



(ISSN: 2602-4047)

Altunay, F., Kurdal, C., & Değirmenci, Y. (2026). Understanding AI literacy among preservice teachers: An examination across different variables, *International Journal of Eurasian Education and Culture*, 11(32), 340-358.

DOI: <http://dx.doi.org/10.35826/ijoecc.2920>

Article Type : Research Article

UNDERSTANDING AI LITERACY AMONG PRESERVICE TEACHERS: AN EXAMINATION ACROSS DIFFERENT VARIABLES

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Received: 24.04.2026

Accepted: 14.08.2026

Published: 02.09.2026

ABSTRACT

Rapid advances in artificial intelligence (AI) have begun to reshape numerous domains, with education standing out as one of the most profoundly affected. Within educational settings, AI-powered technologies create substantial potential for adaptive learning pathways, diversified content delivery, and more responsive instructional support. Given this context, understanding the degree to which preservice teachers are prepared to engage with AI in their future classrooms carries considerable significance. The present study investigated preservice teachers' AI literacy levels in relation to a range of demographic, socioeconomic, and technology-related variables. Participants consisted of 426 preservice teachers during the 2024–2025 academic year. A quantitative survey approach was adopted, and data were gathered using a Demographic Information Form alongside a 12-item AI Literacy Scale. Statistical procedures included normality testing, independent samples t-tests, and one-way analysis of variance. Results revealed that variables such as gender, class standing, department affiliation, family educational background, household income, internet access patterns, social media engagement, and general digital tool use did not produce meaningful variation in AI literacy scores. By contrast, participants who incorporated AI tools into their educational routines and who engaged with AI more regularly demonstrated notably stronger AI literacy. On the basis of these findings, the study advocates for the inclusion of experiential, practice-centered AI literacy components within initial teacher preparation programs.

Keywords: Artificial intelligence, AI literacy, preservice teachers.

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Ethics Committee Approval: Approval was granted by the Bayburt University Ethics Committee on 27.06.2025 (Decision No. 368, Session No. 8).

Plagiarism/Ethics: This article has been reviewed by at least two referees and has been confirmed to comply with research and publication ethics, containing no plagiarism.

INTRODUCTION

Over the past several decades, artificial intelligence has transitioned from a narrow technical discipline into a wide-ranging transformative force that is reshaping economic structures, social institutions, and educational systems alike (Haenlein & Kaplan, 2019; Alpaydin, 2004). The rapid proliferation of generative AI platforms built on large language models has fundamentally altered how knowledge is sought, produced, and applied in everyday life (Lo, 2023). In this climate of accelerating change, passive consumption of AI outputs is no longer sufficient; individuals are increasingly expected to develop the capacity to interrogate how AI systems function, exercise critical judgment regarding their reliability and act responsibly when operating within ethically complex boundaries. As a result, AI literacy has emerged as an indispensable competency in contemporary society (Long & Magerko, 2020).

Scholars have conceptualized AI literacy as a multidimensional capability comprising the ability to comprehend the underlying logic of AI technologies, deploy them with intentionality and discernment, critically appraise AI-generated outputs, and maintain ethical vigilance concerning potential harms (Long & Magerko, 2020; Wang et al., 2022). This construct extends well beyond purely technical proficiency to encompass cognitive engagement, moral awareness, and a reflective understanding of AI's broader societal footprint (Carolus et al., 2023; Pinski & Benlian, 2023). Drawing on these foundations, Wang et al. (2022) articulated a four-dimensional model of AI literacy spanning awareness, use, evaluation, and ethics and operationalized it through a validated measurement instrument. Subsequent adaptation of this scale for Turkish-speaking populations (Çelebi et al., 2023) has opened important avenues for exploring AI literacy in Turkish educational research.

The significance of AI literacy transcends individual skill development; it carries profound implications for equity, governance, and social welfare. Concerns surrounding biased algorithms, vulnerabilities in personal data protection, and opacity in automated decision systems underscore the urgency of cultivating populations that can engage with AI critically and responsibly (Haenlein & Kaplan, 2019). While AI literacy intersects with adjacent constructs such as digital and information literacy, it demands a qualitatively richer and more expansive set of competencies that adjacent constructs alone cannot fully address (Long & Magerko, 2020). Accordingly, educational systems must go beyond producing skilled technology users and instead nurture reflective, informed citizens who can actively contribute to shaping ethical AI practices.

Education represents one of the arenas most profoundly affected by AI-driven transformation. The potential of AI to enable individualized learning trajectories, augment instructional materials, and introduce more nuanced and dynamic assessment strategies is well documented (Kurdal & Kaplan, 2026; Lo, 2023). Nevertheless, realizing these benefits in practice depends substantially on the readiness and competence of classroom teachers (Yavuz Aksakal & Ülgen, 2021). In this light, preservice teachers occupy a uniquely strategic position within the educational ecosystem: their evolving knowledge, dispositions, and skills with respect to AI will shape not only their own professional trajectories but also the technology-mediated experiences of the students they will one day teach.

