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Research Article

Artificial Intelligence Literacy as a Catalyst for Overcoming Student Resistance to Digital Transformation in Higher Education

Yükseköğretimde Dijital Dönüşüme Karşı Öğrenci Direncinin Aşılmasında Yapay Zekâ Okuryazarlığının Katalizör Rolü

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Abstract: This study investigates how students' resistance to change and AI literacy influence their attitudes toward artificial intelligence (AI) in higher education. With the aim of contributing to overcoming psychological barriers encountered in the digital transformation process, this study examines the mediating role of AI literacy in the negative effect of resistance to change on students' attitudes toward AI. Using a quantitative, cross-sectional research design, data were collected from 564 university students in Türkiye through a structured questionnaire. To test the proposed hypotheses, the research utilized Structural Equation Modeling (SEM) alongside Hayes' PROCESS Model 4 for mediation analysis. The findings reveal that increased resistance to change significantly and negatively impacts both AI literacy and attitudes toward AI. Furthermore, AI literacy has a positive effect on students' attitudes toward AI and partially mediates the relationship between resistance to change and attitude. An original contribution is offered by empirically establishing an integrated RTC→AIL→AIA pathway and by specifying AIL as a developable competence that converts resistance-related ambiguity into perceived control, thereby clarifying how attitudes are improved through knowledge-based mechanisms. The results show that knowledge-based trust and cognitive preparation significantly contribute to the strengthening of positive attitudes towards AI. This research contributes to the literature by presenting an integrated conceptual framework linking resistance to change, AI literacy, and attitude toward AI. In practical terms, design-addressable implications are specified for educational programming, indicating that embedding ethics–privacy–bias content and explainability-oriented feedback can translate the mediation mechanism into routine practice and help reduce resistance-related frictions. It emphasizes that addressing cognitive competencies is essential in promoting sustainable learning behaviors in digitally transforming educational environments.

Keywords: Higher Education, Digital Transformation, AI literacy, Resistance to Change, Attitude toward AI

Özet: Bu çalışma, öğrencilerin değişime direnci ve yapay zekâ okuryazarlığının yükseköğretimde yapay zekaya (YZ) karşı tutumlarını nasıl etkilediğini araştırmaktadır. Bu çalışmada, dijital dönüşüm sürecinde karşılaşılan psikolojik engellerin aşılmasına katkı sağlamak amacıyla, özellikle değişime direncin yapay zekâya yönelik tutumlar üzerindeki olumsuz etkilerinde yapay zekâ okuryazarlığının aracılık rolünün belirlenmesi amaçlanmaktadır. Nicel, kesitsel bir araştırma tasarımı kullanılarak, Türkiye'deki 564 üniversite öğrencisinden yapılandırılmış bir anket aracılığıyla veri toplanmıştır. Çalışmada, önerilen hipotezleri test etmek için Yapısal Eşitlik Modeli (YEM) ve Hayes'in PROCESS Model 4 kullanılmıştır. Bulgular, değişime direncin artışının hem YZ okuryazarlığını hem de YZ'ye karşı tutumları önemli ölçüde ve olumsuz etkilediğini ortaya koymaktadır. Ayrıca, YZ okuryazarlığı öğrencilerin YZ tutumları üzerinde olumlu bir etkiye sahiptir ve değişime direnç ile tutum arasındaki ilişkiyi kısmen aracılık etmektedir. Bütünleşik bir RTC→AIL→AIA yolu deneysel olarak kurularak ve AIL'yi dirençle ilişkili belirsizliği algılanan kontrole dönüştüren geliştirilebilir bir yetkinlik olarak belirleyerek özgün bir katkı sunulmaktadır. Böylece tutumların bilgiye dayalı mekanizmalar aracılığıyla nasıl iyileştirildiği açıklığa kavuşturulmaktadır. Sonuçlar, bilgiye dayalı güven ve bilişsel hazırlığın, yapay zekâya yönelik olumlu tutumların güçlenmesine anlamlı katkı sunduğunu göstermektedir. Bu çalışma, değişime direnç, YZ okuryazarlığı ve YZ'ye karşı tutumları birbirine bağlayan entegre bir kavramsal çerçeve sunarak literatüre katkıda bulunmaktadır. Pratik açıdan, tasarım odaklı çıkarımlar eğitim programlaması için belirtilmiş olup, etik-gizlilik-önyargı içeriklerinin ve açıklanabilirlik odaklı geri bildirimlerin entegre edilmesinin arabuluculuk mekanizmasını rutin uygulamaya dönüştürebileceğini ve dirençle ilişkili sürtüşmeleri azaltmaya yardımcı olabileceğini göstermektedir. Dijital dönüşüm geçiren eğitim ortamlarında sürdürülebilir öğrenme davranışlarını

