

Artificial intelligence in teacher education: exploring the role of AI literacy on attitudes

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Abstract

Purpose – In this context, the present study aims to address three significant gaps in the literature. First, it investigates the predictive relationship between AI literacy and attitudes toward AI, aligning with the call by the Beijing Consensus (UNESCO, 2019) for evidence-based policy making in teacher education. Second, it examines the potential differences based on gender, academic year, and department, providing multidimensional data. Third and most importantly, it provides empirical data from the Turkish context to evaluate the universal applicability of global AI competency standards. In summary, this study focuses on the intersection of cognitive (AI literacy) and affective (attitudes toward AI) domains among pre-service teachers, aiming to contribute to the restructuring of teacher education programs. **Problem Statement** Despite the global push for AI integration led by organizations like UNESCO and the European Commission, a significant “competency-attitude gap” persists in teacher education. Although curriculum developers aim to enhance digital skills, the mechanism by which AI literacy translates into professional attitudes remains a “black box.” Without understanding how specific dimensions of literacy especially ethical and critical evaluation – predict attitudes across different academic years and departments, teacher training programs risk remaining superficial and disconnected from the complex demands of the AI-driven classroom. **Research Questions** (1) What are the levels of pre-service teachers’ attitudes toward artificial intelligence? (2) What are the levels of pre-service teachers’ artificial intelligence literacy? (3) Do pre-service teachers’ attitudes toward artificial intelligence significantly differ according to gender, academic year, and department? (4) Do pre-service teachers’ AI literacy levels significantly differ according to gender, academic year, and department?

Design/methodology/approach – This study was designed within the framework of a correlational research design. This quantitative method aims to statistically examine the direction and strength of relationships between two or more variables.

Findings – The results indicated that AI literacy levels collectively explained a substantial 57% of the total variance in attitudes toward AI ($R^2 = 0.568$). Notably, while the regression model was highly significant, individual sub-dimensions awareness, usage, evaluation, and ethics did not function as independent predictors, suggesting that AI literacy operates as a holistic competency. Furthermore, significant differences were identified across academic years and departments, with a “mid-program peak” in third-year students and higher engagement in science education compared to mathematics. No significant gender-based differences were observed. These findings underscore the necessity of an integrated, 4-year curriculum that aligns with the UNESCO (2024) AI Competency Framework, moving beyond isolated technical skills toward a transdisciplinary pedagogical approach. The study provides critical insights for teacher educators aiming to foster evidence-based digital dispositions in the AI era.

Originality/value – First, it investigates the predictive relationship between AI literacy and attitudes toward AI, aligning with the call by the Beijing Consensus (UNESCO, 2019) for evidence-based policy making in teacher education. Second, it examines the potential differences based on gender, academic year, and department, providing multidimensional data. Third and most importantly, it provides empirical data from the Turkish context to evaluate the universal applicability of global AI competency standards. In summary, this study focuses on the intersection of cognitive (AI literacy) and affective (attitudes toward AI) domains among pre-service teachers, aiming to contribute to the restructuring of teacher education programs.

Keywords Teacher education, Artificial intelligence, Attitudes toward AI, UNESCO AI framework

Paper type Research article



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Introduction

Artificial intelligence (AI) plays a central role in industrial processes and the structural transformation of educational systems. Particularly in areas such as instructional design, assessment, and personalized learning, AI-based systems are redefining the teaching profession (Luckin and Holmes, 2016; Knight *et al.*, 2019). This transformation requires teachers to recognize AI and understand its operational logic, ethical implications, and pedagogical applications. Therefore, pre-service teachers' levels of AI literacy and attitudes toward AI technologies have become integral components of contemporary teacher competencies (Ismail *et al.*, 2024; Zawacki-Richter *et al.*, 2019). This necessity is further underscored by the UNESCO AI Competency Framework for Teachers (2024), which advocates for a shift from passive AI consumption to critical pedagogical engagement.

In the literature, Artificial Intelligence Literacy (AIL) has recently undergone a paradigm shift, especially following the widespread emergence of Generative AI. It is no longer viewed merely as a subset of digital literacy but as a specialized socio-technical competency framework (Ismail *et al.*, 2024). While foundational models like Long and Magerko (2020) focus on technical awareness and use, the UNESCO AI Competency Framework for Teachers (2024) emphasizes that for educators, literacy must evolve from "technological fluency" to "pedagogical stewardship." This finding involves the critical judgment of AI-generated content and the mitigation of algorithmic bias. Thus, AIL is increasingly seen as a multidimensional construct where ethical discernment and critical evaluation are as vital as technical operational skills.

Parallel to this, attitudes toward AI represent a complex interplay of emotional, cognitive, and behavioral inclinations toward technology. These inclinations are deeply rooted in established socio-psychological frameworks, specifically the Theory of Planned Behavior (TPB) developed by Ajzen (1991), which posits that attitudes and perceived control are primary drivers of behavioral intentions. Building upon this foundation, Davis (1989) introduced the Technology Acceptance Model (TAM), specifically adapting these constructs to explain user acceptance of information systems. Unlike traditional applications of TAM, attitudes toward AI are uniquely characterized by a "dual-valence," where high perceived utility often coexists with "AI anxiety" regarding job displacement, loss of control, and ethical risks (Southworth *et al.*, 2023; Zhang and Dafoe, 2021). For pre-service teachers, these attitudes are crucial because they act as "second-order barriers" to technology integration. Positive dispositions, such as perceptions of innovativeness and self-efficacy (Teo, 2011; Yuen *et al.*, 2013), are found to be strong predictors of Technological Pedagogical Content Knowledge (TPACK) development, while negative perceptions may hinder the successful adoption of AI in future classroom settings (Chiu, 2021; Tondeur *et al.*, 2025).

