.00	4.87	1.38	High
PA	219	1.29	7.00	4.59	1.43	Moderate
ITEUS	219	1.55	6.97	4.59	1.44	Moderate
EAA	219	1.36	7.00	4.60	1.24	Moderate
CR	219	1.50	7.00	4.61	1.34	Moderate
CC	219	1.36	7.00	4.60	1.25	Moderate
IP	219	1.33	7.00	4.61	1.30	Moderate
AIERS	219	1.75	6.92	4.59	1.30	Moderate
AIEA	219	1.60	7.00	4.62	1.37	Moderate
AICE	219	1.00	7.00	4.61	1.41	Moderate
AISG	219	1.00	7.00	4.62	1.47	Moderate

As seen in Table 6, the pre-service teachers' mean scores on the AILS and its subdimensions of TU and CA were at a high level ($M = 4.74$, $M = 4.72$, $M = 4.87$, respectively), whereas their participation in the PA subdimension was at a moderate level ($M = 4.59$). On the ITEUS, mean scores for the total and all subdimensions were at a moderate

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level (M = 4.59, M = 4.60, M = 4.61, M = 4.60, M = 4.61, respectively). Likewise, on the AIERS, mean scores for the total and all subdimensions were at a moderate level (M = 4.59, M = 4.62, M = 4.61, M = 4.62, respectively). Findings regarding participation levels on the instruments and their subdimensions by field of study are provided in Table 7.

Table 7
Participation Levels by Field of Study

Variables	Field of Study	*N*	*M*	*SD*	*t*	*p*
AILS	Science Education	87	4.22	1.33	-4.485	< .001*
	Mathematics Education	132	5.04	1.31		
TU	Science Education	87	4.43	1.36	-4.013	< .001*
	Mathematics Education	132	5.17	1.31		
CA	Science Education	87	4.06	1.36	-4.680	< .001*
	Mathematics Education	132	4.94	1.37		
PA	Science Education	87	4.06	1.40	-4.646	< .001*
	Mathematics Education	132	4.94	1.37		
ITEUS	Science Education	87	4.53	1.27	-.689	.492
	Mathematics Education	132	4.65	1.23		
EAA	Science Education	87	4.54	1.35	-.555	.580
	Mathematics Education	132	4.65	1.34		
CR	Science Education	87	4.50	1.33	-.892	.373
	Mathematics Education	132	4.66	1.20		
CC	Science Education	87	4.55	1.28	-.562	.575
	Mathematics Education	132	4.65	1.32		
IP	Science Education	87	4.52	1.34	-.657	.512
	Mathematics Education	132	4.64	1.28		
AIERS	Science Education	87	4.35	1.40	-2.363	.019*
	Mathematics Education	132	4.79	1.32		
AIEA	Science Education	87	4.31	1.45	-2.582	.010*
	Mathematics Education	132	4.81	1.36		
AICE	Science Education	87	4.40	1.41	-1.812	.071
	Mathematics Education	132	4.77	1.49		
AISG	Science Education	87	4.48	1.67	-.895	.372
	Mathematics Education	132	4.67	1.49		

According to Table 7, mean scores on the AILS and its TU, CA, and PA factors and on the AIERS and its AIEA subdimension differed significantly by field of study, in favor of mathematics pre-service teachers. In contrast, mean scores on the ITEUS and its subdimensions, as well as on the AICE and AISG subdimensions of the AIERS, did not differ significantly by field. Correlations among the study variables are presented in Table 8.

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Table 8
Correlation Matrix for the Variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13
1.AILS	1												
2.TU	0.985*	1											
3.CA	0.977*	0.939*	1										
4.PA	0.964*	0.928*	0.920*	1									
5.ITEUS	0.383*	0.384*	0.380*	0.347*	1								
6.EAA	0.359*	0.359*	0.359*	0.323*	0.962*	1							
7.CR	0.385*	0.380*	0.393*	0.348*	0.954*	0.885*	1						
8.CC	0.357*	0.363*	0.342*	0.333*	0.965*	0.898*	0.889	1					
9.IP	0.365*	0.370*	0.363*	0.320*	0.931*	0.864*	0.864	0.882*	1				
10.AIERS	0.677*	0.683*	0.647*	0.641*	0.377*	0.386*	0.386	0.328*	0.334*	1			
11.AIEA	0.681*	0.684*	0.648*	0.655*	0.344*	0.352*	0.360	0.292*	0.305*	0.957*	1		
12.AICE	0.579*	0.587*	0.556*	0.539*	0.348*	0.351*	0.353	0.306*	0.315*	0.895*	0.784	1	
13.AISG	0.018	0.033	0.020	-0.016	0.122	0.139*	0.106	0.100	0.125	0.093	0.077	0.057	1