The growing prominence of AI tools such as generative chatbots in educational practice has catalyzed a surge of scholarly interest in this area (Kaplan & Kurdal, 2025; Kasneci et al., 2023; Lo, 2023). These tools have introduced new possibilities for on-demand learning support, immediate formative feedback, and customized content generation. Simultaneously, the field has seen intensifying debates about the pedagogical, ethical, and epistemological consequences of their widespread adoption. A comprehensive review by Zawacki-Richter et al. (2019) underscored a persistent imbalance in the AI-in-education literature, with the preponderance of studies centering on technical system design rather than on teacher competency development or issues of pedagogical integration.

Equipping teachers and preservice teachers with the competencies needed to navigate AI-driven transformation is accordingly recognized as a strategic educational priority. Holmes, Bialik, and Fadel (2019) have argued that effective AI use in professional educational practice requires not merely technical familiarity but also pedagogical flexibility and a well-developed ethical sensibility. In alignment with this view, UNESCO (2024) has articulated a comprehensive AI Competency Framework for Teachers organized around human-centered values, ethical stewardship, instructional integration, and continuous professional learning.

Despite the growth of research on AI literacy, studies that specifically examine preservice teachers as a population of interest remain sparse. In the Turkish context, scholarly attention has concentrated primarily on broader notions of digital competency and attitudes toward educational technology (Ferikoğlu & Akgün, 2022), with work directly addressing AI literacy representing a more recent and still emergent body of inquiry (Çelebi et al., 2023). Moreover, most existing studies have analyzed the relationship between AI literacy and background characteristics within relatively narrow conceptual frameworks, without providing the kind of comprehensive, multivariate analysis focused specifically on preservice teachers that the field requires.

Building on a multidimensional conceptualization of AI literacy that encompasses cognitive, technical, and ethical dimensions (Ng et al., 2021), the present study responds to calls in the literature (Laupichler et al., 2023) for more targeted investigation of AI literacy in specific educational populations. The study seeks to characterize AI literacy levels among preservice teachers and to explore whether those levels vary as a function of a broad array of individual, contextual, and technology-related characteristics.

Purpose of the Study

The central objective of this study is to document the AI literacy levels of preservice teachers and to determine whether meaningful variation in those levels can be attributed to a range of personal and contextual characteristics. Specifically, the investigation attends to preservice teachers' comprehension of AI, their capacity to make purposeful use of AI-powered tools, their ability to appraise the merits and limitations of AI outputs, and their orientations toward the ethical dimensions of AI in educational contexts. The following research questions organize the inquiry:

What are the AI literacy levels of preservice teachers?

Are there statistically significant differences in preservice teachers' AI literacy levels in terms of selected demographic characteristics, including gender, academic department, and grade level?

Do preservice teachers' AI literacy levels differ significantly according to their demographic characteristics (gender, grade level, academic department, parental education level, and income status) and technology-related characteristics (internet use, social media use, perceived technology competence, frequency of digital tool use, use of AI educational tools, and frequency of AI use)?

The following hypotheses were formulated and tested within the scope of this study:

- H1: Preservice teachers' AI literacy levels differ significantly according to gender.
- H2: Preservice teachers' AI literacy levels differ significantly according to academic department.
- H3: Preservice teachers' AI literacy levels differ significantly according to grade level.
- H4: Preservice teachers' AI literacy levels differ significantly according to parental education level.
- H5: Preservice teachers' AI literacy levels differ significantly according to income status.
- H6: Preservice teachers' AI literacy levels differ significantly according to frequency of internet use.
- H7: Preservice teachers' AI literacy levels differ significantly according to frequency of social media use.
- H8: Preservice teachers' AI literacy levels differ significantly according to perceived technology competence.
- H9: Preservice teachers' AI literacy levels differ significantly according to frequency of digital tool use.
- H10: Preservice teachers' AI literacy levels differ significantly according to their use of AI educational tools.
- H11: Preservice teachers' AI literacy levels differ significantly according to frequency of AI use.

It is expected that the findings of this study will contribute to a comprehensive understanding of preservice teachers' AI literacy levels in relation to both their demographic characteristics and technology-related experiences. The findings may also provide an empirical basis for designing teacher education programs that strengthen AI awareness, technology competence, and the meaningful integration of AI into educational practices.

METHOD

Research Model

This investigation was designed as a quantitative, cross-sectional survey study. The survey approach is well-suited to research goals that involve systematically documenting the attitudes, beliefs, and characteristics of a defined population, yielding a structured picture of conditions at a given point in time (Fraenkel & Wallen, 2006; Johnson & Christensen, 2014). Consistent with this tradition, the study employed standardized measurement instruments to assess AI literacy levels and to capture demographic and technology-related characteristics across a sizable participant pool.

