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Artificial Intelligence Knowledge, Attitudes, Awareness, and Anxiety Among University Students at a Regional Turkish University: A Cross-Sectional Study

Bölgesel Bir Türk Üniversitesinde Öğrenim Gören Üniversite Öğrencilerinin Yapay Zekâya İlişkin Bilgi Düzeyleri, Tutumları, Farkındalıkları ve Kaygıları: Kesitsel Bir Çalışma

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Abstract

The rapid integration of artificial intelligence (AI) into higher education necessitates a systematic examination of students' psychological and attitudinal perceptions toward AI. This study aimed to investigate university students' levels of AI-related knowledge, awareness, attitudes, and anxiety, and to determine whether these constructs differ according to gender, age, educational level, daily internet use duration, and AI tool usage status. The study employed a quantitative cross-sectional survey design. The sample consisted of 176 undergraduate and graduate students (111 females, 65 males; Mage = 28.74, SD = 9.24) enrolled at Ağrı İbrahim Çeçen University during the 2025-2026 academic year. Data were collected using the Artificial Intelligence Scale developed by Süleymanoğulları et al. (2024), a 25-item instrument comprising three sub-dimensions (Interaction, Pervasive Impact, and Anxiety) with high internal consistency (Cronbach's $\alpha = .869$). A priori power analysis (G*Power 3.1; Cohen's $f = 0.25$, $\alpha = .05$, $1-\beta = .80$) indicated an adequate total sample size, though group-level adequacy varied. Independent-samples t-tests, one-way ANOVA, Tukey HSD post-hoc analyses, and Pearson correlation analyses were conducted. The findings revealed that female students reported significantly higher levels of AI anxiety than male students ($p = .032$, $d = 0.34$). Age was positively associated with both the Interaction and Pervasive Impact sub-dimensions. Graduate students demonstrated significantly higher Interaction scores than undergraduate students ($p < .001$, $\eta^2p = .13$). Daily internet use duration was positively related to Pervasive Impact awareness. In contrast, AI tool usage status did not produce statistically significant differences across any sub-dimension. Overall, the findings suggest that structural factors, such as educational level, age, and gender-based socialization, play a more influential role in shaping AI perceptions than mere exposure to AI tools.

Keywords: Artificial intelligence attitudes; AI anxiety; AI literacy; university students; Technology Acceptance Model; quantitative survey.

Özet

Yapay zekânın (YZ) yükseköğretime hızla entegre edilmesi, öğrencilerin YZ'ye yönelik psikolojik ve tutumsal algılarının sistematik biçimde incelenmesini gerekli kılmaktadır. Bu çalışma, üniversite öğrencilerinin yapay zekâya ilişkin bilgi, farkındalık, tutum ve kaygı düzeylerini incelemeyi ve bu yapıların cinsiyet, yaş, eğitim düzeyi, günlük internet kullanım süresi ve YZ araçlarını kullanma durumuna göre farklılaşıp farklılaşmadığını belirlemeyi amaçlamaktadır. Nicel kesitsel tarama modelinde yürütülen araştırmaya, 2025-2026 eğitim-öğretim yılında Ağrı İbrahim Çeçen Üniversitesi'nde öğrenim gören 176 lisans ve lisansüstü öğrenci (111 kadın, 65 erkek; Ortalama yaş = 28.74, SS = 9.24) katılmıştır. Veriler, Süleymanoğulları vd. (2024) tarafından geliştirilen, üç alt boyuttan (Etkileşim, Yaygın Etki, Kaygı) oluşan 25 maddelik Yapay Zekâ Ölçeği ile toplanmıştır (Cronbach's $\alpha = .869$). Güç analizi (G*Power 3.1; Cohen's $f = 0.25$, $\alpha = .05$, $1-\beta = .80$), toplam örneklem büyüklüğünün yeterli olduğunu ancak grup düzeyindeki yeterliliğin değişkenlik gösterdiğini ortaya koymuştur. Verilerin analizinde bağımsız örneklemler t-testi, tek yönlü ANOVA, Tukey HSD ve Pearson korelasyon analizleri kullanılmıştır. Bulgular, kadın öğrencilerin yapay zekâ kaygısının erkeklerden anlamlı düzeyde yüksek olduğunu göstermiştir ($p = .032$, $d = 0.34$). Yaş değişkeni, etkileşim ve yaygın etki alt boyutlarıyla pozitif yönde ilişkili bulunmuştur. Lisansüstü öğrencilerin etkileşim puanları lisans öğrencilerinden anlamlı düzeyde yüksektir ($p < .001$, $\eta^2p = .13$). Günlük internet kullanım süresi yaygın etki alt boyutuyla pozitif ilişki göstermiştir. Buna karşın, YZ araçlarını kullanma durumu hiçbir alt boyutta anlamlı farklılık oluşturmamıştır. Bulgular, YZ algılarında araç kullanımından ziyade eğitim düzeyi, yaş ve toplumsal cinsiyet temelli yapısal faktörlerin daha belirleyici olduğunu göstermektedir.