Despite the conceptual relevance, empirical data on the relationship between AI literacy and AI attitudes remain limited. While previous studies have often treated AI literacy as a purely technical skill, there is a lack of evidence regarding how its multi-dimensional nature (including ethics and evaluation) reshapes the affective dispositions of future educators. Erdoğan and Çakır (2024) observed that increased AI knowledge was associated with higher ethical sensitivity among engineering students. However, research focusing specifically on teacher candidates is scarce. In their study in Taiwan, Hwang *et al.* (2022) noted that although teacher candidates had high levels of knowledge about AI, they lacked ethical and practical competencies. In their study in Taiwan, Hwang *et al.* (2022) noted that although teacher candidates had high levels of knowledge about AI, they lacked ethical and practical competencies. Building on this, Wang *et al.* (2022) demonstrated that AI literacy levels are a major determinant of pre-service teachers' intentions to adopt AI tools, explaining over 50% of the variance in behavioral intentions, which underscores the predictive power of literacy on professional dispositions. Studies in the Turkish context have generally remained at a descriptive level; for instance, Erdoğan and Çakır (2024) reported that while teacher candidates had a generally positive view of AI technologies, their awareness was relatively superficial.

Moreover, there is a scarcity of studies testing the influence of demographic variables on AI literacy and attitudes. While some studies indicate no significant gender differences (Panagou *et al.*, 2025), others suggest that women may score higher in ethical dimensions (Zawacki-Richter *et al.*, 2019). Variables such as academic year and department have been examined less frequently. Recent research by Chiu (2021) indicates that science-oriented pre-service teachers may exhibit faster adoption rates and more positive attitudes compared to their mathematics counterparts due to the inquiry-based nature of their curriculum. However, Hwang *et al.* (2022) observed that AI literacy increases during instructional periods that include technology-focused content. However, these findings are mostly based on cross-sectional rather than longitudinal or comparative designs.

Despite the burgeoning research on AI in education, a significant gap remains regarding how multi-dimensional literacy dimensions reshape the affective dispositions of future educators. While many studies focus on active teachers, the “second-order barriers” (Tondeur *et al.*, 2025)—the internal beliefs and attitudes—of pre-service teachers remain under-explored. Specifically, there is a lack of evidence on whether literacy serves as a holistic predictor or a set of fragmented skills across different disciplinary backgrounds. As emphasized by Ismail *et al.* (2024), understanding AI literacy as a unified pedagogical competency is vital for overcoming internal barriers. By empirically testing the TAM constructs within this specific context, this study moves beyond descriptive analysis to provide actionable insights for teacher preparation curricula.

In this context, the present study aims to address three significant gaps in the literature. First, it investigates the predictive relationship between AI literacy and attitudes toward AI, aligning with the Beijing Consensus (UNESCO, 2019) for evidence-based policy making in teacher education. Second, it examines potential differences based on gender, academic year, and department, providing multidimensional data. Third and most importantly, it provides empirical data from the Turkish context to evaluate the universal applicability of global AI competency standards. Furthermore, as the landscape of educational technology shifts rapidly, it is imperative for the next generation of educators to remain at the forefront of these developments. This study aligns with the growing necessity for preservice teachers to be up-to-date with all emerging educational technologies, particularly the fast-evolving tools associated with AI. By exploring this relatively new intersection of AI literacy and affective dispositions, the research provides a critical foundation for understanding how innovative educational ideas can be sustainably integrated into modern teacher training programs. In summary, this study focuses on the intersection of cognitive (AI literacy) and affective (attitudes toward AI) domains among pre-service teachers, aiming to contribute to the restructuring of teacher education programs.

Problem statement

Despite the global push for AI integration led by organizations like UNESCO and the European Commission, a significant “competency-attitude gap” persists in teacher education. Although curriculum developers aim to enhance digital skills, the mechanism by which AI literacy translates into professional attitudes remains a “black box.” Without understanding how specific dimensions of literacy—especially ethical and critical evaluation—predict attitudes across different academic years and departments, teacher training programs risk remaining superficial and disconnected from the complex demands of the AI-driven classroom.

Research questions

- (1) What are the levels of pre-service teachers’ attitudes toward artificial intelligence?
- (2) What are the levels of pre-service teachers’ artificial intelligence literacy?

- (3) Do pre-service teachers' attitudes toward artificial intelligence significantly differ according to gender, academic year, and department?
- (4) Do pre-service teachers' AI literacy levels significantly differ according to gender, academic year, and department?
- (5) To what extent do pre-service teachers' AI literacy levels predict their attitudes toward artificial intelligence?

Method

Research model

This study was designed within the framework of a correlational research design. This quantitative method aims to statistically examine the direction and strength of relationships between two or more variables (Creswell, 2012). The study investigated the relationship between pre-service teachers' attitudes toward artificial intelligence (AI) and their levels of AI literacy. It also analyzed whether these variables differed significantly according to demographic factors such as gender, academic year, and department. In this respect, the study carries the characteristics of both comparative and predictive correlational designs.

Study group

The study group comprised 98 pre-service teachers from the Gazi University Gazi Faculty of Education. Of the participants, 23 (23.5%) were from science education, 22 (22.4%) from mathematics education, and 53 (54.1%) from physics education departments. The participants' ages ranged from 18 to 34, with an average age of 21.3. Among the participants, 34 (34.7%) were male, and 64 (65.3%) were female. In terms of academic year, 41 (41.8%) were in their first year, 31 (31.6%) in their second year, 8 (8.2%) in their third year, and 18 (18.4%) in their fourth year. Using purposive sampling, participants were selected to ensure a broad perspective across gender, academic year, and departmental backgrounds.

Context and curriculum structure. The study group was enrolled in 4-year undergraduate teacher education programs designed to prepare educators for the middle and high school levels (Grades 5–12). The curriculum for these programs is standardized by the Council of Higher Education (YÖK) and follows a progressive structure. In the first and second years, students primarily focus on “General Culture” and “Basic Content Knowledge” (e.g. General Physics, Mathematics). Pedagogical content knowledge and instructional technology courses are heavily concentrated in the third year, where students are introduced to digital literacy and innovative teaching methods. The fourth year is almost exclusively dedicated to “Teaching Practice” (school internships) and professional seminars, often shifting the focus from technological exploration toward administrative and classroom management responsibilities.