Participants

The study drew on data collected from 426 preservice teachers enrolled across multiple programs during the 2024–2025 academic year. Participants were recruited through convenience sampling, a non-probability strategy that allows researchers to work efficiently with accessible populations while keeping logistical demands manageable (Fraenkel et al., 2012; McMillan & Schumacher, 2014). A full account of the demographic composition of the sample is provided in Table 1.

Table 1. Demographic Characteristics of Participants

Variable	Groups	N	%
Gender	Female	119	27.9
	Male	307	72.1
Grade Level	1st Year	139	32.6
	2nd Year	138	32.4
	3rd Year	85	20
	4th Year	64	15
Department	Social Studies Teaching	102	23.9
	Elementary Mathematics Education	69	16.2
	English Language Teaching	33	7.7
	Turkish Language Teaching	48	11.3
	Primary School Teaching	57	13.4
	Psychological Counseling and Guidance	117	27.5
	Elementary school	147	34.5
	Middle school	85	20
	High school	102	23.9
Parental Education Status	University	92	21.6
	0-20.000	101	23.7
	21.000-40.000	152	35.7
	41.000-60.000	99	23.2
Family Income Status	60,000 and above	74	17.4
	1-3 hours	59	13.8
	3-5 hours	157	36.9
	More than 5 hours	205	48.1
Internet Usage	Less than 1 hour	5	1.2
	Less than 1 hour	23	5.4
	1-3 hours	126	29.6
	3-5 hours	161	37.8
Social Media Use	More than 5 hours	116	27.2
	Low	23	5.4
	Medium	262	61.5
	High	141	33.1
Technology Use Proficiency	Less than 1 hour	8	1.9
	1-3 hours	72	16.9
	3-5 hours	183	43
	More than 5 hours	163	38.3
Use of AI Educational Tools	Yes	391	91.8
	No	35	8.2
Frequency of AI Use	Never	10	2.3
	Rarely	46	10.8
	Sometimes	183	43
	Frequently	151	35.4
	Very Often	36	8.5
Total		426	100

Based on the data presented in Table 1, it can be inferred that the majority of preservice teachers were male, with 307 participants (72.1%), while 119 participants (27.9%) were female. Additionally, 139 participants (32.6%) were identified as first-year students. Among the various departments, the highest representation was from the Guidance and Psychological Counseling (RPD) department, comprising 117 participants (27.5%). Regarding parental education levels, the largest proportion of participants, 147 (34.5%), reported that their parents had completed elementary school. In terms of monthly family income, the greatest number of participants, 152 (35.7%), reported an income between 21,000 and 40,000 TL. With respect to internet usage, 205 participants (48.1%) indicated that they spent more than five hours per day online, whereas 161 participants (37.8%) reported using social media for 3 to 5 hours daily. Furthermore, 262 participants (61.5%) rated their technology proficiency as intermediate. The majority of respondents (391 participants, 91.8%) stated that they had previously used artificial intelligence-based educational tools, while 183 participants (43%) indicated that they used AI tools occasionally.

Data Collection Tool

Artificial Intelligence Literacy Scale

The AI Literacy Scale introduced by Çelebi et al. (2023), initially validated with a sample of 402 adult respondents, was employed to measure AI literacy in this study. The instrument adopts a seven-point Likert response format running from "Strongly Disagree" to "Strongly Agree" and encompasses 12 items organized into four thematic subscales (awareness, use, evaluation, and ethics); three items are reverse-coded. Possible total scores range from 12 to 84. The original validation study reported Cronbach's alpha internal consistency indices of .72, .74, and .76 for the Awareness, Use, and Evaluation subscales, respectively, and .85 for the full scale. Sample items include: "I can distinguish between devices that incorporate artificial intelligence and those that do not," "I am able to make effective use of AI tools to support my day-to-day activities," "After working with an AI product over time, I can meaningfully evaluate its strengths and constraints," and "My use of AI technologies consistently reflects ethical principles and standards." In the current sample, the overall Cronbach's alpha was computed as .84.

The ethical procedures for the study were as follows:

- Ethics committee approval was obtained from the Bayburt University Ethics Committee (Date: 27.06.2025, Decision No. 368, Session No. 8).
- Informed consent was obtained from the participants.

Data Analysis

Data analysis was performed using SPSS version 27.0. Prior to analysis, incomplete forms were removed from the dataset. The normality of the data distribution was assessed using descriptive indicators (mean, median, coefficient of variation, skewness, and kurtosis) and visual inspection of histograms. The findings indicated that

the data met the normality assumption. Descriptive statistics, including frequencies, percentages, means, and standard deviations, were used to summarize the data.

Independent-samples t-tests and one-way analyses of variance (ANOVA) were conducted to examine whether preservice teachers' AI literacy levels differed according to demographic, socioeconomic, and technology-related variables. Homogeneity of variances was assessed using Levene's test. When the homogeneity assumption was met, the conventional ANOVA results were reported and Bonferroni post-hoc comparisons were conducted for statistically significant omnibus tests. When the assumption was violated, Welch's ANOVA was used; for statistically significant Welch tests, Games–Howell post-hoc comparisons were performed because this procedure does not require equal variances and is suitable when group sizes may differ. The significance level was set at $p < .05$. Effect sizes were reported as eta squared (η^2) and interpreted as small (.01–.05), medium (.06–.137), and large ($\geq .138$), following Cohen's (2007) criteria.

