Id: 1951216

Participatory Educational Research (PER)
Vol.13(6), pp. 233-249, November 2026
Available online at http://www.perjournal.com
ISSN: 2148-6123
http://dx.doi.org/10.17275/per.26.86.13.6

Digital Literacy as a Predictor of AI Literacy: A Gender Paradox and a Knowledge–Belief Gap

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Article history
Received:
14.05.2026

Received in revised form:
02.06.2026

Accepted:
10.07.2026

Key words:
digital literacy, artificial intelligence literacy, university students, gender differences, hierarchical regression

This study investigates the relationship between university students' digital literacy and artificial intelligence (AI) literacy. Participants were 770 undergraduate students (227 male, 543 female; M_{age} = 21.27, SD = 2.75) recruited through online convenience and snowball sampling, with recruitment centered at Karamanoğlu Mehmetbey University (Karaman, Türkiye), representing more than 120 academic programs. Data were collected with the Turkish forms of Ng's (2012) Digital Literacy Scale (α = .931) and Wang et al.'s (2022) AI Literacy Scale (α = .803). Three findings stand out. First, digital literacy and AI literacy were strongly and positively related ($r = .596$, $p < .001$). A three-step hierarchical regression analysis identified digital literacy as the only significant predictor of AI literacy ($\beta = .599$, $p < .001$), explaining 35.5% of the variance ($R^2 = .355$, $F(1, 768) = 422.57$, $p < .001$); adding gender and age ($\Delta R^2 = .002$) and internet use frequency ($\Delta R^2 = .000$) did not significantly improve the model. Second, a small gender difference favoring men emerged in digital literacy (Cohen's d = 0.201) but not in AI literacy (d = 0.031), a pattern we describe as a gender paradox. Third, although 85.1% of participants believed in AI's future impact, only 22.7% rated their own AI knowledge as sufficient—a knowledge–belief gap. Self-rated AI knowledge, but not belief, differed significantly by gender ($\chi^2 = 11.05$, $p = .004$; Cramér's V = .120). Implications for digital and AI literacy education in higher education are discussed.

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Introduction

Artificial intelligence has moved quickly into everyday life, and the arrival of generative tools such as ChatGPT in late 2022 gave new urgency to an old question of which digital skills people now need and whether AI literacy should be considered one of them (Long & Magerko, 2020; Ng et al., 2021). Digital literacy refers to a person's ability to find, evaluate, produce, and ethically use digital content (Ng, 2012). AI literacy describes a related but distinct set of competencies: evaluating AI critically, working with it effectively, and using it responsibly at home, at work, and online (Long & Magerko, 2020). The idea that AI literacy rests on a foundation of digital literacy is widely shared, but it has seldom been tested directly. In particular, we still know little about how strongly digital literacy predicts AI literacy once demographic factors are taken into account, and even less about this relationship in Turkish higher education.

The present study focuses on two patterns that appear, at first glance, to pull in opposite directions. The first concerns a gender paradox. Work on the digital divide has long reported that men rate their advanced digital skills more highly than women do (van Deursen & van Dijk, 2014); yet because generative AI is used through ordinary language rather than technical commands, that gap may not carry over into the AI domain. The second is a knowledge–belief gap. AI is routinely described as the defining technology of the coming decades, but belief that runs ahead of understanding can encourage uncritical use, which makes the distance between believing in AI and actually understanding it a genuine concern for education and policy (Long & Magerko, 2020).

The research gap addressed in this study is straightforward. Few studies measure digital literacy and AI literacy with validated instruments in the same sample and then ask how well one predicts the other. Those that come closest have examined neighbouring constructs, such as digital well-being (Caz et al., 2024), or mediated relationships in other populations, such as academics (Işık & Çamur, 2024), rather than the direct link among university students. We take up that link with a large sample (N = 770) and a three-step hierarchical regression.

With this in mind, the study set out to describe students' digital and AI literacy, to examine how these competencies relate to several demographic variables, and, above all, to provide evidence regarding the gender and knowledge–belief patterns just described. Five research questions guided the work:

(1) What are the levels of digital literacy and AI literacy among university students?
(2) Is there a significant relationship between digital literacy and AI literacy?
(3) Do gender, age, and self-reported AI knowledge level produce significant differences in the two types of literacy?
(4) Is there a significant relationship between gender and (a) self-reported AI knowledge level and (b) belief in AI's future impact?
(5) To what extent do digital literacy, gender, age, and frequency of internet use predict AI literacy?

These questions translate into the following hypotheses:

- H1 (non-directional): University students' digital and AI literacy levels will fall in the moderate-to-high range.
- H2 (directional): Digital literacy and AI literacy will be positively and significantly correlated.