Data collection

The data were collected using the Artificial Intelligence Attitude Scale (AIAS) and the Artificial Intelligence Literacy Scale (AIL). Both instruments were administered via an online form (Google Forms), following the provision of informed consent. Participants were briefed about the aim of the study, confidentiality principles, and the voluntary nature of participation. During the data collection process, participants were encouraged to consider a broad range of AI technologies, including generative AI (e.g. ChatGPT, Gemini), AI-driven creative tools (e.g. Canva Magic Studio), and adaptive learning platforms.

- (1) *Artificial Intelligence Attitude Scale (AIAS):* Developed by Aktay *et al.* (2024), this scale measures the affective and evaluative dispositions of pre-service teachers toward AI through 13 items on a 5-point Likert scale. The instrument evaluates three distinct subdimensions: “Perceived Benefits of AI”, “Perceived Risks of AI”, and “Use of AI”.

“Perceived Benefits” assesses the belief in AI’s potential to enhance human life (e.g. “I believe that AI will make significant contributions to humanity”). “Perceived Risks” captures concerns regarding human-AI replacement or ethical erosion (e.g. “I am concerned that AI will replace human labor”). Finally, “Use of AI” measures the practical inclination and enjoyment of AI integration (e.g. “I like using AI to generate textual content”). Reliability analyses indicated that the Cronbach’s alpha coefficients were 0.78, 0.73, and 0.68 for the respective subdimensions, and 0.80 for the overall scale.

- (2) *Artificial Intelligence Literacy Scale (AIL)*: To measure AI literacy as a multi-dimensional socio-technical competency, the scale developed by Wang *et al.* (2022) and adapted into Turkish by Çelebi *et al.* (2023) was employed. This 12-item scale is structured as a 7-point Likert-type instrument and evaluates literacy through four pillars: “Awareness” involves identifying AI’s presence in daily applications (e.g. “I can describe the AI technology used in many products”); “Usage” focuses on the self-efficacy to apply AI for productivity (e.g. “I can use AI applications to help me with my work”); “Evaluation” measures the critical ability to judge AI outputs and limitations (e.g. “I can evaluate the capacity and limits of an AI application”); and “Ethics” evaluates the commitment to responsible use (e.g. “I always follow ethical principles when using AI”). Reliability analysis revealed Cronbach’s alpha coefficients of 0.72, 0.74, 0.76, and 0.72 for the respective subdimensions, and 0.85 for the total scale.

To further illustrate the operational definitions and the nature of the questions posed to the participants, sample items representing each sub-dimension of the AIL and AIAS scales are presented in Table 1.

Data analysis

The normality of the data distribution was assessed through multiple criteria. In accordance with Çokluk *et al.* (2012), the proximity of mean, median, and mode values was examined as a primary indicator. Furthermore, skewness and kurtosis coefficients for all sub-dimensions were found to be within the ± 2 range, which is considered acceptable for proving a normal distribution in social sciences (George and Mallery, 2024). Although the Kolmogorov-Smirnov test is sensitive to sample size, the obtained significance values ($p > 0.05$) and the distribution of descriptive indices confirm that the data are suitable for parametric analyses.

The research questions were addressed using a hierarchical statistical approach. First, descriptive statistics were calculated to determine the baseline levels of AI literacy and attitudes. Second, One-way Multivariate Analysis of Variance (MANOVA) was employed to examine potential differences in the sub-dimensions of AIAS and AIL based on gender, academic year, and department. MANOVA was specifically chosen to account for the

Table 1. Sample items from AIL and AIAS

Scale	Sub-dimension	Sample item
AIAS	Benefits	“I believe that AI will make significant contributions to humanity.”
	Risks	“I am concerned that AI will replace human labor.”
	Use	“I like using AI to generate textual content.”
AIL	Awareness	“I can describe the AI technology used in many applications.”
	Use	“I can use AI applications to increase my productivity at work.”
	Evaluation	“I can evaluate the capacity and limits of an AI application.”
	Ethics	“I always follow ethical principles when using AI products.”

intercorrelations between the sub-dimensions (e.g. Awareness, Ethics, and Risks) and to reduce Type I error. Finally, Multiple Linear Regression analysis was conducted to test the extent to which AI literacy dimensions predict overall AI attitudes, providing an empirical test for the TAM constructs within a teacher education context. Descriptive statistics for the total scores of the scales are presented in [Table 2](#).

As shown in [Table 2](#), pre-service teachers reported the highest mean score in the Ethics sub-dimension of AI literacy ($\bar{x} = 2.92$). This suggests a strong baseline commitment to responsible use, such as following ethical principles when interacting with AI products. Conversely, the Benefits sub-dimension of the attitude scale showed the lowest mean ($\bar{x} = 1.94$), indicating that participants may still hold a cautious or skeptical view regarding AI’s significant contributions to humanity, reflecting the “dual-valence” attitude discussed in the literature.

First, a One-Way Multivariate Analysis of Variance (MANOVA) was performed to determine whether the sub-dimensions of the Artificial Intelligence Attitude Scale (AIAS) and the Artificial Intelligence Literacy Scale (AIL) differed significantly based on the independent variable of department. Before conducting the MANOVA, the necessary assumptions were tested.

- (1) Homogeneity of variances was examined using Levene’s test, and it was found that the assumption was satisfied ($p > 0.05$).
- (2) Equality of covariance matrices among the groups was assessed using Box’s M test, and the assumption was confirmed (Box’s M = 0.000; F = 0.000; $p = 1.000$).
- (3) To determine the source of significant differences, Tukey’s HSD multiple comparison test was applied. Furthermore, effect sizes (eta squared, η^2) were calculated and interpreted according to [Cohen’s \(1988\)](#) classification: 0.01 = small, 0.06 = medium, and 0.14 or above = large.