Furthermore, Cronbach's alpha coefficients were calculated to assess the reliability of the scales used in the study. Descriptive analyses confirmed that the data were normally distributed. Table 2 presents the descriptive statistical results for the scales included in the study.

Table 2. Descriptive Statistics for the Data Collection Tool

Scale	Cronbach's alpha	$\bar{X}$	ss.	Skewness	Kurtosis
AI Literacy Scale	.84	61.22	10.42	-.34	.02

As shown in Table 2, the Cronbach's Alpha coefficient of the Artificial Intelligence Literacy Scale was calculated as .84, indicating high internal consistency reliability. The mean score of the scale was 61.22 with a standard deviation of 10.42, suggesting that participants' scores were moderately dispersed around the mean. The skewness value was found to be -0.34, indicating a slight negative skewness; in other words, scores tended to cluster slightly toward the higher end of the scale. The kurtosis value was calculated as 0.02, which is very close to zero, suggesting that the distribution of scores approximates a normal distribution with no significant peakedness or flatness.

FINDINGS

Findings Regarding Preservice Teachers' AI Literacy Levels

Findings regarding the artificial intelligence literacy levels of preservice teachers are presented in Table 3.

Table 3. Findings Regarding the Artificial Intelligence Literacy Levels of Prospective Teachers

Scale	n	$\bar{x}$	df
AI Literacy Scale	426	4.96	.68

Based on the data obtained, as shown in Table 3, the overall mean item score of the preservice teachers on the Artificial Intelligence Literacy Scale was found to be $\bar{x}=4.96$. The AI Literacy Scale consists of 12 items rated on a seven-point Likert scale, with total scores ranging from 12 to 84; however, in this study, mean item scores were

reported for ease of interpretation. This indicates that their responses were between “somewhat agree” and “agree” regarding statements about AI literacy. Additionally, the relatively low standard deviation ($SD = .68$) suggests that participants’ views were relatively homogeneous, with little variability within the group. Considering that the scale ranges from 1 to 7 per item, a mean score close to 5 implies that preservice teachers have a generally positive perception of AI literacy. However, this perception is not at the highest possible level.

Findings Regarding the Differentiation of AI Literacy Levels of Preservice Teachers According to Gender, Grade Level, and Department

The findings regarding preservice teachers’ artificial intelligence literacy scores by gender (Table 4), grade level (Table 5), and department (Table 6) are presented below.

Table 4 presents the results of the independent samples t-test conducted to examine whether preservice teachers’ AI literacy levels differed by gender. The analysis tested the assumption of homogeneity of variances and compared the AI literacy scores of male and female preservice teachers.

Table 4. Comparison of Teacher Candidates’ AI Literacy Levels by Gender							
	Levene Test						
	F	p	t	df	p	Confidence Interval	η^2
AI Literacy Scale	2.75	.09	-.52	424	.60	-2.80 1.63	.001

As shown in Table 4, the Levene’s test for homogeneity of variances was not significant ($F=2.75$, $p=.09$), indicating that the assumption of homogeneity of variances was met. An independent samples t-test was conducted to examine whether preservice teachers’ AI literacy scores differed by gender. The results showed that there was no significant difference between male ($\bar{x}=60.80$, $SD=11.33$) and female ($\bar{x}=61.38$, $SD=10.06$) preservice teachers in terms of their AI literacy levels ($t_{(424)} = -.520$, $p=.60$, 95% CI [-2.80, 1.63], $\eta^2 = .001$).

A one-way analysis of variance (ANOVA) was conducted to examine whether preservice teachers’ AI literacy levels differed by grade level. The results showed that the assumption of homogeneity of variances was met (Levene(3,422)=2.61, $p=.05$). According to the analysis, there was no significant difference in AI literacy scores across grade levels ($F_{(3,422)}=1.68$, $p=.17$). The findings are presented in Table 5.

Table 5. Examination of Teacher Candidates AI Literacy According to Grade Level Variables						
	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	544.65	3	181.55	1.68	.17	.012
Within Groups	45610.61	422	108.08			
Total	46155.26	425				

As shown in Table 5, there was no significant difference in preservice teachers’ AI literacy levels across grade levels, and the effect size was found to be small ($F_{(3, 422)}=1.68$, $p=.17$, $\eta^2=.012$).

A one-way analysis of variance (ANOVA) was conducted to examine whether preservice teachers’ AI literacy levels differed by department. The results indicated that the assumption of homogeneity of variances was met

(Levene(5,420)=1.46, $p=.20$). According to the analysis, there was no significant difference in AI literacy scores across departments ($F_{(5,420)}=.90$, $p=.48$). The findings are presented in Table 6.