- H3a (non-directional): There will be a significant gender difference in digital literacy.
- H3b (non-directional): There will be no significant gender difference in AI literacy.
- H3c (non-directional): AI knowledge level will be associated with significant differences in both digital and AI literacy.
- H4a (non-directional): Gender will be significantly associated with self-rated AI knowledge level.
- H4b (non-directional, null expected): Gender will not be significantly associated with belief in AI's future impact.
- H5 (directional): Digital literacy will be a significant positive predictor of AI literacy.

Beyond its empirical contribution to the Turkish literature, the study aims to inform interventions that aim to close the gap between awareness of AI and real understanding of it among university students.

Literature Review

Digital Literacy: Conceptual Framework and Development

Eshet-Alkalai (2004) described digital literacy as a set of survival skills for digital environments, spanning photo-visual, reproduction, branching, information, and socio-emotional components, thereby demonstrating that the construct extends well beyond technical know-how. Ng (2012) later condensed this richer picture into three overlapping domains, technical, cognitive, and socio-emotional, and the scale built on that model has since been used widely in international and Turkish research. At the policy level, the DigComp 2.2 framework (Vuorikari et al., 2022) sets out 21 sub-competencies across five areas and, notably, adds indicators for how citizens engage with AI systems, drawing an explicit line between digital and AI literacy. What this well-developed literature has not settled is how far digital literacy actually functions as a precursor to these newer, AI-specific skills, a question that can only be answered by measuring the two together.

Artificial Intelligence Literacy: Definitions, Dimensions, and Frameworks

Long and Magerko (2020) identified 17 core competencies for AI literacy, covering ethical, critical, and communicative concerns. Ng et al. (2021), reviewing 30 peer-reviewed articles, grouped the construct into four areas: knowing and understanding AI, using and applying it, evaluating and creating with it, and dealing with its ethical issues. Wang et al. (2022) turned these ideas into a 12-item scale for non-expert users, covering awareness, use, evaluation, and ethics. The construct is also relevant beyond education; analysing 270 articles, Çetindamar et al. (2022) mapped AI literacy onto technological, human–machine interaction, and learning dimensions in the workforce. For all their conceptual reach, these frameworks are designed to define and measure AI literacy rather than to explain what gives rise to it.

The Relationship Between Digital Literacy and AI Literacy

That AI literacy builds on digital literacy is widely assumed. Long and Magerko (2020) state it directly, Ng et al. (2021) treat AI literacy as a competency set adapted from earlier forms of literacy, and DigComp 2.2 (Vuorikari et al., 2022) encodes the same kinship by placing AI-interaction indicators within digital competence areas. Direct evidence regarding the extent to which digital literacy predicts AI literacy remains limited. In Türkiye, Caz et al. (2024) found a significant path from digital well-being to AI literacy among 220 sport sciences students, but

digital well-being is a related construct rather than digital literacy itself. Testing the two central constructs together, in a large sample and with hierarchical regression, therefore remains largely unaddressed.

Gender and Digital/AI Skills

Hargittai and Shafer (2006) found that women and men differed little in measured online skills, yet women rated their own skills markedly lower, which suggests that gender gaps often surface in self-assessment rather than in performance. van Deursen and van Dijk (2014) showed that the divide has shifted from access toward differences in use that track gender, age, and education. Whether these patterns reappear for AI is still unclear, and the early evidence is mixed: some studies report negligible gender differences in AI literacy (Vosoughmatin, 2025), while others document sizeable gaps in AI adoption and use (Humlum & Vestergaard, 2025; Møgelvang et al., 2024). Because generative AI relies on everyday language, the traditional gender divide may narrow; whether the older gender difference in self-assessment carries over has not yet been examined closely.

Belief and Knowledge Regarding AI: The Knowledge–Belief Gap

In a national UK survey (N = 1,078), Cave et al. (2019) found that only 42% of respondents could define AI reasonably, and that familiar narratives about AI provoked considerable anxiety, suggesting that public attitudes may be shaped more by narratives than by knowledge. The same tension matters in education. Students may hold firm expectations about AI's future while understanding little of how it works, and that mix of high expectation and low knowledge can encourage uncritical use (Long & Magerko, 2020). So far, belief and knowledge have mostly been surveyed at the population level rather than examined together within university samples, which is precisely what the present study does.

Studies on Digital Literacy and AI Literacy in Türkiye

Turkish work on digital literacy measurement gathered pace in 2017, when two teams independently adapted Ng's (2012) scale (Üstündağ et al., 2017; Hamutoğlu et al., 2017). Adaptations for AI literacy followed in 2023: Çelebi et al. (2023) adapted Wang et al.'s (2022) 12-item scale, and Karaoğlan Yılmaz and Yılmaz (2023) adapted the 31-item instrument of Laupichler et al. (2023). On the substantive side, Caz et al. (2024) reported a positive link between digital well-being and AI literacy, and Elçiçek (2024), surveying 870 students, found low AI literacy that varied with gender and daily internet use. None of these studies, however, brought digital literacy and AI literacy together in one sample or tested the predictive structure between them with multivariate methods, which is the gap addressed by the present study.