Second, Multiple Linear Regression analysis was employed to examine the extent to which pre-service teachers’ AI literacy levels explain their attitudes toward AI. This approach provides an empirical test for the TAM, exploring how cognitive competencies (literacy) serve as precursors to affective dispositions (attitudes) in an educational context. This multivariate approach is essential for understanding how specific cognitive dimensions—such as knowledge, awareness, evaluation, and ethical sensitivity—predict affective dispositions. In this model, the sub-dimensions of the AIL scale were treated as independent variables, while the total AIAS score and its sub-dimensions served as dependent variables. This robust statistical method aimed to reveal the predictive weight of literacy components in shaping future educators’ attitudes, aligning with the [UNESCO \(2024\)](#) call for evidence-based

Table 2. Descriptive statistics of the scale scores

	Sub-dimension	Mean	SD	Median	Mode	Skewness	Kurtosis	K-S
AIAS	Benefits	1.94	1.27	1.33	1.00	1.43	1.45	0.96
	Risks	2.74	0.77	2.60	2.40	0.28	0.29	0.11
	Use	2.38	0.96	2.33	2.33	0.80	0.82	0.65
	Total	2.43	0.76	2.27	1.85	1.05	1.06	0.99
AIL	Awareness	2.75	0.66	2.67	2.33	-0.21	-0.22	0.51
	Use	2.67	0.56	2.67	2.33	-0.06	-0.06	0.26
	Evaluation	2.38	0.96	2.33	2.00	0.39	0.39	-0.66
	Ethics	2.92	0.54	3.00	3.00	0.10	0.10	1.00
	Total	2.68	0.50	2.58	2.33	0.18	0.19	0.76

Note(s): Normality was confirmed primarily based on skewness and kurtosis values falling within the ± 2 range

assessment of teacher competencies. All analyses were conducted at the sub-dimension level, and the results are presented in the findings section.

Results

The results of the One-way Multivariate Analysis of Variance (MANOVA) conducted to determine whether there were significant differences between male and female pre-service teachers' scores on the scales are presented in [Table 3](#).

Before conducting the analysis, the assumption of homogeneity of variances was tested using Levene's test, and the assumption of homogeneity of covariance matrices was tested using Box's M test. According to the results of Levene's test, the assumption of equal variances was satisfied for all variables ($p > 0.05$).

However, the results of Box's M test indicated that the assumption of homogeneity of covariance matrices was not met (Box M = 187.602; $F_{(55, 19,433.565)} = 3.022$; $p < 0.001$). In such cases where the assumptions of multivariate analysis are violated, it is recommended that the Pillai's Trace statistic be interpreted instead of Wilks' Lambda. The results are presented in [Table 3](#).

The results indicated that gender does not play a significant role in how pre-service teachers perceive or understand AI. For instance, both female ($\bar{x} = 2.37$) and male ($\bar{x} = 2.54$) participants showed similar levels of overall attitude, suggesting that dispositions such as perceived benefits (e.g. belief in AI's contribution to humanity) or concerns about risks (e.g. fear of job displacement) are shared across genders. Similarly, in terms of AI literacy, no significant gap was found in their technical usage (e.g. ability to use AI for productivity) or ethical awareness, indicating a balanced level of digital readiness among the next generation of educators regardless of gender.

Findings related to the academic year variable

Before proceeding with the analysis, the assumption of homogeneity of variances was tested using Levene's test, and the assumption of homogeneity of covariance matrices was examined using Box's M test. According to Levene's test, the assumption of equal variances was met for all variables ($p > 0.05$).

However, Box's M test results indicated that the assumption of homogeneity of covariance matrices was not satisfied (Box M = 270.024; $F_{(90, 9450.811)} = 2.475$; $p < 0.001$). Therefore, the Pillai's Trace statistic was used for interpretation. The results are presented in [Table 4](#).

Table 3. MANOVA results for AIAS and AIL based on gender

	Sub-dimension	Female Mean	Female SD	Male Mean	Male SD	F	p
AIAS	Benefits	1.85	1.21	2.12	1.38	1.154	0.29
	Risks	2.64	0.66	2.91	0.92	3.03	0.08
	Use	2.38	1.04	2.40	0.80	0.01	0.91
	Total	2.37	0.79	2.54	0.69	1.20	0.28
AIL	Awareness	2.74	0.72	2.77	0.56	0.06	0.80
	Use	2.65	0.59	2.69	0.50	0.13	0.72
	Evaluation	2.35	0.95	2.44	0.98	0.22	0.64
	Ethics	2.89	0.51	2.98	0.61	0.70	0.41
	Total	2.66	0.53	2.72	0.44	0.41	0.53

Note(s): AIAS sub-dimensions reflect attitudes such as perceived benefits (e.g. AI's contribution to humanity) and risks (e.g. replacement of human labor). AIL sub-dimensions reflect literacy components such as usage (e.g. technical proficiency) and ethics (e.g. following ethical principles)

Table 4. MANOVA results for AIAS and AIL based on academic year

	Sub-dimension	Class 1		Class 2		Class 3		Class 4		F	p	η^2
		Mean	SD	Mean	SD	Mean	SD	Mean	SD			
AIL	Benefits	1.50	0.90	1.78	0.78	3.54	1.67	1.63	1.04	16.67	0.00	0.32
	Risks	2.60	0.75	2.61	0.78	3.39	0.61	2.63	0.66	5.88	0.00	0.15
	Use	2.21	0.88	2.31	0.59	2.99	1.33	2.30	1.06	3.12	0.03	0.08
	Total	2.21	0.57	2.32	0.42	3.25	1.03	2.30	0.79	10.91	0.00	0.24
	Awareness	2.85	0.60	2.56	0.57	3.28	0.59	2.33	0.67	8.86	0.00	0.20
	Use	2.63	0.51	2.51	0.45	3.15	0.51	2.56	0.65	6.51	0.00	0.16
	Evaluation	2.24	0.91	2.16	0.81	3.28	1.02	2.17	0.79	7.52	0.00	0.18
	Ethics	2.89	0.63	3.04	0.42	2.96	0.48	2.74	0.58	1.26	0.29	0.04
	Total	2.65	0.44	2.56	0.38	3.17	0.48	2.45	0.57	9.37	0.00	0.21