Anahtar Kelimeler: Yapay zekâ tutumları; yapay zekâ kaygısı; yapay zekâ okuryazarlığı; üniversite öğrencileri; Teknoloji Kabul Modeli; nicel tarama araştırması.

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INTRODUCTION

Although AI technologies are increasingly embedded within higher education ecosystems, current scholarship has disproportionately emphasized technological affordances and instructional efficiency, while offering comparatively limited insight into students' psychological adaptation and attitudinal responses to AI-mediated learning environments. This limitation becomes especially pronounced in regional and resource-constrained university settings, where disparities in digital readiness and AI literacy may substantially shape students' educational experiences (Zawacki-Richter et al., 2019; Hwang et al., 2020). Yet the efficacy of this technological integration is not determined solely by the sophistication of the systems deployed; it is fundamentally mediated by the cognitive, affective, and behavioral orientations that students bring to their encounters with AI (Davis, 1989; Venkatesh et al., 2003; Çakır & Çatıkkaş, 2025).

University students constitute a theoretically significant population for studying AI perceptions for several reasons. First, they represent the leading cohort of future professional practitioners who will design, implement, and critique AI systems across domains. Second, they occupy an institutional context -the university- that is itself undergoing structural transformation due to AI-enabled pedagogies (Roll & Wylie, 2016; Çakır et al., 2023; Uluca et al., 2024). Third, their AI-related attitudes, formed during this formative professional period, are likely to exhibit downstream effects on career-related technology acceptance and ethical reasoning (Shin, 2021). Accordingly, understanding the determinants of AI knowledge, awareness, attitudes, and anxiety among this population is not merely descriptive but strategically significant for educational policy and curriculum design.

The present study is anchored within the Technology Acceptance Model (TAM; Davis, 1989) and its extensions, particularly the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003). TAM posits that perceived usefulness and perceived ease of use are the primary cognitive antecedents of behavioral intention to adopt a technology, while UTAUT extends this framework to incorporate social influence, facilitating conditions, and individual difference moderators including gender, age, and experience. Applied to AI specifically, Schepman and Rodway (2020) proposed that general AI attitudes comprise both positive valence (anticipation of beneficial applications) and negative valence (concern about risks and displacement), and demonstrated that these orthogonal dimensions predict technology-specific behaviors independently.

Complementing these adoption-focused frameworks, the construct of AI anxiety - defined as a domain-specific form of techno-anxiety characterized by apprehension about AI-powered systems, their unpredictability, and their socioeconomic consequences (Mitzner et al., 2018; Wang et al., 2023) -has emerged as a theoretically distinct and practically important variable. Unlike general computer anxiety, AI anxiety encompasses concerns about algorithmic decision-making, surveillance, labor displacement, and the opacity of machine learning systems (Brynjolfsson & McAfee, 2014; Bostrom, 2014). Its relationship to knowledge and awareness is complex and contested: some studies report an inverse association (greater knowledge, lower anxiety;

Chatterjee & Sinha, 2022), while others find that increased AI awareness paradoxically heightens concern among informed populations (Guo et al., 2021).

A systematic review of 146 empirical studies by Zawacki-Richter et al. (2019) identified that AI research in higher education has concentrated disproportionately on system effectiveness and learning outcomes, with comparatively scant attention to students' subjective AI perceptions. Studies that do examine perceptions tend to assess single constructs (typically attitudes or anxiety in isolation), employ non-validated measures, or confine analyses to single disciplines -most commonly computer science and engineering -thereby limiting generalizability to broader student populations (Hwang et al., 2020; Luan et al., 2020).

With respect to gender, a pattern of higher AI anxiety among women has been reported across multiple national contexts (Howard & Dai, 2022; Wang & Wang, 2022), though findings are not universal. Savaş et al. (2023), examining sport sciences students, found no significant gender differences in AI anxiety, suggesting that disciplinary culture and peer environment may moderate gender effects. The mechanisms underlying gender differences -whether reflecting differential technology self-efficacy, occupational concern, or sociocultural gender-role expectations -remain under-theorized.

The relationship between age and AI perceptions has received inconsistent treatment. Gunkel (2020) proposed that older individuals may exhibit greater resistance due to lower technology self-efficacy, while Laupichler et al. (2022) demonstrated a positive association between age and AI awareness among graduate student populations, attributing this to accumulation of domain-specific knowledge through academic study. These contrasting findings underscore the need to examine age-AI perception relationships within stratified educational level samples.

Perhaps most counterintuitive is the emerging evidence that actual AI tool usage does not reliably predict more positive or more informed AI attitudes. Tundrea (2020) argued that passive, instrumentalized use of AI-powered tools (e.g., recommendation algorithms, autocomplete systems) proceeds without users developing conceptual understanding of underlying mechanisms, thereby failing to generate the epistemic foundations necessary for meaningful attitudinal change. This hypothesis, if supported, has profound implications for educational technology policy that assumes exposure-based benefits.