Method

Research Design

The present investigation adopted a quantitative approach and used a relational survey design to examine how university students' digital and AI literacy levels are interconnected and how these competencies vary across selected demographic factors. The relational survey design belongs to the broader family of survey approaches and seeks to establish whether—and to what degree—two or more variables covary (Karasar, 2020). Accordingly, the study empirically tested both correlational links among the focal variables and between-group differences along key demographic dimensions.

Participants

Participants were recruited through online convenience and snowball sampling, with recruitment centered at Karamanoğlu Mehmetbey University, a state university situated in the Central Anatolia Region of Türkiye. Because the survey link was disseminated online, a portion of the participants may have been enrolled at other universities; institutional affiliation was not recorded in the questionnaire. Although 1,030 students initially completed the survey, the multi-stage cleaning protocol described below reduced the analytic sample to 770. As program information was collected as free text, different spellings and abbreviations referring to the same program were consolidated semantically; the final sample included students from more than 120 distinct academic programs spanning 12 faculty-level fields. Within this final sample, women constituted 70.5% (n = 543) and men 29.5% (n = 227); participants' mean age was 21.27 years (SD = 2.75), ranging from 17 to 35 years. The gender imbalance partly reflects the over-representation of programs in which female students are predominantly enrolled. The five largest programs in the sample were Early Childhood Education (n = 84; 82.1% female), Primary School Education (n = 53; 73.6% female), Elementary Mathematics Education (n = 41; 80.5% female), Nursing (n = 35; 65.7% female), and Guidance and Psychological Counseling (n = 33; 78.8% female). These five programs, together with Child Development (n = 16; 93.8% female), accounted for approximately one third of the sample (n = 262), and 78.2% of the participants in these programs were female.

Data Collection Instruments

A demographic information form and two scales were used as data collection instruments.

Digital Literacy Scale

Digital literacy was assessed using the instrument originally developed by Ng (2012), in the Turkish adaptation by Üstündağ, Güneş, and Bahçivan (2017). The scale exhibited a unidimensional structure and comprises 10 items that tap three competence domains—cognitive, socio-emotional, and technical skills. Responses are recorded on a five-point agreement scale ranging from 1 (strongly disagree) to 5 (strongly agree). The Turkish adaptation reported a total explained variance of 40% and an internal consistency coefficient of .86 (Üstündağ et al., 2017). For the current dataset, Cronbach's α reached .931, which corresponds to excellent reliability (Tavakol & Dennick, 2011).

Artificial Intelligence Literacy Scale

AI literacy was measured using the Turkish version of Wang, Rau, and Yuan's (2022) AI Literacy Scale, adapted by Çelebi, Yılmaz, Demir, and Karakuş (2023). The instrument has a four-factor structure, with twelve items distributed equally across four subscales—awareness, use, evaluation, and ethics—with three items in each subscale. The original version employs a seven-point agreement format, and three items (numbers 2, 5, and 11) require reverse coding before scoring. Çelebi et al.'s (2023) confirmatory factor analysis demonstrated acceptable fit indices in the Turkish cultural context, with an overall internal consistency coefficient of .85. For the present sample, Cronbach's α was estimated at .803.

Scale Format Conversion

Because the AI Literacy Scale was originally administered with a seven-point response format whereas the Digital Literacy Scale uses a five-point format, AI Literacy Scale scores

were converted to a five-point response metric to enable direct comparison and combined analyses across the two instruments. The conversion followed Dawes (2008), who demonstrated that 5-, 7-, and 10-point Likert scales produce similar means, standard deviations, and psychometric properties. The transformation is not a purely linear arithmetic rescaling; it is based on a mapping that preserves the semantic meaning of each response category. Specifically, the partial-agreement categories ("Kısmen Katılmıyorum" [Somewhat Disagree] and "Kısmen Katılıyorum" [Somewhat Agree]) were mapped to their semantically closest full categories rather than to the neutral midpoint. The complete mapping was as follows:

- Strongly Disagree → 1 (Strongly Disagree)
- Disagree → 2 (Disagree)
- Somewhat Disagree → 2 (Disagree)
- Neither Agree nor Disagree → 3 (Undecided)
- Somewhat Agree → 4 (Agree)
- Agree → 4 (Agree)
- Strongly Agree → 5 (Strongly Agree)

Following the conversion, the three negatively worded items of the AI Literacy Scale (items 2, 5, and 11) were reverse-coded using the formula New Score = (k + 1) − Old Score, where k = 5 for a five-point Likert scale (DeVellis, 2017).