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teşvik etmek için bilişsel yetkinliklerin ele alınmasının gerekli olduğunu vurgulamaktadır.

Anahtar Kelimeler: Yükseköğretim, Dijital Dönüşüm, YZ Okuryazarlığı, Değişime Direnç, Yapay Zekâ Tutumu

1. Introduction

Digital transformation represents not merely a technological evolution, but a deep-rooted paradigm shift that reshapes how students acquire knowledge, determine learning strategies, and engage with educational technologies. For instance, AI-enabled early-warning dashboards that flag at-risk learners, adaptive tutoring systems delivering personalized exercises, and automated feedback tools that shorten response cycles have already reshaped day-to-day learning routines and instructor–student interaction. This shift is particularly visible in education, where the integration of artificial intelligence (AI), big data, and automation is transforming learning environments while simultaneously demanding new cognitive, psychological, and technological competencies from students (Dwivedi et al., 2021; Vial, 2021, p. 52).

The proliferation of AI-powered learning platforms and intelligent systems has raised fundamental questions regarding students' behavioral intentions and learning engagement. While the potential benefits of such technologies are well-documented, students' willingness to adopt them is shaped by a more complex interplay of psychological resistance, uncertainty avoidance, and digital competencies such as AI literacy (AIL) (Shin, 2021). Among these factors, resistance to change (RTC) emerges as a critical psychological barrier that influences the acceptance of innovative educational tools (Oreg, 2003, p. 685). This resistance can hinder students' adaptation to new technologies, negatively impacting both personal learning outcomes and broader organizational transformation efforts.

Grounded in foundational acceptance and attitude-formation theories—TAM and UTAUT concerning perceived usefulness/ease and behavioral control, TPB concerning the role of attitudes and perceived control, and self-efficacy theory concerning capability beliefs—a triadic mechanism is conceptualized whereby a dispositional barrier (resistance to change, RTC) is posited to depress key antecedents of acceptance (e.g., perceived ease, usefulness, control, trust), whereas a capability resource (AI literacy, AIL) is posited to counteract these effects by reducing uncertainty and strengthening efficacy. The resultant evaluative stance is reflected in attitudes toward AI (AIA) (Park & Woo, 2022; Yadrovskaia, et al., 2023). Accordingly, the dyads RTC → AIA, RTC → AIL, and AIL → AIA are treated as theoretically coupled pathways that jointly account for students' interaction with AI in education (Davis, 1989; Ajzen, 1991; Bandura, 1997; Venkatesh et al., 2003; Oreg, 2003; Long & Magerko, 2020; Wang, Rau & Yuan, 2023; Kong et al., 2021; Laupichler et al., 2022; Chiu et al., 2024; Alamäki et al., 2024).