Against this background, three principal research gaps motivate the present investigation: (1) the joint examination of knowledge, awareness, attitudes, and anxiety within a psychometrically validated unified instrument is rare in Turkish higher education contexts; (2) the simultaneous analysis of multiple demographic and behavioral predictors allows examination of their independent contributions, which is methodologically superior to bivariate analyses conducted in isolation; and (3) the inclusion of AI tool adoption status as a predictor enables direct empirical testing of the exposure-benefit assumption. The present study therefore aims to address these gaps through a rigorously designed quantitative cross-sectional survey.

Research Questions and Hypotheses

The following research questions and corresponding directional hypotheses were formulated a priori:

- R_{Q1}: Do gender differences exist in AI-related interaction, pervasive impact awareness, and anxiety among university students?
- H_{1a}: Female students will report significantly higher AI Anxiety scores than male students.
- H_{1b}: No significant gender differences will be observed in Interaction and Pervasive Impact dimensions.
- R_{Q2}: Are age and daily internet use duration positively associated with AI-related perceptions?
- H_2: Age and internet use duration will exhibit significant positive correlations with Interaction and Pervasive Impact sub-dimensions.
- R_{Q3}: Do AI perceptions differ as a function of educational level?
- H_3: Graduate students will score significantly higher than undergraduates on the Interaction sub-dimension.
- R_{Q4}: Does AI tool adoption status predict differential AI perceptions?
- H_4 (null): AI tool usage will not significantly predict differences in any sub-dimension, consistent with the passive-use hypothesis.

METHODS

Study Design

This investigation employed a quantitative cross-sectional survey design. Cross-sectional designs are appropriate when the research objective is the systematic description of population characteristics at a single time point and the examination of associations between variables (Creswell & Creswell, 2018).

Participants and Sampling

The target population comprised all students enrolled at Ağrı İbrahim Çeçen University during the 2025-2026 academic year (approximate N = 16,000). Participants were recruited via convenience sampling across five faculties and one graduate institute: the Faculty of Sports Sciences, the Faculty of Economics and Business Administration, the Faculty of Education, the Faculty of Pharmacy, the Vocational School, and the Graduate School of Sciences. Convenience sampling was selected based on practical access constraints; this approach is appropriate for exploratory investigations and is widely used in analogous student-population survey research (Creswell & Creswell, 2018). Recruitment was voluntary, and no compensation was provided.

The final analytical sample consisted of N = 176 participants (111 women [63.1%], 65 men [36.9%]; M_{age} = 28.74 years, SD = 9.24, range: 15-38). Educational level distribution was: associate degree students n = 10 (5.7%), undergraduate students n = 103 (58.5%), and graduate students n = 63 (35.8%). Mean daily internet use was 4.57 hours (SD = 2.28, range: 1-16 h). A total of 121 participants (68.8%) reported current use of at least one AI-powered tool, while 55 (31.2%) indicated non-usage.

Statistical Power Analysis

A formal a priori power analysis was conducted using G*Power 3.1 (Faul et al., 2007) to determine the minimum sample size required at conventional significance ($\alpha = .05$) and statistical power ($1-\beta = .80$) levels. For independent-samples t-tests (R_{Q1}, R_{Q4}), a medium effect size (Cohen's d = 0.50) was assumed, consistent with prior research on AI attitudes and anxiety (Howard & Dai, 2022; Wang & Wang, 2022). The analysis indicated a minimum of 64 participants per group (N = 128). The final sample (N = 176; 111 females, 65 males) exceeded this threshold and provided adequate power ($1-\beta \approx .83$) for detecting medium-sized gender differences. For one-way ANOVA analyses (R_{Q3}), a medium effect size (Cohen's f = 0.25) across three educational groups was assumed (Chatterjee & Sinha, 2022), yielding a required sample size of N = 159. Although the overall sample size was sufficient, the associate degree subgroup (n = 10) was substantially underpowered ($1-\beta \approx .27$). Accordingly, findings related to this subgroup were interpreted cautiously and treated as preliminary. In contrast, the undergraduate (n = 103) and graduate (n = 63) groups met acceptable power requirements for theoretically relevant comparisons. For Pearson correlation analyses (R_{Q2}), detecting a small-to-medium effect size (r = .20) required N = 197 for .80 power, whereas N = 138 was sufficient for .70 power. The present sample (N = 176) yielded an estimated power of approximately .74, which was considered acceptable given the exploratory nature of the correlational analyses, although small effects should be interpreted cautiously.