To verify that converting the AI Literacy Scale from its original seven-point format to a five-point format did not distort the findings, the primary analyses were rerun using the original seven-point item scores. The five-point and seven-point AI-literacy composites were almost perfectly correlated ($r = .99$), and the key results were virtually unchanged: the correlation between digital literacy and AI literacy was $r = .596$ for the five-point scoring versus $r = .602$ for the seven-point scoring; in the full hierarchical model, digital literacy remained the only significant predictor, with $\beta = .599$ versus $\beta = .606$, and the explained variance was $R^2 = .357$ versus $R^2 = .364$. Although collapsing the partial-agreement categories entails a modest loss of measurement granularity, this robustness check confirms that the conversion, adopted to place both scales on a common metric, did not materially affect the substantive conclusions.

Data Preparation and Cleaning

Online survey data are routinely exposed to threats such as careless responding, duplicate submissions, and outlying observations, and these threats need to be addressed in a systematic manner (Meade & Craig, 2012). The dataset was therefore screened through a four-stage cleaning protocol, summarized in Table 1. First, two duplicate records (identical timestamps) were removed, reducing N from 1,030 to 1,028. Second, a straight-lining index was computed for each participant as the proportion of Likert responses matching the modal response; participants with a straight-lining proportion ≥ .80 across the 22 Likert items were flagged as careless responders and excluded (n = 239), following Meade and Craig (2012). Third, an initial age screen excluded participants younger than 17 (n = 8) or older than 40 (n = 6), reducing N to 775. Fourth, five additional participants aged 36–38 were excluded because their ages were substantially outside the distribution of the target sample (approximately five standard deviations above the mean), suggesting that they may not have belonged to the target undergraduate population. Mahalanobis-distance screening for multivariate outliers (Mahalanobis, 1936) flagged no additional cases beyond those already removed at earlier stages. Because all items were set as required at the collection stage, the dataset contained no missing responses for any of the 22 Likert items. The final analytic sample comprised 770

respondents. We acknowledge that the overall exclusion rate (23.2% at the straight-lining stage) is substantial; however, it is consistent with published online survey studies applying rigorous careless-responder screens, and the Cronbach's alpha values of both scales were nearly identical after duplicate removal (n = 1,028; α = .954 and .809) and in the final sample (n = 770; α = .931 and .803), indicating that the cleaning process did not systematically distort the internal structure of the scales.

Table 1. Data cleaning protocol

Stage	Procedure	Cases removed	Remaining N
1	Removal of duplicate records (identical timestamps)	2	1,028
2	Straight-line responding screen (≥ .80 identical responses across 22 items; Meade & Craig, 2012)	239	789
3	Initial age screen (younger than 17: n = 8; older than 40: n = 6)	14	775
4	Final age ceiling of 35 (cases aged 36–38; no missing data)	5	770

Note. One additional case aged 37 fell within the 36–38 range but had already been excluded at Stage 2 as a straight-line responder, so it does not appear in the Stage 4 count.

Data Analysis

All statistical procedures were carried out in IBM SPSS Statistics. An alpha level of .05 was adopted throughout, and the assumptions of parametric tests were assessed via skewness and kurtosis indices. Scale-level reliability was indexed by Cronbach's α (Cronbach, 1951). Bivariate associations were inspected through Pearson r. For dichotomous grouping variables (e.g., male vs. female), mean comparisons were performed with independent-samples t-tests; when the grouping variable had three levels, a one-way ANOVA was conducted. To assess relationships between two categorical variables, the chi-square test of association was applied. Finally, a three-step hierarchical regression was estimated to identify the predictors of AI literacy. The homogeneity of variance assumption for the ANOVAs was evaluated with Levene's test; because the assumption was violated, Tukey HSD post-hoc tests were complemented by Games–Howell comparisons, which do not assume equal variances (Field, 2018). Internal consistency coefficients were interpreted against the thresholds recommended by Tabachnick and Fidell (2013). Effect sizes were computed for all inferential tests—Cohen's d for t-tests, η^2 for ANOVAs, and Cramér's V for chi-square analyses—and interpreted following Cohen (1988).

A Priori and Sensitivity Power Analyses

Because the central analysis is the hierarchical multiple regression predicting AI literacy from digital literacy, gender, age, and frequency of internet use, an a priori power analysis was conducted in G*Power 3.1.9.7 (Faul, Erdfelder, Lang, & Buchner, 2007) using the "Linear multiple regression: Fixed model, R^2 deviation from zero" procedure. Based on a medium effect size ($f^2 = 0.15$; Cohen, 1988), α = .05, statistical power (1 − β) = .95, and four predictors, the required minimum sample size was N = 85; the achieved sample of N = 770 substantially exceeds this requirement.

In addition, a sensitivity power analysis was conducted to document the smallest effect sizes that the achieved sample could reliably detect. With $\alpha = .05$ and power = .80, the sample of N = 770 is sufficient to detect effects as small as Cohen's d = 0.222 for the independent-samples t-test ($n_1 = 227$, $n_2 = 543$), Cohen's f = 0.112 for the one-way ANOVA (k = 3), and Cohen's $f^2 = 0.016$ for the hierarchical multiple regression (four predictors). All values were computed in G*Power 3.1.9.7 using the noncentral F distribution.