First, the dyadic link RTC → AIA is grounded in TPB and acceptance research: dispositional resistance elevates anxiety and reduces openness, thereby lowering perceived control and usefulness—key antecedents of favorable attitudes (Ajzen, 1991; Davis, 1989; Venkatesh et al., 2003). Empirically, higher RTC has been associated with reluctance to explore novel tools and more negative evaluations of technology (Oreg, 2003; Castro, Zambaldi & Ponchio, 2020; Frick et al., 2021; Li et al., 2023; Shahid et al., 2024). Second, the dyadic link RTC → AIL follows from self-efficacy and habit-persistence arguments: resistance fosters avoidance of learning-intensive transitions and adherence to familiar routines, which constrains opportunities to acquire AI-related knowledge and skills (Bandura, 1997; Frick et al., 2021; Li et al., 2023; Amin et al., 2025). Accordingly, higher RTC is expected to suppress AI literacy by discouraging exploratory learning and practice. Third, the dyadic link AIL → AIA is supported by TAM/UTAUT mechanisms through perceived understanding, control, and trust: literacy clarifies capabilities and limits of AI, reduces uncertainty, and enhances perceived usefulness—thereby improving attitudes (Davis, 1989; Venkatesh et al., 2003; Wang, Rau & Yuan, 2023; Long & Magerko, 2020). Recent studies in higher education contexts corroborate these effects, reporting greater engagement and more positive evaluations among students with higher AI literacy (Kong et al., 2021; Laupichler et al., 2022; Chiu et al., 2024; Alamäki et al., 2024).

Synthesis of these dyads indicates a triadic pathway: RTC can impair AIA directly (dyad 1) and indirectly by depressing AIL (dyad 2), while AIL improves AIA by increasing perceived understanding, control, and trust (dyad 3). Accordingly, AIL is posited as a knowledge-based mediator that channels the effect of RTC onto AIA by translating initial resistance into more informed, less anxious evaluations of AI—consistent with pathway-based views of acceptance (Ajzen, 1991; Venkatesh et al., 2003; Wang et al., 2023; Chiu et al., 2024). This synthesis motivates the hypotheses presented below and clarifies why mediation is theoretically expected to accompany (not replace) the direct RTC → AIA path.

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Although each of these constructs has been studied in isolation, holistic models that analyze the triadic relationship between RTC, AIL, and AIA in educational settings remain scarce. This study addresses this critical gap by proposing a conceptual model that explores the causal relationships among these variables and empirically examines their influence on university students—students who are both current learners and future decision-makers.

Guided by this relationship-oriented perspective, four hypotheses are proposed, each preceded by a brief rationale:

Resistance to change and habitual rigidity elevate anxiety and reduce openness toward new technologies, which weakens favorable evaluations of AI (Oreg, 2003; Castro, Zambaldi & Ponchio, 2020; Frick et al., 2021; Li et al., 2023; Shahid et al., 2024) (▶**Figure 1**). Hence:

H1: Resistance to change negatively affects students' attitudes toward AI.

High RTC is associated with avoidance of learning-intensive transitions and persistence with familiar routines, limiting opportunities to acquire AI-related competencies (Frick et al., 2021; Li et al., 2023; Amin et al., 2025). Hence:

H2: Resistance to change negatively affects students' AI literacy levels.

AIL equips students to understand AI capabilities and limits, strengthens perceived control and ethical awareness, and thus fosters trust and perceived usefulness (Wang, Rau & Yuan, 2023; Long & Magerko, 2020; Kong et al., 2021; Laupichler et al., 2022; Chiu et al., 2024; Alamäki et al., 2024). Hence:

H3: AI literacy positively affects students' attitudes toward AI.

By reducing uncertainty and strengthening perceived control and trust, AIL offers a knowledge-based pathway through which RTC influences AIA; higher AIL should attenuate the negative effect of RTC on AIA (Kong et al., 2021; Laupichler et al., 2022; Chiu et al., 2024; Alamäki et al., 2024). Hence:

H4: AI literacy mediates the relationship between RTC and attitudes toward AI.

In order to explain the formation of students' attitudes towards artificial intelligence, the research model proposed in this study predicts causal relationships between the variables of RTC, AIL and attitude towards AI based on theoretical foundations.