Data Collection Tools

The Artificial Intelligence Scale (AIS; Süleymanoğulları et al., 2024) was employed as the primary data collection instrument. The AIS is a 25-item, five-point Likert-type measure (1 = strongly disagree, 5 = strongly agree) comprising three theoretically and empirically derived sub-dimensions. The Interaction sub-dimension (8 items) assesses respondents' self-reported knowledge of artificial intelligence, familiarity with AI technologies, active use of AI-supported tools, engagement with AI-related developments, and perceived competence in utilizing AI in daily and educational contexts. The Pervasive Impact sub-dimension (10 items) evaluates beliefs and awareness regarding the broad societal, economic, and functional impacts of AI, including its perceived contributions to efficiency, productivity, flexibility, economic development, and future societal transformation. The Anxiety sub-dimension (7 items) measures AI-related concerns and apprehensions, including fears associated with job displacement, loss of human control, technological dependency, ethical misuse, and potential threats posed by AI systems.

The scale contains no reverse-scored items; higher scores on all sub-dimensions indicate higher levels of the respective construct. Sub-dimension scores are computed as item means (range: 1-5). The original developers reported satisfactory internal consistency (Cronbach's $\alpha = .869$ for the full scale) and confirmatory factor analytic support for the three-factor structure (CFI = .936, RMSEA = .059; Süleymanoğulları et al., 2024). In the present sample, reliability was Cronbach's $\alpha = .88$ (full scale), with sub-dimension alphas of $\alpha = .84$ (Interaction), $\alpha = .79$ (Pervasive Impact), and $\alpha = .82$

(Anxiety). McDonald's omega (ω) was calculated as $\omega = .883$ for the full scale, providing an alternative reliability estimate that is less susceptible to violations of tau-equivalence (McNeish, 2018).

A personal information form additionally captured age (continuous), gender (binary: woman/man), educational level (associate/undergraduate/graduate), daily internet use duration (continuous, hours), and AI tool adoption status (yes/no).

Data Collection Procedure

Data were collected between November and December 2025 through structured questionnaires administered via Google Forms. 'Participants were fully informed about the voluntary nature of participation, anonymity, confidentiality, and their unconditional right to withdraw at any stage without consequence. Completed surveys were screened for careless responding using longstring analysis and within-person response standard deviations; no surveys met exclusion criteria. The final dataset of N = 176 represented a response rate of approximately 89% of distributed questionnaires (N = 198 distributed; 22 excluded due to incompleteness).

Statistical Analysis

All analyses were performed in R software (v.4.4.2; R Foundation for Statistical Computing, Vienna, Austria) using the *stats*, *psych*, and *effectsize* packages. The significance threshold was set at $\alpha = .05$ (two-tailed) for all tests. Normality of continuous variables was evaluated via Shapiro-Wilk tests (recommended for $N \leq 2000$; Razali & Wah, 2011), examination of Q-Q plots, and inspection of skewness and excess kurtosis values; all fell within acceptable ranges (|skewness| <1.0, |kurtosis| <1.5; Tabachnick & Fidell, 2013), supporting the use of parametric procedures.

Independent-samples t-tests were used to compare gender and AI tool adoption groups across sub-dimensions. The homogeneity of variance assumption was assessed via Levene's test; Welch-corrected degrees of freedom were applied when violated. Effect sizes were quantified using Cohen's d with 95% confidence intervals obtained via non-central t-distribution (Cumming, 2014). One-way ANOVA was employed to examine educational level differences, followed by Tukey's Honestly Significant Difference (HSD) post-hoc test to control family-wise error rate. Partial eta-squared ($\eta^2 p$) was computed as the ANOVA effect size metric. Pearson product-moment correlations quantified bivariate linear associations for continuous predictors; the coefficient of determination (r^2) is reported to facilitate interpretation of practical significance. The Bonferroni correction was applied to control for Type I error inflation across the three sub-dimension comparisons within each analysis family (adjusted $\alpha = .017$).

Results

Descriptive Statistics and Normality

Table 1 presents descriptive statistics and normality indices for all study variables.

Table 1. Descriptive Statistics, Internal Consistency, and Normality Indices for the AIS Sub-dimensions

Sub-dimension	n	M	SD	Min	Max	α	ω	Skewness	Kurtosis
Interaction	176	2.97	0.96	1.00	5.00	.84	.85	.23	−.55
Pervasive Impact	176	3.69	0.78	1.00	5.00	.79	.80	−.41	−.40
Anxiety	176	3.47	0.89	1.00	5.00	.82	.83	−.30	−.43
Full Scale	176	3.36	0.71	1.40	5.00	.88	.88	−.18	−.39

M = mean; SD = standard deviation; α = Cronbach's alpha; ω = McDonald's omega. All Shapiro-Wilk tests indicated non-significant departures from normality (p> .05). Skewness and kurtosis values fall within the ±1.5 thresholds recommended by Tabachnick and Fidell (2013). Sub-dimension scores represent item means (scale: 1–5).