Table 6. Examination of Teacher Candidates AI Literacy According to Department

	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	488.63	3	97.73	.90	.48	.011
Within Groups	45666.63	420	108.73			
Total	46155.26	425				

As shown in Table 6, there was no significant difference in preservice teachers' AI literacy levels across departments, and the effect size was found to be small ($F_{(5, 420)}=.90$, $p=.48$, $\eta^2=.011$).

Findings Regarding the Differentiation of AI Literacy Levels of Preservice Teachers According to Parental Education and Income Status

The findings regarding preservice teachers' AI literacy scores by parental education level (Table 7) and income status (Table 8) are presented below.

A one-way analysis of variance (ANOVA) was conducted to examine whether preservice teachers' AI literacy levels differed according to their parents' education levels. The results showed that the assumption of homogeneity of variances was met (Levene(3,422)=1.497, $p=.215$). According to the analysis, there was no significant difference in AI literacy scores across parental education levels ($F_{(3,422)}=0.50$, $p=.68$). The findings are presented in Table 7.

Table 7. Examination of Teacher Candidates AI Literacy According to Parental Education Variables

	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	163.42	3	54.47	.50	.68	.004
Within Groups	45991.84	422	108.99			
Total	46155.26	425				

As shown in Table 7, there was no significant difference in preservice teachers AI literacy levels across parental education, and the effect size was found to be small ($F_{(3, 422)}=.50$, $p=.68$, $\eta^2=.004$).

A one-way analysis of variance (ANOVA) was conducted to examine whether preservice teachers' AI literacy levels differed according to their income status. The results showed that the assumption of homogeneity of variances was violated (Levene(3,422)=3.27, $p=.012$). Therefore, Welch's ANOVA was conducted. The results indicated that preservice teachers' AI literacy scores did not differ significantly across income-status groups, Welch's $F_{(3, 205.238)} = 1.19$, $p = .314$. The findings are presented in Table 8.

Table 8. Examination of Teacher Candidates AI Literacy According to Income Status Variables

	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	320.29	3	106.76	.98	.40	.007
Within Groups	45834.97	422	108.61			
Total	46155.26	425				

As shown in Table 8, Welch's ANOVA indicated no significant difference in preservice teachers' AI literacy levels across income-status groups, Welch's $F_{(3, 205.238)} = 1.19$, $p = .314$.

Findings Regarding the Differentiation of AI Literacy Levels of Preservice Teachers According to Internet Use, Social Media Use, Technology Competence, Digital Tool Use, Use of AI Educational Tools, and AI Usage Levels

The findings regarding preservice teachers AI literacy scores by internet use (Table 9), social media use (Table 10), technology competence (Table 11), digital tool use (Table 12), use of AI educational tools (Table 13), and AI usage levels (Table 14) are presented below.

A one-way analysis of variance (ANOVA) was conducted to examine whether preservice teachers' AI literacy levels differed according to their internet use. The results showed that the assumption of homogeneity of variances was met ($Levene(3,422)=2.160$, $p=.092$). According to the analysis, there was no significant difference in AI literacy scores across internet use groups ($F_{(3,422)}=0.383$, $p=.765$). The findings are presented in Table 9.

Table 9. Examination of Teacher Candidates' AI Literacy Levels According to Internet Use

	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	125.27	3	41.76	.38	.77	.003
Within Groups	46029.99	422	109.08			
Total	46155.26	425				

As shown in Table 9, there was no significant difference in preservice teachers' AI literacy levels across internet use groups, and the effect size was found to be small ($F_{(3, 422)}=0.38$, $p=.77$, $\eta^2=.003$).

A one-way analysis of variance (ANOVA) was conducted to examine whether preservice teachers' AI literacy levels differed according to their social media use. The results showed that the assumption of homogeneity of variances was met ($Levene(3,422)=1.169$, $p=.321$). According to the analysis, there was no significant difference in AI literacy scores across social media use groups ($F_{(3,422)}=0.847$, $p=.469$). The findings are presented in Table 10.

Table 10. Examination of Teacher Candidates' AI Literacy Levels According to Social Media Use

	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	276.19	3	92.07	.85	.47	.006
Within Groups	45879.07	422	108.72			
Total	46155.26	425				

As shown in Table 10, there was no significant difference in preservice teachers' AI literacy levels across social media use groups, and the effect size was found to be small ($F_{(3, 422)}=0.85$, $p=.47$, $\eta^2=.006$).

A one-way analysis of variance (ANOVA) was conducted to examine whether preservice teachers' AI literacy levels differed according to their technology competence. The results showed that the assumption of homogeneity of variances was met ($Levene(2,423)=2.209$, $p=.111$). According to the analysis, there was a significant difference in AI literacy scores across technology competence groups ($F_{(2,423)}=11.323$, $p<.001$). Post-

hoc Bonferroni tests revealed that candidates with high technology competence had significantly higher AI literacy scores than those with medium ($p<.001$) and low ($p<.001$) competence levels, while there was no significant difference between the low and medium groups ($p=.171$). The findings are presented in Table 11.