Results

The following section reports the empirical findings regarding university students' digital and AI literacy levels. All analyses were based on the final dataset of 770 respondents, and the results are organized in seven tables (Tables 2–8) that mirror the research questions.

Descriptive Statistics

Descriptive statistics regarding participants' demographic characteristics and scale scores are presented in Table 2.

Table 2. Demographic characteristics and descriptive statistics

Variable	N	M	SD	Min	Max
Digital Literacy	770	3.33	0.89	1.00	5.00
AI Literacy	770	3.49	0.65	1.75	4.92
Age	770	21.27	2.75	17	35
Variable		n		%	
Gender: Male		227		29.5	
Gender: Female		543		70.5	
AI Knowledge: No knowledge		43		5.6	
AI Knowledge: Basic level		552		71.7	
AI Knowledge: Sufficient level		175		22.7	
Belief in AI's Future: Yes		655		85.1	
Belief in AI's Future: No opinion		74		9.6	
Belief in AI's Future: No		41		5.3	
Internet Use: <1 hour/day		10		1.3	
Internet Use: 1–2 hours/day		79		10.3	
Internet Use: 3–4 hours/day		314		40.8	
Internet Use: 5–6 hours/day		236		30.6	
Internet Use: ≥7 hours/day		131		17.0	

As Table 2 makes clear, mean scores on digital literacy (M = 3.33, SD = 0.89) and AI literacy (M = 3.49, SD = 0.65) fell within the moderate-to-high range when read against the five-point response metric. Respondents averaged 21.27 years of age (SD = 2.75), and women predominated in the sample (70.5%). Turning to self-rated AI knowledge, the majority of respondents (71.7%) judged their own knowledge to be at a basic level, with only 22.7%

claiming a sufficient level. At the same time, an overwhelming share (85.1%) endorsed the view that AI will play an important role in the future—an asymmetry suggesting that students' expectations of AI outstrip their present-day self-efficacy.

Table 3. Reliability of the scales

Scale	Number of Items	Cronbach's α
Digital Literacy Scale	10	.931
Artificial Intelligence Literacy Scale	12	.803

Both internal consistency estimates substantially exceed the conventional .70 threshold. The Digital Literacy Scale achieved excellent reliability (α = .931), and the AI Literacy Scale displayed very good reliability (α = .803), in line with the benchmarks of Tavakol and Dennick (2011).

Table 4. Correlations among variables

Variable	1	2	3
1. Digital Literacy	—		
2. AI Literacy	.596***	—	
3. Age	-.012	-.024	—

Note. $N = 770$. ***$p < .001$.

The analyses yielded a significant positive coefficient of large magnitude between digital literacy and AI literacy ($r = .596$, $p < .001$). Following Cohen's (1988) benchmarks—where $r \geq .50$ denotes a large effect—this result points to a substantial conceptual linkage between the two competencies.

Throughout the Results, effect sizes are interpreted using the benchmarks recommended by Cohen (1988): for Pearson's r, .10 = small, .30 = medium, and .50 = large; for Cohen's d, 0.20 = small, 0.50 = medium, and 0.80 = large; for η^2, .01 = small, .06 = medium, and .14 = large; and for Cramér's V, .10 = small, .30 = medium, and .50 = large.

Table 5. Group comparisons by gender and AI knowledge level

Variable	Group	n	M	SD	Test Statistic	p	Effect Size
Digital Literacy	Gender				t(768) = 2.54	.011*	d = 0.201
	Male	227	3.45	0.98			
	Female	543	3.28	0.85			
	AI Knowledge				F(2, 767) = 5.71	.003**	η^2 = .015
	No knowledge	43	2.90	0.75			
	Basic	552	3.37	0.80			
	Sufficient	175	3.29	1.15			
AI Literacy	Gender				t(768) = 0.40	.691	d = 0.031
	Male	227	3.51	0.72			

Variable	Group	n	M	SD	Test Statistic	p	Effect Size
	Female	543	3.49	0.62			
	AI Knowledge				F(2, 767) = 10.99	<.001***	η^2 = .028
	No knowledge	43	3.05	0.51			
	Basic	552	3.51	0.59			
	Sufficient	175	3.53	0.82			

Note. *p < .05. **p < .01. ***p < .001. *d = Cohen's d; η^2 = eta squared (Cohen, 1988).*

Independent-samples t-tests indicated a significant gender effect on digital literacy: male respondents (M = 3.45, SD = 0.98) reported higher scores than their female counterparts (M = 3.28, SD = 0.85), t(768) = 2.54, p = .011. The same comparison for AI literacy failed to reach significance, with male (M = 3.51, SD = 0.72) and female (M = 3.49, SD = 0.62) students performing at comparable levels, t(768) = 0.40, p = .691.