As shown in Table 1, the AIS sub-dimensions and the full scale demonstrated acceptable-to-high internal consistency, with Cronbach's alpha coefficients ranging from .79 to .88 (full scale α = .878) and McDonald's omega coefficients ranging from .80 to .88, while skewness and kurtosis values indicated that all variables were approximately normally distributed.

Gender Differences in AI Perceptions (R_{Q1})

Independent-samples t-tests were conducted to compare men and women on all three AIS sub-dimensions. Results are presented in Table 2.

Table 2. Independent-Samples t-Test Results for Gender Differences in AIS Sub-dimensions

Sub-dimension	Women (n = 111) M (SD)	Men (n = 65) M (SD)	t(174)	p	d	95% CI [d]	Hypothesis
Interaction	2.93 (0.94)	3.11 (0.99)	−1.20	.230	−0.19	[−0.49, 0.12]	Supported (H1b)
Pervasive Impact	3.66 (0.77)	3.74 (0.82)	−0.62	.537	−0.10	[−0.40, 0.21]	Supported (H1b)
Anxiety	3.57 (0.89)	3.27 (0.89)	2.16	.032*	0.34	[0.03, 0.65]	Supported (H1a)

**p <.05 (uncorrected). CI = confidence interval around Cohen's d. Bonferroni-corrected significance threshold: p <.017. The Anxiety comparison (p = .032) does not survive Bonferroni correction.*

Consistent with H1a, female students reported significantly higher AI Anxiety than male students (t(174) = 2.16, p = .032, d = 0.34), representing a small-to-medium effect. The 95% confidence interval for d [0.03, 0.65] is wide and excludes zero, though the interval extends close to zero on its lower bound, indicating that the true population effect may be small. Consistent with H1b, no significant gender differences were observed for Interaction (p = .230) or Pervasive Impact (p = .537), with effect sizes in the negligible range (d <0.20). Levene's test supported the assumption of homogeneity of variance across all comparisons (all p> .10).

Correlations of Age and Internet Use with AI Perceptions (R_{Q2})

Pearson product-moment correlations between continuous predictor variables (age, daily internet use duration) and AIS sub-dimensions are presented in Table 3.

Table 3. Pearson Correlation Matrix: Age, Internet Use Duration, and AIS Sub-dimensions

Variable	1	2	3	4	5	M	SD
1. Age	-					28.74	9.24
2. Internet Use (h/day)	.08	-				4.57	2.28
3. Interaction	.25**	.12	-			2.97	0.96
4. Pervasive Impact	.17*	.20**	.51**	-		3.69	0.78
5. Anxiety	−.05	.12	−.15*	−.10	-	3.47	0.89

**p <.05. **p <.01. Bonferroni-corrected threshold for age–sub-dimension comparisons: p <.017; corrected threshold for internet use-sub-dimension comparisons: p < .017. Age–Interaction (r = .25, p = .001) and Internet Use–Pervasive Impact (r = .20, p = .007) survive correction. Age-Pervasive Impact (r = .17, p = .027) does not survive correction. Interaction-Anxiety correlation (r = −.15, p = .048) is exploratory.*

In partial support of H2, age was significantly and positively correlated with Interaction (r = .25, p = .001, r^2 = .06) and Pervasive Impact (r = .17, p = .027, r^2 = .03). The Interaction-Age association survived Bonferroni correction (p <.017), whereas the Pervasive Impact-Age association did not. Daily internet use duration was significantly associated with Pervasive Impact (r = .20, p = .007, r^2 = .04), which survived Bonferroni correction. Neither age nor internet use was significantly associated with Anxiety (r =-.05 and r = .12, respectively; both p> .10). The moderate positive intercorrelation between Interaction and Pervasive Impact (r = .51, p <.001) indicates substantive construct overlap, yet their differential predictor profiles -particularly the distinct roles of age and internet use duration -support the discriminant utility of treating them as separate sub-dimensions

Educational Level Differences in AI Perceptions (R_{Q3})

One-way ANOVA was conducted to examine educational level (associate, undergraduate, graduate) differences across AIS sub-dimensions. Table 4 presents group means, standard deviations, and inferential statistics, including post-hoc comparisons.

Table 4. One-Way ANOVA Results: Educational Level Differences in AIS Sub-dimensions with Post-Hoc Comparisons

Sub-dimension	Associate (n=10) M (SD)	Undergraduate (n=103) M (SD)	Graduate (n=63) M (SD)	F (2,173)	p	η^2p	Sig. Pairs (Tukey HSD)
Interaction	3.30 (0.91)	2.70 (0.77)	3.42 (1.07)	13.21	<.001**	.13	GR> UG†
Pervasive Impact	3.66 (0.60)	3.58 (0.76)	3.88 (0.83)	2.80	.064	.03	n.s.
Anxiety	3.70 (0.97)	3.50 (0.86)	3.37 (0.95)	0.75	.473	.01	n.s.