The results of MANOVA indicated significant differences across academic years in all AIAS dimensions: perceived benefits ($F_{(3, 94)} = 16.67; p < 0.001; \eta^2 = 0.32$), perceived risks ($F = 5.88; p = 0.001; \eta^2 = 0.15$), use of AI ($F = 3.12; p = 0.03; \eta^2 = 0.08$), and the overall AIAS score ($F = 10.91; p < 0.001; \eta^2 = 0.24$). Regarding AI literacy (AIL), a significant difference was primarily observed in the awareness sub-dimension ($F = 8.86; p < 0.001; \eta^2 = 0.20$), as well as in use ($F = 6.51; p < 0.001; \eta^2 = 0.16$) and evaluation ($F = 7.52; p < 0.001; \eta^2 = 0.18$).

Post-hoc comparisons via Tukey HSD revealed a consistent pattern: third-year students ($\bar{x} = 3.25 \pm 1.03$) exhibited significantly higher positive attitudes and literacy levels compared to both first-year and fourth-year peers. Specifically, in the perceived benefits dimension (e.g. belief in AI's contribution to humanity), third-year students ($\bar{x} = 3.54 \pm 1.67$) scored remarkably higher than fourth-year students ($\bar{x} = 1.63 \pm 1.04$). Similarly, their higher scores in awareness (e.g. identifying AI in products) and usage (e.g. technical self-efficacy) suggest that the third-year curriculum may be more effective in fostering a sense of competence, which, as suggested by TAM (Davis, 1989), directly enhances their willingness to adopt these technologies.

Examining the effect sizes, the academic year variable explained 32.4% of the variance in perceived benefits and 23.9% in overall attitudes. These findings suggest a “mid-program peak” in AI engagement, followed by a notable decline in the final year, highlighting a potential lack of curricular continuity in the transition to professional practice.

Findings related to department variable

Prior to the primary analysis, statistical assumptions were rigorously examined. For each dependent variable, the homogeneity of variances was tested using Levene's test, while the equality of group covariance matrices was evaluated via Box's M test.

According to the Levene test results, the assumption of homogeneity of variances was satisfied for most variables ($p > 0.05$). Although the assumption was slightly violated for the perceived benefits sub-dimension ($p = 0.031$), MANOVA is generally considered robust to minor violations of homogeneity when group sizes are relatively balanced. Furthermore, Box's M test results indicated that the assumption of equal covariance matrices was fully met (Box M = 0.000; $F = 0.000; p = 1.000$), confirming the appropriateness of using MANOVA for comparing variance-covariance matrices across departments. The detailed results are presented in Table 5.

The results of MANOVA indicated that the department variable significantly influenced pre-service teachers' attitudes and certain literacy dimensions. Significant differences were found in the AIAS sub-dimensions of perceived benefits ($F_{(2, 95)} = 3.67; p = 0.002; \eta^2 = 0.18$), use of AI ($F = 2.36; p = 0.036; \eta^2 = 0.12$), and the total AIAS score ($F = 0.87;$

Table 5. MANOVA results for AIAS and AIL based on department

	Sub-dimension	Science		Physics		Math		F	p	η^2
		Mean	SD	Mean	SD	Mean	SD			
AIAS	Benefits	2.24	1.42	1.97	1.33	1.55	0.77	1.43	0.002*	0.18
	Risks	2.74	0.60	2.82	0.86	2.49	0.70	1.10	0.35	0.03
	Use	2.46	1.29	2.38	0.88	2.32	0.71	0.14	0.036*	0.12
	Total	2.52	0.97	2.46	0.72	2.24	0.54	0.62	0.013*	0.15
AIL	Awareness	2.82	0.68	2.76	0.63	2.65	0.76	0.4	0.76	0.01
	Use	2.82	0.56	2.67	0.58	2.47	0.44	1.66	0.18	0.05
	Evaluation	2.45	1.05	2.37	1.00	2.30	0.77	0.13	0.050*	0.14
	Ethics	2.98	0.38	2.88	0.57	2.97	0.66	0.28	0.84	0.01
	Total	2.77	0.55	2.67	0.52	2.60	0.41	0.50	0.034*	0.15

Note(s): *Significant at $p < 0.05$

$p = 0.013$; $\eta^2 = 0.15$). Regarding AI literacy (AIL), significant differences were identified in the evaluation sub-dimension ($F = 2.67$; $p = 0.050$; $\eta^2 = 0.14$) and the total AIL score ($F = 2.96$; $p = 0.034$; $\eta^2 = 0.15$). No significant differences were observed in the perceived risks sub-dimension or other AIL components ($p > 0.05$).

According to the results of the Tukey HSD post-hoc test conducted to identify the source of these differences.

- (1) In the perceived benefits sub-dimension (e.g. viewing AI as a significant contributor to humanity) and the total AIAS score, science education students ($\bar{x} = 2.24 \pm 1.42$) had significantly higher scores than mathematics education students ($\bar{x} = 1.55 \pm 0.77$). Furthermore, in the AIL evaluation sub-dimension (e.g. the capacity to judge AI outputs and limitations), science education students scored significantly higher than physics education students. This suggests that the experimental and inquiry-based nature of the science education curriculum may foster a more critical and positive stance toward technological innovation. These findings align with the TAM, as the higher evaluation literacy among science students potentially serves as a precursor to their stronger perceived utility of AI tools.
- (2) In the AIL evaluation sub-dimension, science education students ($\bar{x} = 2.45 \pm 1.05$) scored significantly higher than physics education students ($\bar{x} = 2.37 \pm 1.00$).
- (3) For the total AIL score, science education students ($\bar{x} = 2.70 \pm 0.55$) again demonstrated higher average scores compared to their peers in mathematics education ($\bar{x} = 2.48 \pm 0.42$).