Note. $*p < .01$

When Table 8 is examined, correlations among variables range from -0.13 to 0.98. The lowest observed relationship is between the EAA subdimension of the ITEUS and the AISG subdimension of the AIERS ($r = 0.139$, $p < .05$). The highest correlation is between the TU subdimension of the AILS and the total AILS score ($r = 0.985$, $p < .01$). Overall, relationships among observed variables are generally positive, strong, and significant. However, the relationship between the PA subdimension of the AILS and the AISG subdimension of the AIERS is negative, weak, and nonsignificant ($r = -0.016$, $p > .05$).

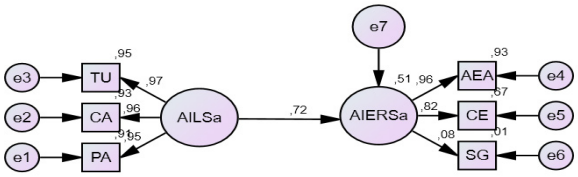
Findings from Testing the Measurement/Structural Model

To investigate the effect of AI literacy on ethical reflection on AI, a direct path from the independent variable AILS to the dependent variable AIERS was specified in the structural model presented in Figure 5. Analyses demonstrated that AI literacy significantly and positively predicted ethical reflection on AI ($\beta = 0.72$, $SE = 0.05$, $t = 13.28$, $p < .001$). The model also explained 51% of the total variance in ethical reflection on AI ($R^2 = 0.51$). In line with these findings, hypothesis H1 was supported.

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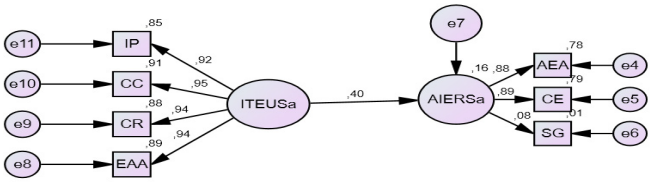
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Figure 5
Model for Testing Hypothesis H1



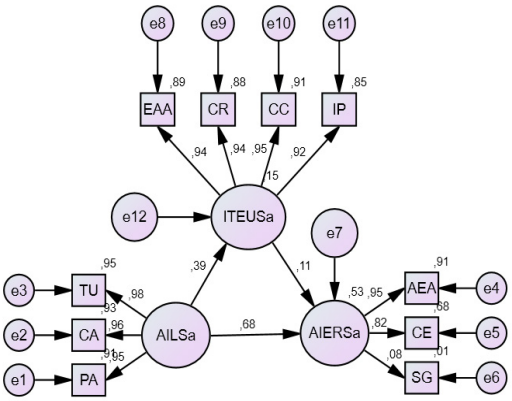
To examine the effect of the ethical use of information technologies on ethical reflection on AI, a direct path from ITEUS (independent) to AIERS (dependent) was specified in the structural model presented in Figure 6. The analyses indicated that ethical use of information technologies significantly and positively predicted ethical reflection on AI ($\beta = 0.40$, $SE = 0.07$, $t = 5.39$, $p < .001$). The model explained 16% of the total variance in ethical reflection on AI ($R^2 = 0.016$). Accordingly, hypothesis H2 was supported.

Figure 6
Model Pertaining to the Test of H2



To test the mediating role of ethical use of information technologies in the relationship between AI literacy and AI ethical reflection, the model in Figure 7 was specified.

Figure 7
Model for Testing Hypotheses H3 and H4



The results indicated that AI literacy demonstrated a significant positive effect on ethical use of information technologies ($\beta = 0.39$, $SE = .06$, $t = 6.02$, $p < .001$). Accordingly, hypothesis H3 was supported. Within the indirect path, the model demonstrated that the mediating effects of ethical use of information technologies between AI literacy and ethical reflection on AI were not statistically significant ($\beta = 0.12$, $SE = 0.06$, $t = 1.91$, $p > .05$), so ethical use of information technologies did not create a mediating effect. Therefore, the H4 hypothesis was rejected.