*η^2p = partial eta-squared. **p <.001. GR = Graduate; UG = Undergraduate; n.s. = non-significant. †Tukey HSD post-hoc test confirmed Graduate> Undergraduate (mean difference = 0.72, SE = 0.14, p <.001, d = 0.74, 95% CI [0.42, 1.02]). The Associate degree group (n = 10) demonstrated insufficient statistical power (~.27) for reliable comparison; accordingly, post-hoc comparisons involving this group are not interpreted. The Pervasive Impact comparison approached but did not reach significance (p = .064), and the small η^2p = .03 suggests negligible practical effect.*

Results supported H3. A significant educational level effect was found for the Interaction sub-dimension (F (2, 173) = 13.21, p <.001, η^2p = .13), reflecting a medium-large effect. Tukey HSD post-hoc analysis confirmed that graduate students scored significantly higher than undergraduates (mean difference = 0.72, SE = 0.14, p <.001, d =

0.74, 95% CI [0.42, 1.02]), indicating that graduate-level academic socialization is associated with meaningfully greater AI engagement and interaction propensity. No significant differences emerged for Pervasive Impact ($p = .064$) or Anxiety ($p = .473$).

AI Tool Adoption Status (R_{Q4})

Independent-samples t-tests compared AI tool users ($n = 121$) and non-users ($n = 55$) across sub-dimensions. Results are presented in Table 5.

Table 5. Independent-Samples t-Test Results: AI Tool Adoption Status and AIS Sub-dimensions

Sub-dimension	Users (n=121) M (SD)	Non-users (n=55) M (SD)	t (174)	p	d	95% CI [d]	Hypothesis
Interaction	3.06 (0.96)	2.88 (0.95)	1.25	.213	0.19	[−0.11, 0.49]	Supported (H_4)
Pervasive Impact	3.71 (0.83)	3.66 (0.70)	0.47	.638	0.07	[−0.23, 0.37]	Supported (H_4)
Anxiety	3.50 (0.93)	3.40 (0.84)	0.50	.616	0.11	[−0.19, 0.41]	Supported (H_4)

All 95% CIs for d cross zero, confirming null effects. No comparison approached significance at either the uncorrected ($p < .05$) or Bonferroni-corrected ($p < .017$) threshold. H4 predicted no significant differences, consistent with the passive-use hypothesis.

In full support of H4, no statistically significant differences were observed between AI tool users and non-users on any AIS sub-dimension (all $p > .20$; all $|d| < 0.20$). Confidence intervals for all effect sizes spanned zero, indicating that the data are consistent with a true null effect. This finding challenges the assumption that AI tool adoption, operationalized as binary usage status, is sufficient to produce differential AI perceptions.

Discussion

This study investigated AI-related knowledge, awareness, attitudes, and anxiety among 176 university students, examining five demographic and behavioral predictors within a unified psychometric framework. The findings collectively advance understanding of the structural determinants of AI perceptions in higher education, with several results carrying implications for theory, educational policy, and future research design.

Gender and AI Anxiety: A Differential Socialization Account

The finding that female students reported higher AI Anxiety than their male counterparts ($d = 0.34$) replicates a pattern documented in multiple international studies (Howard & Dai, 2022; Wang & Wang, 2022) and may be theoretically interpreted through the lens of gender-differentiated technology socialization. Prior scholarship suggests that STEM-related Technologies -and, by extension, AI -have historically been framed as male-dominated domains, potentially contributing to lower AI self-efficacy and elevated technology-related anxiety among women (Cheryan et al., 2017). However, whether comparable gender–STEM dynamics operate similarly within the Turkish higher education context remains unclear, given the influence of distinct cultural norms, institutional structures, and labor market conditions. Accordingly, the cross-cultural transferability of these explanatory mechanisms should not be assumed and warrants context-specific empirical investigation.

This interpretation is strengthened by the selectivity of the gender effect: women and men did not differ on Interaction or Pervasive Impact, suggesting that the anxiety difference may not be fully explained by information deficits or lower general AI awareness, may instead reflect a distinct affective response to the perceived personal threat that AI systems pose. However, interpretive caution is warranted on two grounds. First, the effect ($d = 0.34$) is small-to-medium and the finding did not survive Bonferroni correction ($p = .032$ vs. corrected $\alpha = .017$), meaning that Type I error cannot be excluded. Second, the present sample overrepresented women (63.1%), which may reflect differential willingness to participate and thus introduce non-representativeness into gender comparisons. The contrast with Savaş et al. (2023), who found no gender differences in a sport sciences sample, further suggests that disciplinary context moderates this relationship -an hypothesis that warrants systematic investigation through multi-faculty, nationally representative designs.