The starting point of the model is that the emotional, cognitive and behavioral tendencies that students develop towards these technologies when they encounter artificial intelligence systems are closely related to their psychological resistance levels and technological knowledge competencies (Fig. 1). This starting point has been supported in prior work showing, first, that attitudes are structured along cognitive, affective, and behavioral dimensions (Eagly & Chaiken, 1993; Ajzen, 2001); second, that dispositional resistance to change shapes technology-related evaluations and intentions (Oreg, 2003; Kim & Kankanhalli, 2009); and third, that AI literacy—as competence in awareness, use, evaluation, and ethics—is positively associated with attitudes and uptake (Long & Magerko, 2020).

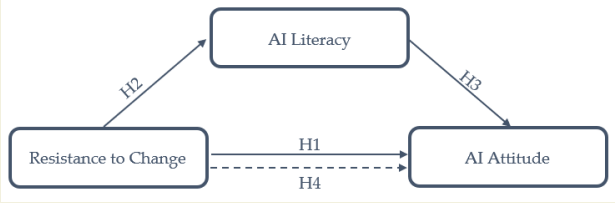

Figure 1. Research Model

RTC is a multidimensional structure consisting of psychological components such as a student's tendency to avoid uncertainty, desire to maintain habits, and discomfort towards innovations (Frick et al., 2021, p. 239; Castro et al., 2020, p. 443; Oreg, 2003, p. 685). In the literature, it is emphasized that this construct plays a determining role in shaping students' attitudes towards new technologies.

Building on the above rationale and hypotheses, the novelty of this study lies in offering an integrated theoretical framework that connects psychological predispositions (resistance), technological knowledge (AIL), and behavioral outcomes (AIA) within the context of educational technologies. By examining these constructs in an integrated manner, the study seeks to advance understanding of the cognitive and behavioral dynamics that underpin digital transformation processes in educational settings. This approach aligns with recent calls for knowledge-based perspectives in promoting sustainable learning behaviors (Erbey, Gündüz & Fidan, 2025).

In addition to H1–H4, the following descriptive research questions were specified:

RQ1: What are the sample's gender distribution, age

range, and typical levels of daily internet use among participating university students?

RQ2. What are the baseline levels and dispersions of AI literacy, attitudes toward AI, and resistance to change among participating students?

RQ3. What are the directions and magnitudes of the pairwise associations among AI literacy, attitudes toward AI, and resistance to change?

The remainder of this article summarizes the proposed research model, presents the methodology, reports empirical findings, and discusses conclusions.

2. Method

In this study, the hypotheses formed in the theoretical framework were tested in order to examine the effects of RTC and AIL variables in determining students' attitudes towards AI. For this purpose, a quantitative, explanatory and cross-sectional research design was adopted. Data were collected using a structured questionnaire administered through both online platforms and in-person sessions.

2.1. Research Design and Participants

All procedures involving human participants complied with the ethical standards of the institutional and/or national research committee and with the 1964 Declaration of Helsinki and its later amendments. Participation was voluntary and anonymous; informed consent was obtained before data collection. The study protocol was reviewed and approved by the Uşak University Social and Human Sciences Scientific Research and Publication Ethics Committee (Decision No. 2025-116, 15 April 2025).

The study was conducted in 2025 with participants enrolled at 7 universities across Türkiye. A convenience sampling approach was adopted due to institutional access constraints and timing of ethics approvals; universities and departments were contacted through existing academic networks and student offices, and participation was open to all eligible students who received the invitation. The final sample comprised 564 students aged 18 – 40 (M = 21.74, SD = 3.04), after listwise deletion of incomplete responses and attention-check failures. Employing a cross-sectional and explanatory design, the study was intended to assess university students' current attitudes toward AI. Participant characteristics are summarized in ▶**Table 1**.

The sample skews female and, as expected for a university population, is overwhelmingly concentrated in the 18–25 age band. A multi-device ecology is evident: smartphones are nearly ubiquitous, laptops are widely used for study-related tasks, whereas desktops appear noticeably less common; tablets and "other" devices are adopted to a moderate degree, with wearables—especially smartwatches—most frequently cited under the open-ended option. The distribution of total devices indicates a modal pattern around three devices, with a substantial share reporting four or more, consistent with pervasive cross-device access. Average daily internet use is high with considerable dispersion, suggesting heterogeneous usage intensity across participants.