The effect sizes (η^2) ranged from 0.12 to 0.18. According to [Cohen's \(1988\)](#) criteria, these values represent a medium effect size, indicating that the department variable has a practically meaningful impact on pre-service teachers' AI-related attitudes and evaluation competencies.

Findings related to the relationship between AIL and AIAS

Multiple linear regression analysis was conducted to determine the extent to which pre-service teachers' AI literacy (AIL) levels predict their attitudes toward artificial intelligence (AIAS). In this predictive model, the AIL sub-dimensions (Awareness, Use, Evaluation, and Ethics) were treated as independent variables, while the AIAS sub-dimensions and the total score were treated as dependent variables. The results, including R^2 , F-values, and standardized coefficients (β), are presented in [Table 6](#).

The regression models for all dependent variables were found to be statistically significant ($p < 0.001$). The model with the highest explanatory power was for the Total AIAS score,

Table 6. Results of multiple regression analysis for AIAS and AIL scores

Bağımlı Değişken	R^2	F	p	Awareness		Use		Evaluation		Ethics	
				β	p	β	p	β	p	β	p
Benefits	0.52	22.00	0.001*	-1.29	0.49	-1.12	0.56	-0.68	0.718	-1.53	0.42
Risks	0.21	5.37	0.001*	0.95	0.51	1.50	0.32	1.02	0.48	0.85	0.56
Use	0.44	15.93	0.001*	0.57	0.71	1.08	0.49	1.02	0.50	0.63	0.68
Total AIAS	0.57	26.9	0.001*	0.20	0.85	0.64	0.56	0.55	0.60	0.15	0.89

Note(s): *Significant at $p < 0.001$

where AI literacy sub-dimensions collectively explained 57% of the total variance ($R^2 = 0.568$; $F = 26.90$; $p < 0.001$).

However, an examination of the individual predictors revealed that none of the AIL sub-dimensions (Awareness, Use, Evaluation, Ethics) made a statistically significant independent contribution to the models ($p > 0.05$). This result indicates that while the AIL constructs collectively exert a powerful influence on AI attitudes, their individual effects are suppressed due to the high inter-correlation between literacy dimensions. This finding suggests that AI literacy functions as a holistic competency rather than a set of isolated skills in shaping the affective dispositions of pre-service teachers. In other words, a pre-service teachers' attitude—such as their belief in AI's benefits or their readiness to use it—is not merely driven by technical "Usage" or "Awareness" alone. Instead, it emerges from the synergy of all literacy dimensions, where "Ethics" and "Evaluation" provide the necessary critical framework for technical skills. This holistic influence provides strong empirical support for the TAM, suggesting that "perceived ease of use" in complex technologies like AI is a multi-dimensional construct. For future educators, fostering a positive attitude toward innovative teaching requires a curriculum that treats AI literacy as a unified pedagogical stewardship rather than fragmented technical training.

Discussion

This study examined the relationship between pre-service teachers' attitudes toward artificial intelligence (AI) and their levels of AI literacy, within the context of gender, academic year, and department variables. The findings indicate that AI literacy levels explain approximately 57% of the total variance in attitudes toward AI. Notably, this explanatory power does not stem from the individual contribution of the AIL subdimensions—awareness, use, evaluation, and ethics—but rather from the interaction of these components as a whole. This finding aligns with Long and Magerko's (2020) conceptualization of AI literacy as a multilayered construct encompassing technical skills, ethical sensitivity, critical evaluation, and awareness of social context. Furthermore, this predictive relationship mirrors the core tenets of the TAM and the TPB. As explored by Clubbs and Sclater (2021), an individual's attitude toward a new technology is a pivotal precursor to their behavioral intention, often mediated by their perceived competence. In this sense, a holistic AI literacy acts as a catalyst for "perceived ease of use," transforming technical knowledge into a positive psychological stance toward AI integration. In addition, this holistic interaction resonates with the UNESCO AI Competency Framework for Teachers (2024), which emphasizes that teacher professional development should transcend isolated technical skills to include a tripartite model of human-centric vision, ethics, and pedagogical application. Thus, individual attitudes toward AI appear to result from a complex and integrated learning experience that cannot be explained solely by unidimensional cognitive competencies.

However, this result diverges from some studies in the literature. For instance, Cave and Dihal (2020) argued that attitudes toward AI are more shaped by emotional tendencies, media

representations, and political discourse, with the effect of knowledge being limited. This discrepancy may be explained by the fact that the current study's sample consists of pre-service teachers, who typically possess pedagogical sensitivities. Indeed, [Hwang et al. \(2022\)](#) found that systematic AI education for pre-service teachers significantly and directly affected their attitudes. In this context, the present findings suggest that individuals involved in pedagogical formation processes develop their attitudes through technical knowledge and awareness of AI within educational contexts, supporting the Beijing Consensus ([UNESCO, 2019](#)), which advocates for the systematic integration of AI literacy into teacher education to ensure a sustainable digital transformation in schools.

Regarding the gender variable, the study revealed no significant differences in pre-service teachers' AI attitudes and literacy levels. This finding is consistent with the study by [Panagou et al. \(2025\)](#), which reported that gender-based differences in attitudes toward AI among university students are diminishing, particularly with increased exposure to education. However, the meta-analysis by [Zawacki-Richter et al. \(2019\)](#) showed that female pre-service teachers tended to approach AI with greater caution and ethical awareness. The absence of gender differences in the current study may be attributed to the sample's homogeneity or the increasing democratization of digital access in teacher training programs, reflecting a global trend toward closing the "Digital Gender Gap."