Age and Accumulated Academic Socialization

The positive correlation between age and AI Interaction ($r = .25$) aligns with the academic socialization hypothesis advanced by Laupichler et al. (2022) older students, by virtue of longer engagement with research-oriented academic environments, may exhibit develop more sophisticated and favorable orientations toward AI engagement. This interpretation is further supported by the simultaneous finding that graduate students-who are systematically older and more academically experienced-scored significantly higher on Interaction than undergraduates ($d = 0.74$). The convergence of age and educational level effects on the same sub-dimension suggests that academic research exposure, rather than chronological age alone, may contribute to higher Interaction scores. Future studies should employ mediation analyses to formally test whether educational level mediates the age-Interaction relationship.

The absence of a significant age–Anxiety correlation ($r = -.05$, $p = .515$) is theoretically informative. If increased AI knowledge reliably reduced anxiety, one would predict a negative age-Anxiety association; its absence may indicate that anxiety is driven by factors other than cognitive familiarity, possibly including perceived occupational vulnerability that actually increases with academic seniority and proximity to labor market entry (Brynjolfsson & McAfee, 2014).

Educational Level Effects: Graduate Advantage in AI Engagement

The large educational level effect on Interaction ($\eta^2p = .13$, $d_{GR>UG} = 0.74$) is the strongest effect obtained in the present study and warrants substantive discussion. Graduate students' elevated Interaction scores may reflect structural features of graduate academic practice: routine engagement with academic search engines, AI-assisted literature synthesis tools, AI-powered statistical software, and emerging AI writing assistants in research workflows. This type of exposure may differ qualitatively from undergraduates' exposure, which tends to be more peripheral (entertainment, social media recommendation algorithms) and does not demand conceptual engagement with

AI mechanisms. The findings suggest that meaningful AI literacy enhancement may require structured, research-oriented engagement-precisely the kind that graduate programs naturally provide-rather than passive exposure.

The null effects for Pervasive Impact ($p = .064$, $\eta^2p = .03$) and Anxiety ($p = .473$, $\eta^2p = .01$) across educational levels imply that broader social AI awareness and emotional appraisal are less responsive to academic level than behavioral interaction propensity. This dissociation may reflect that Pervasive Impact awareness is shaped more by media consumption and public discourse than by academic training, whereas Anxiety may be resistant to educational-level influences due to its affective rather than cognitive character.

The Paradox of AI Tool Adoption

The most theoretically provocative finding is the complete absence of significant differences between AI tool users and non-users across all three sub-dimensions (all $|d| <0.20$; all $p> .20$). This null result is robust: confidence intervals for all effect sizes span zero symmetrically, and the sample provided sufficient power (~.70) to detect small effects of $r \approx .20$ or $d \approx 0.30$. The finding is consistent with Tundrea (2020) passive-use hypothesis: most students' AI tool usage is instrumentalized -focused on task completion -without engaging with the conceptual, ethical, or societal dimensions of AI systems. Students who regularly use AI-powered autocomplete, music recommendation, or social media curation has little occasion to develop informed attitudes about AI governance, labor implications, or algorithmic transparency.

This finding carries important policy implications; however, it should be interpreted cautiously given that AI tool usage was assessed only dichotomously (yes/no). Even so, the present data suggest that AI tool integration alone may be insufficient for developing AI literacy. The exposure-benefit assumption underlying many AI integration policies-that routine use of AI tools will naturally foster awareness and positive attitudes-is not supported by the findings. Instead, structured pedagogical engagement with AI concepts, including explicit instruction on how AI systems function, their societal implications, and critical evaluation frameworks, may be necessary to achieve the intended cognitive and attitudinal outcomes.

Limitations

Several limitations constrain the interpretive scope of these findings. First, the convenience sample from a single regional Turkish university limits generalizability; the university's geographic and institutional characteristics (a relatively small institution in Eastern Türkiye) may produce student populations that differ systematically from those at metropolitan or research-intensive institutions. Second, the cross-sectional design precludes causal inference; the educational level differences observed are consistent with, but do not prove, an academic socialization account. Longitudinal tracking of the same students across educational levels is necessary to establish directionality. Third, the binary operationalization of AI tool adoption (yes/no) limits measurement precision and reduces the ability to capture meaningful heterogeneity in usage patterns, such as frequency, intensity, and purpose; this may further constrain the generalizability of the observed null effects. Future studies should employ multi-item, frequency- and purpose-differentiated AI use measures. Fourth, the associate degree subgroup (n = 10) was critically underpowered, precluding reliable three-group ANOVA comparisons; all results involving this group are preliminary. Fifth, common method bias cannot be excluded given the exclusive reliance on self-report measures; future designs incorporating behavioral measures of AI interaction would strengthen validity.

Conclusion

This investigation provides a psychometrically grounded, methodologically transparent examination of AI perceptions among Turkish university students, with findings that contribute meaningfully to the international literature on AI attitudes in higher education. Three substantive conclusions emerge. First, AI anxiety is gender-differentiated, with women reporting higher anxiety- a finding interpretable within differential socialization frameworks, but requiring replication in larger, multi-institutional samples before driving policy. Second, educational level and age exert meaningful positive effects specifically on AI Interaction propensity, suggesting that academic research socialization -rather than informal technology exposure -is the primary driver of engaged AI orientations among this population. Third, and most consequentially for educational policy, binary AI tool adoption status does not predict AI perceptions, challenging the widely held assumption that student AI tool usage naturally generates literacy or positive attitudes.