Table 11. Examination of Teacher Candidates' AI Literacy Levels According to Technology Competence

	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	2345.39	2	1172.69	11.32	<.001	.051
Within Groups	43809.87	423	103.57			
Total	46155.26	425				
	Mean Difference (I-J)		p	Direction		
Low-High	-8.45		<.001	High > Low		
Medium – High	-4.23		<.001	High > Medium		

As shown in Table 11, there was a significant difference in preservice teachers' AI literacy levels across technology competence groups, and the effect size was found to be medium ($F_{(2, 423)}=11.32$, $p<.001$, $\eta^2=.051$).

A one-way analysis of variance (ANOVA) was conducted to examine whether preservice teachers' AI literacy levels differed according to their digital tool use. The results showed that the assumption of homogeneity of variances was met (Levene(3,422)=0.877, $p=.453$). According to the analysis, there was no significant difference in AI literacy scores across digital tool use groups ($F_{(3,422)}=0.074$, $p=.974$). The findings are presented in Table 12.

Table 12. Examination of Teacher Candidates' AI Literacy Levels According to Digital Tool Use

	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	24.30	3	8.10	.07	.97	.001
Within Groups	46130.96	422	109.32			
Total	46155.26	425				

As shown in Table 12, there was no significant difference in preservice teachers' AI literacy levels across digital tool use groups, and the effect size was found to be small ($F_{(3, 422)}=0.07$, $p=.97$, $\eta^2=.001$).

Table 13 presents the results of the independent samples t-test conducted to examine whether preservice teachers' AI literacy levels differed according to their use of AI educational tools. The analysis tested the assumption of homogeneity of variances and compared the AI literacy scores between those who reported using AI educational tools and those who did not.

Table 13. According to Their Use of AI Educational Tools

	Levene Test						
	F	p	t	df	p	Confidence Interval	η^2
AI Literacy Scale	0.51	.48	5.08	424	<.001	5.57 12.59	.057

As shown in Table 13, Levene's test for homogeneity of variances was not significant ($F=0.51$, $p=.48$), indicating that the assumption of homogeneity of variances was met. An independent samples t-test was conducted to examine whether preservice teachers' AI literacy scores differed according to their use of AI educational tools. The results showed that there was a significant difference between those who used AI educational tools ($\bar{x}$

=61.97, SD=10.09) and those who did not ($\bar{x}$ =52.89, SD=10.52) in terms of their AI literacy levels ($t_{(424)}=5.08$, $p<.001$, 95% CI [5.57, 12.59], $\eta^2 = .057$).

A one-way analysis of variance was conducted to examine whether preservice teachers' AI literacy levels differed according to their frequency of AI use. The homogeneity of variances assumption was violated, Levene's $F(4, 421) = 3.273$, $p = .012$. Therefore, Welch's ANOVA was conducted. The analysis indicated a significant difference in AI literacy scores across AI usage-frequency groups, Welch's $F_{(4, 51.021)} = 10.246$, $p < .001$. Games–Howell post-hoc comparisons were conducted to identify the source of the differences. The findings are presented in Table 14.

Table 14. According to Frequency of AI Use

	Sum of Squares	df	Mean Square	F	p	η^2
Between Groups	5031.75	4	1257.94	12.88	<.001	.109
Within Groups	41123.51	421	97.68			
Total	46155.26	425				
	Mean Difference (I-J)		p	Direction		
Rarely – Frequently	-5.116		.004	Frequently > Rarely		
Rarely – Very Frequently	-7.417		.005	Very Frequently > Rarely		

As shown in Table 14, there was a significant difference in preservice teachers' AI literacy levels according to their AI usage levels ($F_{(4, 421)}=12.88$, $p<.001$, $\eta^2=.109$). Games–Howell post-hoc comparisons revealed that preservice teachers who reported using AI frequently had significantly higher AI literacy scores than those who reported using it rarely (mean difference = 5.116, $p = .004$). Likewise, those who reported using AI very frequently had significantly higher AI literacy scores than those who reported using it rarely (mean difference = 7.417, $p = .005$). No other pairwise comparisons were statistically significant.

CONCLUSION and DISCUSSION

The present investigation set out to characterize AI literacy among preservice teachers and to determine whether that literacy varied in relation to demographic, socioeconomic, and technology-related characteristics. Taken together, the findings paint a picture of a group that has developed a moderate but not fully mature level of AI literacy—one that encompasses foundational awareness, practical engagement with tools, and nascent ethical sensibilities, yet has not consolidated into a sophisticated, professionally applicable competency. This portrait aligns with theoretical frameworks that situate AI literacy as a multidimensional construct requiring integrative understanding, critical evaluation capacity, and ethical reflexivity, rather than technical fluency alone (Long & Magerko, 2020; Ng et al., 2021; Wang et al., 2022).