On the other hand, the results related to the academic year revealed more pronounced differences. In particular, third-year pre-service teachers scored significantly higher in AI attitudes and AI literacy, suggesting that the curriculum in this year may place greater emphasis on technology-based content. [Ismail et al. \(2024\)](#) demonstrated that when AI is addressed at technical, pedagogical, and ethical dimensions within teacher education programs, competencies improve significantly. Interestingly, a decline in some indicators was observed among fourth-year students. This result may suggest that instructional programs lack continuity and depth, echoing concerns raised by the [European Commission's \(2022\)](#) Ethical Guidelines for Educators, which highlight that AI competencies must be part of a continuous, lifelong professional learning path rather than isolated elective modules.

Similarly, analyses based on the department revealed significant differences. Science education students scored higher in attitudes and literacy than in other disciplines, potentially due to the experimental and technology-oriented nature of the field. [Tang et al. \(2023\)](#) noted that positive attitudes toward AI in science disciplines are reinforced through hands-on content. Conversely, mathematics education students' relatively lower AI literacy scores suggest that numerical thinking does not automatically translate into technological sensitivity. This result reflects a global challenge identified in the DigCompEdu framework ([Redecker, 2017](#)): the need to bridge "disciplinary silos" in digital competence. As [Zhang and Dafoe \(2021\)](#) argued, technical skills do not inherently enhance an individual's ethical, critical, or societal awareness regarding technology, necessitating a more transdisciplinary approach in teacher training.

In summary, the findings reveal that pre-service teachers' attitudes toward AI are significantly associated with their levels of AI literacy through a multidimensional structure. However, the fact that individual subdimensions were not significant predictors indicates the need to restructure instructional processes. Abstract components such as ethics, evaluation, and awareness should not be taught solely through knowledge transmission but supported through case studies, scenario-based learning, and interdisciplinary approaches. Redesigning teacher education programs to address AI literacy not only cognitively but also affectively and ethically, as proposed by [UNESCO \(2024\)](#), would constitute one of the most meaningful contributions to preparing the next generation of educators for an AI-enhanced future.

Conclusion and recommendations

This study provides empirical evidence that for future educators, knowing AI is key to accepting AI. With a 57% explanatory power, AI literacy is no longer an optional skill but a

foundational pillar of teacher professional identity. Aligning with the mission of fostering innovative teaching practices, these findings underscore that AI literacy is not just a technical skill but a foundational necessity for contemporary teacher education in the digital age.

Recommendations for policy and practice

Integrative curriculum: Teacher education programs should move away from isolated AI workshops toward an integrated 4-year “AI-Pedagogy” thread to prevent the fourth-year attitudinal decline by ensuring that AI tools are consistently applied to pedagogical tasks throughout the degree.

Focus on ethics and evaluation: Since literacy functions holistically, modules should emphasize Evaluation and Ethics (the “why” and “should”) as much as technical Usage (the “how”). Practically, this involves incorporating scenario-based learning where pre-service teachers analyze ethical dilemmas, such as algorithmic bias or data privacy, rather than just technical tool-tip training.

Pedagogical modeling: Teacher educators must model the use of AI in their own instruction. Demonstrating how to use generative AI for inclusive lesson planning or personalized feedback can bridge the gap between theoretical literacy and practical classroom adoption.

Disciplinary customization: Specific AI curricula should be developed for departments like Mathematics to bridge the perceived utility and literacy gaps. Creating interdisciplinary “AI-Labs” where Science and Math students collaborate could help mitigate the disciplinary silos identified in this study.

Future research directions

To further support and extend these conclusions, future research should adopt longitudinal designs to track how the “mid-program peak” in AI attitudes translates into actual classroom practice during the first years of professional teaching. Additionally, qualitative or mixed-methods investigations are needed to explore the underlying causes of the final-year attitudinal dip. Further studies could also explore the efficacy of specific AI-integrated instructional interventions through experimental designs, providing “gold standard” evidence for the holistic literacy model proposed here. Finally, comparative analyses across different cultural and institutional contexts would help evaluate the universal applicability of AI competency frameworks in teacher education.

Ethical approval

The study was conducted in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments. This research was approved by the Ethics Committee of X University, with decision number E–77082166-604.01-1285014 dated 08/07/2025.

References

- Ajzen, I. (1991), “The theory of planned behavior”, *Organizational Behavior and Human Decision Processes*, Vol. 50 No. 2, pp. 179-211, doi: [10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T).
- Aktay, S., Gok, S. and Yildirim, A. (2024), “Artificial intelligence attitude scale”, *International Technology and Education Journal*, Vol. 8 No. 2, pp. 14-24.
- Cave, S. and Dihal, K. (2020), “The whiteness of AI”, *Philosophy and Technology*, Vol. 33 No. 4, pp. 685-703, doi: [10.1007/s13347-020-00415-6](https://doi.org/10.1007/s13347-020-00415-6).
- Çelebi, C., Yılmaz, F., Demir, U. and Karakuş, F. (2023), “Artificial intelligence literacy: an adaptation study”, *Instructional Technology and Lifelong Learning*, Vol. 4 No. 2, pp. 291-306.