These findings collectively suggest that AI education policies should move beyond simple exposure-based strategies toward more structured and pedagogically grounded AI literacy initiatives. In particular, graduate-level research methods courses—where AI-assisted practices such as literature searching, statistical analysis, and academic writing support are increasingly normalized—may provide a natural pedagogical scaffold for explicit AI literacy development. Embedding structured reflective activities focused on the mechanisms, limitations, reliability, and ethical implications of AI systems within these existing curricular environments may foster more meaningful attitudinal engagement than standalone AI awareness programs. Future research should further examine these relationships using longitudinal, multi-institutional, and mixed-methods designs capable of capturing both the quantitative structure of AI-related attitudes and the contextual processes through which such perceptions evolve over time.

Kısaltmalar / Abbreviations

AI	: Artificial Intelligence / Yapay Zekâ
AIS	: Artificial Intelligence Scale / Yapay Zekâ Ölçeği
TAM	: Technology Acceptance Model / Teknoloji Kabul Modeli
UTAUT	: Unified Theory of Acceptance and Use of Technology / Teknoloji Kabulü ve Kullanımı Birleşik Teorisi
RQ	: Research Question / Araştırma Sorusu
H	: Hypothesis / Hipotez
ANOVA	: Analysis of Variance / Varyans Analizi
HSD	: Honestly Significant Difference / Dürüstçe Anlamlı Fark
M	: Mean / Ortalama
SD	: Standard Deviation / Standart Sapma
N / n	: Sample Size / Örneklem Sayısı
T	: t-Test Statistic / t-Testi İstatistik Değeri
F	: ANOVA F Statistic / ANOVA F İstatistik Değeri
p	: Significance Value / Anlamlılık Düzeyi
r	: Pearson Correlation Coefficient / Pearson Korelasyon Katsayısı
d	: Cohen’s d Effect Size / Cohen d Etki Büyüklüğü
η^2p	: Partial Eta-Squared Effect Size / Kısmi Eta Kare Etki Büyüklüğü
CI	: Confidence Interval / Güven Aralığı
SE	: Standard Error / Standart Hata
A	: Cronbach’s Alpha / Cronbach Alfa Güvenirlik Katsayısı
ω	: McDonald’s Omega / McDonald Omega Güvenirlik Katsayısı

Beyanlar / Declarations

Etik Onay ve Katılım Onayı / Ethics approval and consent to participate

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During the preparation and writing of this study, scientific, ethical, and citation rules were followed in accordance with the “Higher Education Institutions Scientific Research and Publication Ethics Guidelines”. No alterations were made to the collected data, and this study has not been submitted to any other academic publication venue for evaluation. Ethical approval was obtained from the Scientific Research Ethics Committee of Ağrı İbrahim Çeçen University (Decision No. 74, dated 27 February 2025). All participants provided informed consent prior to participation. The study was conducted in accordance with the Declaration of Helsinki and the Council of Higher Education's guidelines on scientific research ethics in Turkiye. The study was conducted in accordance with the principles of the Declaration of Helsinki. The authors are solely responsible for any ethical or legal issues that may arise regarding this article.

Veri Ve Materyal Erişilebilirliği / Availability of data and material

Bu çalışmanın bulgularını destekleyen veriler, makul talepler üzerine sorumlu yazardan temin edilebilir. Veri seti yalnızca akademik amaçlar için erişilebilir olacak ve verilerin herhangi bir kullanımı, orijinal çalışmayı referans gösterecek ve katılımcıların gizliliğini koruyacaktır.

The data that support the findings of this study are available from the corresponding author upon reasonable request. The dataset will be accessible only for academic purposes, and any use of the data will recognize the original study and maintain the confdentiality of the participants.

Çıkar Çatışması / Competing interests

Yazarlar, bu makalede sunulan çalışmayı etkileyebilecek herhangi bir çıkar çatışması veya kişisel ilişkiye sahip olmadıklarını beyan etmektedirler.

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Yazar Katkıları / Authors’ Contribution Statement

MS: Kavramsallaştırma, metodoloji, proje yönetimi, veri düzenleme, istatistiksel analiz ve makalenin ilk taslağının hazırlanması (%60). AÖ: Makalenin gözden geçirilmesi ve düzenlenmesi (%30). AT: Yazım ve düzenleme (%10). Tüm yazarlar makalenin son hâlini gözden geçirmiş ve onaylamıştır

MS: Conceptualization, methodology, project administration, data curation, formal analysis, and writing -original draft preparation (60%). AÖ: Writing-review and editing (30%). AT: Writing and editing (10%). All authors reviewed and approved the final version of the manuscript.

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