The moderately elevated AI literacy profile documented here is broadly corroborated by comparable investigations involving preservice teacher populations. Çetin and Çelen (2025) similarly found that student teachers generally demonstrated strong AI literacy, while also identifying clear connections to experiential variables such as routine AI tool use, participation in technology training, and the academic application of AI. Parallel findings were reported by Deneme Gençoğlu and Nalbant (2025) for English language preservice

teachers, whose AI literacy profiles were characterized by relative strength in critical evaluation but persistent gaps in technical understanding. These converging findings suggest that while preservice teachers have moved beyond unfamiliarity with AI, they continue to require more deliberate and structured educational scaffolding, particularly in areas where deeper technical comprehension and ethical reflection intersect with pedagogical application.

Gender did not emerge as a significant variable in this study, a result that echoes a wider cluster of recent findings in the teacher education literature (Çetin & Çelen, 2025; Deneme Gençoğlu & Nalbant, 2025; Gerlich, 2023; Uyak et al., 2023). This convergence may reflect the degree to which contemporary AI tools, including conversational AI platforms, have lowered access barriers across user groups by emphasizing intuitive, natural language interfaces over technically demanding interaction modalities. However, this finding should not be accepted as universal: Özden, Örgü Yaşar, and Meydan (2025) identified gender as one of several variables that did produce meaningful differentiation in a comparable preservice teacher sample. The divergence across studies likely reflects contextual differences in sampling, measurement approaches, and the varying digital socialization experiences of participants, rather than a definitive cross-contextual pattern. Taken together, the present results suggest that active hands-on engagement with AI technologies may be a more potent shaping force than demographic identity *per se*.

The absence of year of study effects warrants particular attention because it challenges the implicit assumption that longer exposure to university-level education necessarily cultivates AI competency. This result resonates with prior findings in adjacent domains (Güler, 2019; Kaman, 2025; Uyar, 2021), and is reinforced by the comparable pattern reported by Deneme Gençoğlu and Nalbant (2025). The contrasting observation by Özden et al. (2025) that senior students showed stronger AI literacy may point to curriculum-level differences, where AI-adjacent coursework (such as instructional technology or digital material design) is more heavily concentrated in upper-year programs. The lack of differentiation by year in the present sample may therefore signal that AI literacy has not yet been embedded as a systematically progressive strand within teacher preparation, but is instead encountered somewhat incidentally and unevenly.

Departmental affiliation likewise produced no significant differentiation, a finding that carries meaningful theoretical implications. It suggests that AI literacy is not the exclusive province of technically oriented disciplines but functions as a horizontal competency that cuts across all educational fields. As AI-supported tools penetrate areas as varied as language instruction, school counseling, social studies, and primary education, the utility of AI literacy extends correspondingly across subject boundaries. This cross-disciplinary relevance argues for treating AI literacy as a core professional competency in teacher preparation, rather than positioning it as a specialization appropriate only for particular curricular areas.

Parental educational attainment and household income also failed to predict meaningful variation in AI literacy. Çetin and Çelen (2025) obtained a consistent result in this regard. At the level of university study, where access

to AI tools and digital infrastructure is relatively equalized, the influence of family socioeconomic background on AI literacy may be attenuated. It would nevertheless be premature to conclude that socioeconomic factors are irrelevant in this domain more broadly. Long-term access to premium AI subscriptions, stable high-bandwidth connectivity, personal computing devices, and technology-enriched informal learning environments may remain sensitive to socioeconomic position. Future research would benefit from operationalizing socioeconomic status more granularly, capturing dimensions of digital access quality, household technology resources, and the nature of technology use environments rather than relying solely on income brackets.

Daily internet and social media use, along with the sheer duration of digital tool engagement, did not produce meaningful differences in AI literacy. This pattern is consistent with previously reported observations regarding the limited predictive value of quantitative digital exposure for technology-related competencies (Şener, 2019). The implication is that raw hours spent in digital environments do not translate into the kind of reflective, critical engagement with AI systems that AI literacy frameworks demand. Frequent internet browsing or social media consumption, for example, need not involve any meaningful encounter with AI's underlying mechanisms, data practices, or ethical dimensions. This finding should prompt caution regarding assumptions associated with the notion of the "digital native": generational familiarity with digital tools does not by itself generate AI literacy. Rather, that literacy appears to require purposeful, critically framed, and pedagogically meaningful encounters with AI technologies.

Technology competence, however, was a significant predictor of AI literacy, with high self-rated competence associated with substantially stronger AI literacy scores relative to lower competence groups. This finding aligns with conceptualizations of AI literacy as grounded in, though not reducible to, broader digital skill sets. Long and Magerko (2020) characterize AI literacy as encompassing the ability to understand, critically evaluate, and interact productively with AI systems. Within this framework, technical proficiency constitutes a necessary but insufficient foundation; it must be complemented by higher-order capacities such as ethical reasoning, epistemic scrutiny of AI-generated claims, recognition of algorithmic limitations and biases, and sensitivity to the pedagogical appropriateness of AI in specific educational contexts.