The corresponding effect sizes were small for digital literacy (Cohen's d = 0.201) and negligible for AI literacy (d = 0.031). For the one-way ANOVAs by AI knowledge level, Levene's test indicated heterogeneous variances for both outcomes (digital literacy: W(2, 767) = 14.36, p < .001; AI literacy: W(2, 767) = 19.24, p < .001); Tukey HSD post-hoc tests were therefore complemented by Games–Howell comparisons, which do not assume equal variances (Field, 2018), and both procedures yielded the same pattern of significance. For AI literacy, F(2, 767) = 10.99, p < .001, η^2 = .028: participants reporting no AI knowledge scored significantly lower than those with basic-level knowledge (Tukey p < .001; Games–Howell p < .001) and those with sufficient knowledge (Tukey p < .001; Games–Howell p < .001), whereas the basic and sufficient groups did not differ (Tukey p = .924; Games–Howell p = .946). For digital literacy, F(2, 767) = 5.71, p = .003, η^2 = .015: the no-knowledge group again scored significantly lower than the basic-level (Tukey p = .003; Games–Howell p = .001) and sufficient-level groups (Tukey p = .028; Games–Howell p = .022), with no difference between the basic and sufficient groups (Tukey p = .563; Games–Howell p = .677). In short, for both measures the meaningful distinction was between students with no reported AI knowledge and those reporting at least some knowledge.

Table 6. Association between gender and self-rated AI knowledge level

Variable	No knowledge	Basic	Sufficient	χ^2	df	p	V
Gender × AI Knowledge				11.05	2	.004**	.120
Male (n = 227)	8 (3.5%)	151 (66.5%)	68 (30.0%)				
Female (n = 543)	35 (6.4%)	401 (73.9%)	107 (19.7%)				

Note. **p < .01. *V = Cramér's V (Cohen, 1988).*

Table 7. Association between gender and belief in AI's future impact

Variable	Yes	No opinion	No	χ^2	df	p	V
Gender × AI Future Belief				0.32	2	.853	.020

Variable	Yes	No opinion	No	χ^2	df	p	V
Male (n = 227)	194 (85.5%)	20 (8.8%)	13 (5.7%)				
Female (n = 543)	461 (84.9%)	54 (9.9%)	28 (5.2%)				

A chi-square test of association produced a significant link between gender and self-rated AI knowledge, $\chi^2(2, N = 770) = 11.05$, $p = .004$, Cramér's V = .120, a small effect. Whereas 30.0% of male respondents categorized their AI knowledge as sufficient, only 19.7% of female respondents did so. The same test applied to gender and belief in AI's future impact yielded no significant relationship, $\chi^2(2, N = 770) = 0.32$, $p = .853$, Cramér's V = .020, a negligible effect.

Table 8. Variables predicting AI literacy (Hierarchical Regression)

Model	Predictor	B	SE	β	t	p	R^2	ΔR^2	F
1	Constant	2.045	0.073	—	28.07	<.001	.355	—	422.57***
	Digital Literacy	0.435	0.021	.596***	20.56	<.001			
2	Constant	2.015	0.184	—	10.93	<.001	.357	.002	141.62***
	Digital Literacy	0.437	0.021	.599***	20.59	<.001			
	Gender	0.057	0.042	.040	1.36	.173			
	Age	−0.004	0.007	−.015	−0.51	.609			
3	Constant	2.021	0.199	—	10.15	<.001	.357	.000	106.08***
	Digital Literacy	0.437	0.021	.599***	20.45	<.001			
	Gender	0.057	0.042	.040	1.36	.173			
	Age	−0.004	0.007	−.015	−0.52	.605			
	Frequency of Internet Use	−0.001	0.020	−.002	−0.07	.940			

Note. $N = 770$. Dependent variable: AI Literacy. ***$p < .001$. *B = unstandardized regression coefficient; SE = standard error; β = standardized coefficient.*

Model 1 demonstrates that digital literacy on its own accounted for 35.5% of the variance in AI literacy, $F(1, 768) = 422.57$, $p < .001$. The addition of gender and age in Model 2, and frequency of internet use in Model 3, produced no meaningful incremental contribution. Across all three specifications, digital literacy remained the only significant predictor ($\beta = .596–.599$, $p < .001$). Collinearity diagnostics were well within acceptable bounds: tolerance values ranged between .98 and 1.00, and VIFs between 1.00 and 1.02.

Three principal patterns emerge from the present results. First, the two literacies were strongly and positively linked ($r = .596$, $p < .001$), and digital literacy emerged as the leading predictor, explaining approximately one third of the variance in AI literacy. Second, a gender difference favoring male students appeared in digital literacy ($p = .011$) but was not observed when AI literacy was examined ($p = .691$). Third, an overwhelming majority of respondents (85.1%) endorsed belief in AI's future relevance, yet only 22.7% considered their own AI knowledge adequate; this knowledge–belief discrepancy differed significantly by gender in terms of self-rated AI knowledge ($\chi^2 = 11.05$, $p = .004$). Taken together, these results supported all of the study's hypotheses (H1–H5), including the null expectation stated in H4b.