Table 1. Some characteristics of the participants

Gender	n	%	Technology devices owned[ii]	n	%
Female	340	60.3	Desktop computer	337	59.7
Male	224	39.7	Laptop computer	421	74.6
Age[i]	n	%	Tablet	303	53.7
18 – 25 years	517	91.7	Smartphone	513	90.9
26 – 33 years	39	6.9	Other (e.g., wearable technologies)	305	54.1
34 – 40 years	8	1.4	Total number of devices owned	n	%
Average daily internet use (hours)			1 device	21	3.7
Mean	6.51		2 devices	43	7.6
Std. Dev.	3.23		3 devices	286	50.7
			4 devices	156	27.7
			≥ 5 devices	58	10.3

i Age was collected as an open-ended response and recoded into equal-width categories (e.g., 18–22, 23–29, …) for descriptive reporting.

ii Multiple responses were allowed for this item; therefore the sum of selections may exceed the number of participants. Percentages indicate the proportion of participants endorsing each option.

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2.2. Data Collection Procedures and Measurement Instruments

Data were collected via a structured questionnaire administered online (Google Forms) and in person (paper) between April and July 2025. Participation was voluntary and anonymous; informed consent was obtained on the first page. Quality-control procedures included embedded attention checks; questionnaires with missing data, patterned responding, or failed checks were excluded. In total, 11 cases were removed, yielding 564 valid responses for analysis. All items were rated on a 5-point Likert scale.

Attitudes toward AI were assessed with the AI Attitude Scale (AIAS-4) developed by Grassini (2023). In the original validation, a unidimensional, four-item structure was reported. The Turkish adaptation by Satici et al. (2025) corroborated the single-factor structure via confirmatory factor analysis with adequate fit. In the present study, the scale was administered on a 5-point Likert-type format, and the total score was computed as the item means.

AI literacy was measured with the AI Literacy Scale developed by Wang, Rau, and Yuan (2023), for which the original study reports 12 items across four factors—awareness, use, evaluation, and ethics. The Turkish adaptation by Çelebi et al., (2023) confirmed the 12-item, four-factor configuration with acceptable reliability and model fit. In this study, the Turkish version was administered on a 5-point Likert-type scale; subscale and composite indices were computed as item means.

Resistance to change was assessed with Oreg's (2003) Resistance to Change Scale, which comprises 17 items loading on four subdimensions—routine seeking, emotional reaction to imposed change, cognitive rigidity, and short-term focus. The Turkish adaptation reported by Çalışkan (2019) was employed; construct validity and reliability in Turkish samples were supported in the adaptation study. For the current research, responses were collected on a 5-point Likert-type scale, and subscale/total scores were computed as item means following author-specified reverse coding.

Demographic information such as age, gender, and technology usage frequency was also collected to support subgroup analysis.

Prior to conducting the main analyses, the psychometric properties of the measurement instruments were rigorously evaluated. First, internal consistency reliability was examined using Cronbach's alpha coefficients. All scales demonstrated satisfactory reliability, with alpha values exceeding the widely accepted threshold of .80, indicating strong internal coherence among items within each construct.

Subsequently, Exploratory Factor Analysis (EFA) was applied to explore the underlying factor structure of the scales without imposing a predefined model. The results of EFA supported the multidimensional nature of the constructs and accounted for a substantial proportion of the total variance, thereby providing preliminary evidence for construct validity.

Following EFA, Confirmatory Factor Analysis (CFA) was employed to statistically test the hypothesized factor structures derived from the theoretical framework. The CFA results demonstrated an adequate model fit, as evidenced by fit indices (e.g., CMIN/DF, GFI, AGFI, CFI, TLI, RMSEA) falling within acceptable ranges, thus confirming that the observed data align well with the proposed measurement models.