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Discussion

This study explores relations between pre-service science and mathematics teachers' AI literacy (AILS), ethical use of information technologies (ITEUS), and ethical reflections on AI (AIERS). The findings revealed that mean scores for the TU and CA subdimensions of AI literacy were high, whereas the PA subdimension was at a moderate level. In addition, mean scores on both the ITEUS and AIERS, as well as their subdimensions, were at moderate levels. High scores in TU and CA suggest that pre-service teachers possess sufficient theoretical-scientific (episteme) knowledge about AI's core concepts, operating principles, and societal implications. This pattern is consistent with a comprehensive review of AI literacy in teacher education analyzed through Aristotelian knowledge types (Sperling et al., 2024), which indicates that while theoretical-scientific knowledge (episteme) and ethical-professional judgement (phronesis) are emphasized, the practical productive knowledge dimension (techne) tends to remain in the background. Indeed, AI literacy encompasses not only the ability to use AI but also the capacity to critically evaluate AI technologies (Chiu et al., 2024). Frameworks developed for teachers allocate considerable space to theoretical components such as definitions, principles, machine learning, and data structures (Schuller, 2022; van Vaerenbergh & Pérez-Suay, 2022). Yet the moderate level in practical application suggests that theoretical knowledge is not being directly and sustainably transferred to classroom design and practice. Prior work reports limitations in the classroom adaptability and customization capacity of resources offered to teachers (Hwang, 2022). In K-12 contexts, although project/product-oriented activities predominate, designs that systematically strengthen teachers' pedagogical competence remain limited (Su et al., 2022). Critical analyses of primary-level frameworks also indicate a pronounced constructivist-technical emphasis, with human-technology interaction treated rather superficially (Yim, 2024b). The practical-productive knowledge gap observed here can be explained by both the limited space devoted to practice-oriented AI pedagogy in teacher education programs and the insufficient classroom transferability of existing resources (Hwang, 2022; Sperling et al., 2024; Su et al., 2023; Yim, 2024a).

The moderate scores on the ITEUS and AIERS (both total and subdimensions) indicate developmental movement in the ethical domain. AI ethics encompasses multilayered issues such as bias and discrimination, privacy, transparency, accountability, and intellectual property (Laupichler et al., 2022; Temur, 2025b). The use of AI in education inevitably brings these issues to the fore, underscoring the need for robust ethical frameworks (Temur, 2025a). However, the literature on AI for teacher education often treats ethics as theoretical-scientific knowledge reduced to understanding the technical functioning of AI systems; the development of context-sensitive ethical-professional judgement remains limited (Sperling et al., 2024; Yim, 2024b). General information ethics scales of the type adapted by Arikan and Duymaz (2014) measure established topics such as privacy, intellectual property, and accuracy. Yet AI ethics also encompasses new dilemmas such as autonomous decision-making, algorithmic justice, and accountability (Karabag, 2021; Turan et al., 2022). Moreover, technical proficiency does not always correlate positively with ethical behaviour; some studies have demonstrated that unethical use may increase with greater usage skills (Beyhan & Tunc, 2012; Zeybek & Beyhan, 2014). Approaches to digital ethics education grounded in moral reasoning (e.g., Kohlberg) aim to strengthen decision-making/judgement by confronting individuals with dilemmas (Paltiel et al., 2023). Still, deficits in teachers' AI knowledge, skills, and self-efficacy- and the need for specialized instruction- are often reported (Deniz & Bagceci, 2025; Karakus et al., 2024; Su et al., 2023). The spread of generative AI has also brought new ethical concerns, including academic integrity, plagiarism, data privacy, and veracity (Murtezaoglu & Birol, 2025; Qadhi et al., 2024). Thus, beyond mere use, the capacity to appraise the ethical consequences of use has become a key competency.