Discussion

This study examined the relationship between university students' digital literacy and AI literacy levels with the aim of empirically uncovering two critical phenomena: how the traditional digital gender divide behaves specifically in the context of AI, and the discrepancy between belief in AI and self-reported levels of knowledge about it.

The first central finding concerns a positive and significant association of large magnitude between digital literacy and AI literacy ($r = .596$, $p < .001$). Following Cohen's (1988) benchmarks, this coefficient falls within the large-effect range and signals a meaningful conceptual linkage between the two constructs. Of greater consequence, the hierarchical regression revealed that digital literacy by itself accounted for 35.5% of the variance in AI literacy ($\beta = .596$, $p < .001$), while gender, age, and frequency of internet use added no meaningful explanatory power. Thus, digital literacy emerged as the only significant predictor of AI literacy. This pattern provides empirical support for a long-standing conceptual claim that has rarely been tested directly. Ng et al. (2021) frame AI literacy as a continuation of digital literacy, whereas Long and Magerko (2020) characterize them as related yet distinguishable competency clusters. At the policy level, the European Commission's DigComp 2.2 framework (Vuorikari et al., 2022) institutionalizes this conceptual kinship by embedding AI-interaction indicators within the domains of digital competence.

Nevertheless, the fact that the explained variance remains at 35.5% indicates that AI literacy carries distinctive components that cannot be reduced to digital literacy. The remaining 64.5% of the variance may reflect additional factors, such as ethical awareness, AI-specific conceptual understanding, critical evaluation skills, and applied experience (Long & Magerko, 2020; Wang et al., 2022). Consistent with this view, Işık and Çamur (2024) demonstrated that digital literacy plays a significant mediating role in the effect of academics' positive AI attitudes on academic effort.

Among the most striking results of the present study is the observation that, while a gender effect favoring male students surfaced for digital literacy ($p = .011$), the same effect was absent for AI literacy ($p = .691$). This contrast provides empirical support for what we describe as the "gender paradox." We use the term "gender paradox" purely as a descriptive label for this observed pattern — a small gender difference in digital literacy ($d = 0.201$) coexisting with a negligible difference in AI literacy ($d = 0.031$) — rather than as a claim of an established or theoretically defined paradox in the literature. One plausible reading of the paradox lies in the natural-language interaction style of generative AI tools. Conventional digital skills tend to presuppose advanced technical competencies that have historically been associated with male users; by contrast, conversational systems rely on everyday language, lowering the technical threshold for entry. In line with this interpretation, Vosoughmatin (2025) reported only limited gender differences in AI literacy.

However, the international literature also contains evidence to the contrary. In a large-scale study by Humlum and Vestergaard (2025) conducted with 18,000 Danish workers, women were found to be 16 percentage points less likely than men in the same occupation to use ChatGPT. Similarly, Møgelvang et al. (2024) reported that men used generative AI not only more frequently but also for a wider range of purposes. Reports prepared by UNESCO indicate that women's digital technology use skills are approximately 25% lower than those of men (UNESCO, n.d.). It is plausible that this digital literacy gap is reflected in the rate of AI tool adoption. These conflicting findings suggest that gender differences may be context-sensitive and that cultural, educational, and institutional factors may moderate this relationship.

Another important dimension of the gender-related findings is the gender difference in self-reported knowledge level. The results show that 30.0% of male students considered themselves to have sufficient AI knowledge, whereas this proportion remained at 19.7% among female students; the proportion of women reporting no knowledge at all (6.4%) was nearly twice that of men (3.5%) ($\chi^2 = 11.05$, $p = .004$). This finding closely parallels the results reported by Hargittai and Shafer (2006). Recent research indicates that gender differences in AI self-efficacy persist independently of actual AI literacy levels and that such differences can be closed through educational interventions (Cheng et al., 2025; Kong & Yang, 2025).

The third principal finding of the study is that, although 85.1% of participants reported believing in AI's future impact, only 22.7% regarded themselves as sufficiently knowledgeable. This 62.4-percentage-point gap is a striking indicator of what we conceptualize as the "knowledge–belief gap." This finding aligns with the national survey study conducted by Cave et al. (2019) in the United Kingdom. Indeed, a recent study likewise emphasized that the relationship between individuals' AI awareness and AI-related beliefs varies significantly across social groups (Selwyn & Gallo Cordoba, 2022). The intersection of the knowledge–belief gap with gender is also noteworthy. The absence of gender differences at the level of belief (women: 84.9%; men: 85.5%; $p = .853$) alongside the emergence of significant differences at the level of knowledge indicates that female students may exhibit the "believing without knowing" pattern more strongly than do their male counterparts. This asymmetry suggests that AI education interventions should be designed in a gender-sensitive manner.