The strongest effects documented in this study were associated with the use of AI-based educational tools and the frequency of AI engagement. Preservice teachers who had incorporated AI tools into their educational practice demonstrated markedly higher AI literacy than those who had not, corroborating observations by Çetin and Çelen (2025), who linked AI literacy to ownership and applied use of AI applications, and by Deneme Gençoğlu and Nalbant (2025), who identified informal, tool-based learning as a significant predictor. Frequency of AI use similarly differentiated participants in a dose-response fashion, with more habitual users demonstrating higher literacy. These findings collectively point to the primacy of experiential, practice-based learning as a driver of AI literacy development. However, an important qualification applies: the type and purpose of AI use matter as much as its frequency. When AI tools are used primarily to generate ready-made content, offload cognitive effort, or circumvent learning tasks, the result may be shallow familiarity rather than genuine literacy. Developing

authentic AI literacy therefore requires structured guidance around interrogating AI outputs, situating AI use within ethical boundaries, and integrating AI purposefully into substantive pedagogical practice.

These findings resonate closely with the UNESCO (2024) AI Competency Framework for Teachers, which organizes teacher AI competence around five pillars: a human-centered orientation, ethical responsibility, foundational AI knowledge, pedagogical integration, and professional growth. The pattern of results in this study strongly supports the argument that AI literacy should be treated not as an optional supplement to teacher preparation but as a core and compulsory professional competency, cultivated through structured experiential learning opportunities embedded throughout initial teacher education programs.

SUGGESTIONS

Considered in aggregate, the findings of this study indicate that preservice teachers have developed a preliminary but still-maturing AI literacy. Variables including gender, year of study, program affiliation, family background, and patterns of general digital use did not differentiate AI literacy in meaningful ways. Technology competence, habitual use of AI-specific educational tools, and frequency of AI engagement, however, emerged as consistent and significant predictors. This configuration suggests that AI literacy is fundamentally an experiential and practice-mediated competency—one shaped more by the quality and intentionality of individuals' encounters with AI technologies than by their demographic characteristics.

On the strength of these findings, this study recommends the deliberate and systematic integration of AI literacy into preservice teacher preparation at the curricular level. Such programming should extend well beyond introductory tool familiarity to address foundational questions about how AI systems function, the mechanisms through which bias enters algorithmic systems, issues of data protection and academic integrity, copyright and intellectual property considerations in AI contexts, and the pedagogical opportunities and risks associated with AI use across diverse subject areas. Practical opportunities for preservice teachers to apply AI tools in genuine educational design tasks, including developing differentiated learning materials, crafting formative assessments, and providing AI-assisted feedback should be systematically incorporated.

This study carries several limitations that should inform the interpretation of its findings. First, the sample was confined to a single setting, limiting the generalizability of the results. Second, the convenience sampling strategy, while practical, may have introduced selection biases. Third, reliance on self-report data means that participants' assessments of their own AI literacy and technology use may not perfectly reflect their actual capabilities or behaviors, potentially inflating or deflating reported levels. Fourth, the cross-sectional design does not permit causal inference; it is not possible on the basis of these data to determine whether AI use drives AI literacy development, or whether individuals with higher AI literacy are more disposed to use AI tools. Fifth, the exclusive use of quantitative measurement precludes a nuanced exploration of the purposes, contexts, and quality of preservice teachers' AI engagements.

Future research should address these limitations through more diverse and geographically distributed sampling strategies. Complementing survey-based measurement with performance tasks, classroom observations, and interview methods would provide a more complete picture of AI literacy as it is actually exercised in educational practice. Longitudinal designs tracking the evolution of AI literacy over the course of preservice teacher programs would be especially valuable. Experimental and quasi-experimental studies evaluating the impact of specifically designed AI literacy interventions would further strengthen the evidence base. Finally, studies exploring the structural relationships among AI literacy and constructs such as critical thinking, technology acceptance, pedagogical content knowledge, teacher self-efficacy, and academic integrity would contribute substantially to theoretical understanding in this emergent field.

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Ethics Statement: This article complies with the journal writing rules, publication principles, research and publication ethics rules, and journal ethics rules. Responsibility for any violations that may arise regarding the article belongs to the authors. Ethical approval for the research was obtained from the Bayburt University Ethics Committee on 27.06.2025 with Decision No. 368 (Session No. 8).

Declaration of Author(s)' Contribution Rate: The first author contributed 35%, the second author contributed 35%, and the third author contributed 30% to this study.

CONTRIBUTION RATE	CONTRIBUTORS
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Findings	Cem KURDAL – Furkan ALTUNAY
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Funding: This study received no funding or financial support.

Informed Consent Statement: Informed consent was obtained from all participants who took part in the study.

Data Availability Statement: The datasets generated and/or analyzed during the study will be provided by the corresponding author upon request.

Conflict of Interest: The authors declare that there is no conflict of interest with any person, institution, or organization, and no conflict of interest among the authors.



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