Correlations among variables ranged from -0.016 to 0.985. As expected, the very high correlation between AILS TU and the AILS total confirms internal consistency. A notable finding is the low yet significant positive correlation between ITEUS EAA and AIERS AISG. General information ethics often focuses on traditional domains such as intellectual property, privacy, accuracy, and accessibility (Arikan & Duymaz, 2014; Clark et al., 2024; Cooper, 2023; Lawrie, 2023). By contrast, AISG encompasses structural issues such as algorithmic bias, inequality, employment effects, and the digital divide (Karabag, 2021; Turan et al., 2022). Thus, rule/principle knowledge may not automatically and robustly translate into context-specific ethical judgement. The recurrent reduction of ethics to knowledge of technical facts (episteme) in the literature helps explain this gap (Sperling et al., 2024). Evidence from Global South libraries indicates that structural inequalities and inadequate policy frameworks directly limit AI's social benefits (Matsieli & Mutula, 2025). Comparative policy analyses also demonstrate that "social good" varies

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by cultural-political context (Yesilbas Ozenc, 2025). In this light, the low correlation can be viewed as a quantitative indicator of the distance between rule-based awareness and situated ethical judgement.

Structural equation modelling revealed that AILS strongly and significantly predicted AIERS. This indicates that increases in AI literacy account for 51% of the variance in ethical judgement and that AI literacy comprises not only technical knowledge/skills but also a component of critical and ethical reasoning capacity. Conceptually, the definitional inclusion of CA within AI literacy (Chiu et al., 2024) and the Aristotelian view that theoretical-scientific knowledge undergirds ethical-professional judgement (Sperling et al., 2024) support this relationship. Experimental studies likewise report significant positive links between AI literacy and ethical reasoning on AI (Wang et al., 2025). Intervention studies have reported that AI literacy programs enhance not only conceptual understanding but also ethical awareness (Kong et al., 2023). Reviews indicate that AI literacy education is increasingly designed with integrated ethical content to strengthen critical reflection (Laupichler et al., 2022). More granularly, AI literacy may relate to subdimensions of ethical reasoning at different levels; the lowest relationship has been observed with EAA and the highest with "critical evaluation" (Wang et al., 2025). In this context, the strong prediction of AIERS by AILS aligns with the fact that AIERS measures not merely rule knowledge but also critical judgement.

Conclusions and Implications

AI technologies-one of the defining technological developments of the 21st century and now integrated into education as in many other domains-have underscored the need for comprehensive transformation in teacher education programs to cultivate teachers equipped with the knowledge and competencies demanded by the era. Alongside the many benefits AI brings to teaching-learning processes, it has also provoked ethical debates. A key finding is the pronounced gap between theoretical and practical dimensions of AI literacy: While preservice teachers display theoretical and critical awareness regarding what AI is, how it works, and its societal impacts, they are not at the same level of competence in leveraging this knowledge for pedagogical purposes in the classroom-that is, in practical application. This signals a shortfall in translating theoretical knowledge into practice.

Another important result is that both attitudes toward general information technology ethics and AI-specific ethical reflection levels remain moderate. This suggests that pre-service teachers have not yet developed deep competence when confronting complex ethical dilemmas such as bias, fairness, privacy, and transparency. The lag of ethical awareness and reasoning behind theoretical knowledge indicates a need for specialized training in this area. The structural modelling analyses yielded concrete insights into the nature of relationships among AI literacy, ethical use of information technologies, and ethical reflection on AI competency areas. The findings clearly reveal that AI literacy is the strongest and most direct predictor of pre-service teachers' ethical reflections on AI: The better a pre-service teacher understands AI's operating principles and potential risks, the more capable they are of making ethical judgements about the technology. This strong relationship indicates that AI literacy education is a precondition for developing ethical reasoning. However, ethical use of information technologies, namely general information ethics attitudes, did not play a significant mediating role in the strong link between AI literacy and ethical judgement, implying that AI ethics is a distinct and more complex domain not fully encompassed by general digital ethics principles. For a pre-service teacher to exercise ethical judgement about AI, they require a holistic literacy that explicates AI's distinctive dynamics-beyond familiarity with generic digital citizenship rules. In sum, this research reveals that preparing future educators for the AI era requires more than teaching how to use technological tools; it demands cultivating a deep understanding and an ethical stance that enable them to use these tools wisely, justly, and in alignment with human values.

Declaration of Interest

The authors declare no competing interest.

Declaration of Generative AI and AI-assisted Technologies

During the preparation of this work, the authors used ChatGPT to assist with translation. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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