In the present study, age was not significantly related either to digital literacy ($r = -.012$, $p > .05$) or to AI literacy ($r = -.024$, $p > .05$). Frequency of internet use likewise did not emerge as a significant predictor of AI literacy ($\Delta R^2 = .000$). This finding is consistent with approaches in the digital divide literature that emphasize the determining role of "quality of use" rather than "quantity of use" (van Deursen & van Dijk, 2014).

Conclusion

By probing the interrelationship between university students' digital and AI literacy levels, the present investigation offers three principal contributions to the literature. First, it provides empirical evidence that digital literacy stands as the most robust and consistent antecedent of AI literacy. On its own, digital literacy explains 35.5% of the variance in AI literacy, while demographic factors—gender, age, and frequency of internet use—add nothing of substance to this predictive structure. The implication is that educational efforts targeting AI literacy in higher education should be anchored, above all, in the strengthening of foundational digital literacy.

Second, this study empirically documents a phenomenon that may be termed the "gender paradox": while the traditional digital gender divide persists in digital literacy, no significant gender difference is observed in AI literacy. At the same time, the presence of contrary evidence in the international literature (Humlum & Vestergaard, 2025; Møgelvang et al., 2024) indicates that the gender gap is context-sensitive and that cultural, institutional, and educational factors moderate this relationship.

Third, this study reveals the existence of a striking phenomenon that we conceptualize as the "knowledge–belief gap" with respect to AI: while 85.1% of students believe in AI's future impact, only 22.7% consider themselves sufficiently knowledgeable. This 62.4-percentage-point gap carries the risk of normalizing a belief lacking critical evaluation and underscores the need to balance awareness and knowledge in AI education.

In light of these findings, the following recommendations may be offered to higher education institutions: (a) strengthening the digital literacy foundation — motivated by the strong correlation between digital and AI literacy ($r = .596$, $p < .001$) and the finding that digital literacy explains 35.5% of the variance in AI literacy; (b) providing critical AI literacy education designed to close the knowledge–belief gap — motivated by the contrast between 85.1% belief in AI's future impact and only 22.7% reporting sufficient AI knowledge; and (c) implementing gender-sensitive self-efficacy support programs in AI education — motivated by the pattern in which a small gender difference in digital literacy ($d = 0.201$) coexists with no gender difference in AI literacy ($d = 0.031$), while women remain less likely to rate their own AI knowledge as sufficient. For future research, it is recommended that the underlying mechanisms of the knowledge–belief gap be investigated through qualitative methods; that the gender paradox be tested in different cultural contexts; that mixed-methods research be conducted; and that causal direction be tested through longitudinal designs.

Limitations

Several caveats should be borne in mind when interpreting the present results. First, the sample is markedly skewed toward women (70.5% female vs. 29.5% male), and gender-based comparisons may therefore be affected by unequal representation. Sensitivity power analyses nevertheless indicate that the achieved sample provides adequate power to detect gender effects as small as $d = 0.222$; the negligible gender effect observed for AI literacy ($d = 0.031$) should therefore be interpreted as a substantive finding rather than an artifact of insufficient statistical power. Second, recruitment through convenience sampling and online administration constrains the external validity of the findings. In addition, because the survey link was distributed online through snowball sampling and institutional affiliation was not recorded, the sample may include students from more than one institution; generalizations to a single institution should therefore be made with caution. Third, the cross-sectional design rules out causal inferences regarding the relationships among the variables. Fourth, the exclusion of 239 respondents (23.2%) via the straight-line response check may itself have altered the representativeness of the final analytic sample. However, the near-identical reliability coefficients before and after filtering (see Method) suggest that the internal structure of the scales was not distorted by this exclusion. Fifth, rescaling the AI Literacy Scale from a seven-point to a five-point format may have resulted in some loss of measurement precision. Finally, both literacy measures depend on self-report; subsequent studies could enrich the evidence base by incorporating performance-based tasks.

Declarations

Acknowledgments:
The authors would like to thank the participants who voluntarily took part in this study.
Funding:
This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.
Ethics Statements:
Ethical approval for this study was obtained from the Social and Human Sciences Research Ethics Committee of Karamanoğlu Mehmetbey University. The study was conducted in accordance with the principles of the Declaration of Helsinki. All procedures involving human participants were in line with the ethical standards of the institutional research committee.
Conflict of Interest:
The authors declare that they have no conflict of interest.

Informed Consent:
Informed consent was obtained from all individual adult participants included in the study prior to data collection. Participants were informed about the purpose of the research, the voluntary nature of participation, their right to withdraw at any time without consequence, and the anonymous and confidential handling of their responses. Consent was indicated through participants' voluntary completion of the online questionnaire after reading the informed consent statement on the first page.

Data availability:
The datasets generated and analyzed during the current study are not publicly available due to participant privacy considerations but are available from the corresponding author upon reasonable request and subject to ethical approval.

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