- Chiu, T.K. (2021), "A holistic approach to the design of artificial intelligence (AI) education for K-12 schools", *TechTrends*, Vol. 65 No. 5, pp. 796-807, doi: [10.1007/s11528-021-00637-1](https://doi.org/10.1007/s11528-021-00637-1).
- Clubbs, B.H. and Sclater, N. (2021), "Artificial intelligence in education: a critical view", in Littlejohn, J. (Ed.), *Current Issues in Digital Education*, Routledge, pp. 45-68.
- Cohen, J. (1988), "Set correlation and contingency tables", *Applied Psychological Measurement*, Vol. 12 No. 4, pp. 425-434.
- Çokluk, Ö., Şekercioğlu, G. and Büyüköztürk, Ş. (2012), *Sosyal bilimler için çok değişkenli istatistik: SPSS ve LISREL uygulamaları*, Vol. 2, Pegem akademi, Ankara.
- Creswell, J.W. (2012), *Educational Research: Planning, Conducting, and Evaluating Quantitative and Qualitative Research*, 4th ed., Pearson, Boston, MA.
- Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly*, Vol. 13 No. 3, pp. 319-340, doi: [10.2307/249008](https://doi.org/10.2307/249008).
- Erdoğan, F. and Cakir, O. (2024), "Determining teacher candidates' artificial intelligence literacy and perceptions of artificial intelligence", *Journal of Social Sciences in the International Turkish Cultural Geography*, Vol. 9 No. 2, pp. 63-95, available at: <https://izlik.org/JA45XD35SL>
- European Commission (2022), *Ethical Guidelines on the Use of Artificial Intelligence (AI) and Data in Teaching and Learning for Educators*, Publications Office of the European Union.
- George, D. and Mallery, P. (2024), *IBM SPSS Statistics 29 Step by Step: A Simple Guide and Reference*, Routledge.
- Hwang, G.-J., Yin, C. and Yeh, Y.-F. (2022), "A review of artificial intelligence applications in pre-service teacher education: current status, challenges, and future directions", *Computers and Education: Artificial Intelligence*, Vol. 3, 100060, doi: [10.1016/j.caeai.2022.100060](https://doi.org/10.1016/j.caeai.2022.100060).
- Ismail, A., Aliu, A., Ibrahim, M. and Sulaiman, A. (2024), "Preparing teachers of the future in the era of artificial intelligence", *Journal of Artificial Intelligence*, Vol. 44, pp. 31-41, doi: [10.55529/jaimlnn.44.31.41](https://doi.org/10.55529/jaimlnn.44.31.41).
- Knight, K., Zhang, C., Holmes, G., and Zhang, M. L. (Eds) (2019), "Artificial intelligence: second CCF international conference", *ICAI 2019*, Springer, Xuzhou, 22-23 August.
- Long, D. and Magerko, B. (2020), "What is AI literacy? Competencies and design considerations", *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, pp. 1-16, doi: [10.1145/3313831.3376727](https://doi.org/10.1145/3313831.3376727).
- Luckin, R. and Holmes, W. (2016), "Intelligence unleashed: an argument for AI in education", available at: <https://discovery.ucl.ac.uk/id/eprint/1475756/>
- Panagou, D., Stylos, G. and Kotsis, K.T. (2025), "Exploring pre-service teachers' perspectives on integrating artificial intelligence in education", *Journal of Digital Educational Technology*, Vol. 5 No. 2, ep2514, doi: [10.30935/jdet/17297](https://doi.org/10.30935/jdet/17297).
- Redecker, C. (2017), "European framework for the digital competence of educators: DigCompEdu", in Punie, Y. (Ed.), *DigCompEdu*.
- Southworth, J., Migliaccio, K., Glover, J., Glover, J.N., Reed, D., McCarty, C., Brendemuhl, J. and Thomas, A. (2023), "Developing a model for AI across the curriculum: transforming the higher education landscape via innovation in AI literacy", *Computers and Education: Artificial Intelligence*, Vol. 4, 100127, doi: [10.1016/j.caeai.2023.100127](https://doi.org/10.1016/j.caeai.2023.100127).
- Tang, K.Y., Chang, C.Y. and Hwang, G.J. (2023), "Trends in artificial intelligence-supported e-learning: a systematic review and co-citation network analysis (1998-2019)", *Interactive Learning Environments*, Vol. 31 No. 4, pp. 2134-2152, doi: [10.1080/10494820.2021.1875001](https://doi.org/10.1080/10494820.2021.1875001).
- Teo, T. (2011), "Factors influencing teachers' intention to use technology: model development and test", *Computers and Education*, Vol. 57 No. 4, pp. 2432-2440, doi: [10.1016/j.compedu.2011.06.008](https://doi.org/10.1016/j.compedu.2011.06.008).
- Tondeur, J., Trevisan, O., Howard, S.K. and Van Braak, J. (2025), "Preparing preservice teachers to teach with digital technologies: an update of effective SQD-strategies", *Computers & Education*, Vol. 232, 105262, doi: [10.1016/j.compedu.2025.105262](https://doi.org/10.1016/j.compedu.2025.105262).

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- UNESCO (2019), “Beijing consensus on artificial intelligence and education”, available at: <https://unesdoc.unesco.org/ark:/48223/pf0000368303>
- UNESCO (2024), *AI Competency Framework for Teachers*, United Nations Educational, Scientific and Cultural Organization, available at: <https://unesdoc.unesco.org/ark:/48223/pf0000391104>
- Wang, B., Rau, P.-L.P. and Yuan, T. (2022), “Measuring user competence in using artificial intelligence: validity and reliability of artificial intelligence literacy scale”, *Behaviour and Information Technology*, Vol. 42 No. 9, pp. 1324-1337, doi: [10.1080/0144929X.2022.2072768](https://doi.org/10.1080/0144929X.2022.2072768).
- Yuen, A.H.K., Law, N. and Wong, K.C. (2013), “ICT implementation and school leadership: case studies of ICT integration in teaching and learning”, *Journal of Educational Administration*, Vol. 41 No. 2, pp. 158-170, doi: [10.1108/09578230310464666](https://doi.org/10.1108/09578230310464666).
- Zawacki-Richter, O., Marín, V.I., Bond, M. and Gouverneur, F. (2019), “Systematic review of research on artificial intelligence applications in higher education – where are the educators?”, *International Journal of Educational Technology in Higher Education*, Vol. 16 No. 1, p. 39, doi: [10.1186/s41239-019-0171-0](https://doi.org/10.1186/s41239-019-0171-0).
- Zhang, B. and Dafoe, A. (2021), “Artificial intelligence: American attitudes and trends”, Center for the Governance of AI, Future of Humanity Institute, University of Oxford, available at: <https://www.governance.ai/research-paper/artificial-intelligence-american-attitudes-and-trends>

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