2.3. Data Analysis Methodology

Data were analyzed using SPSS 25.0, AMOS 24.0, and Hayes PROCESS Macro. Descriptive statistics and correlation analyses were conducted initially. SEM was employed to test the hypothesized model.

To examine the mediating effect of AIL, Hayes' PROCESS Model 4 was applied. The bootstrapping method with 5000 samples and 95% confidence intervals was used to assess the significance of indirect effects.

Sampling adequacy was verified (KMO ≥ .80; Bartlett's test $p < .001$). Construct reliability and convergent validity were evaluated using composite reliability (CR ≥ .70) and average variance extracted (AVE ≥ .50); all constructs met these thresholds (Fornell & Larcker, 1981; Hair et al., 2019). Discriminant validity was examined via the Fornell–Larcker criterion (√AVE greater than inter-construct correlations), supporting construct distinctiveness. Although generalizability is constrained by the use of convenience sampling and the student-based composition of the sample, potential biases arising from institutional coverage and self-report measurement are acknowledged. These limitations should be considered when interpreting the findings and in delimiting their external validity.

3. Results

3.1. Participant Profile and Key Metrics

The final sample comprised 564 university students,

of whom 60.3% (n = 340) were female and 39.7% (n = 224) were male. The age range varied between 18 and 40 years, with a marked concentration in the 20–22 band. Consistent with the descriptive focus articulated under RQ1 and summarized in ▶**Table 1**, the profile reflects a cohort that is young and highly connected; the average daily internet use was reported as 5 hours for 21.3% and 6 hours for 14.7% of participants. These patterns suggest a technologically engaged and relatively homogeneous student group.

Addressing RQ2, baseline levels show that AI literacy and attitudes toward AI cluster above the scale midpoint, with central tendencies in the agree range and a mild ceiling inclination; a clear majority falls into the higher score bands (▶**Table 2**). Resistance to change centers in the upper-mid range as well, with a non-trivial share of high scores, indicating that resistance remains salient for a meaningful subset of students. Dispersion is moderate across all three scales and spans the full response range, pointing to heterogeneity despite generally favorable profiles.

3.2. Reliability–Validity Evidence and Correlational Findings

Internal consistency reliability for each scale was evaluated using Cronbach's alpha, with all coefficients surpassing the conventional benchmark of .80, thereby indicating robust internal reliability across the measured constructs. It was calculated as $\alpha = 0.886$ for the RTC Scale, $\alpha = 0.887$ for the AI Literacy Scale, and $\alpha = 0.802$ for the Attitude Towards AI Scale.

Reported cutoffs are widely used guidelines rather than hard rules and should be judged jointly with theory and diagnostics (Hu & Bentler, 1999; Kline, 2016) (▶**Table 3**). Acceptable fit is often inferred at $\chi^2/df \leq 3$ (Kline, 2016) and GFI/AGFI ≥ 0.90 (Hair, Black, Babin, & Anderson, 2019). CFI/TLI ≥ 0.95 and SRMR ≤ 0.08 are commonly taken as good fit (Hu & Bentler, 1999). RMSEA ≤ 0.06 indicates close fit and RMSEA ≤ 0.08 reasonable fit (Browne & Cudeck, 1993; Hu & Bentler, 1999). For measurement quality, CR ≥ 0.70 and AVE ≥ 0.50 are frequently used as convergent-validity benchmarks (Fornell & Larcker, 1981; Hair et al., 2019).

Addressing RQ3, AI literacy shows a moderate positive association with attitudes toward AI, whereas resistance to change is moderately and negatively related to both literacy and attitudes. The pattern is consistent with the theoretical expectation that greater competence aligns with more favorable evaluations while dispositional resistance co-occurs with less favorable orientations (▶**Table 4**).

3.3. Structural Model Results

According to the results of the mediation analysis using Hayes' PROCESS Model 4 (bootstrap = 5000), the total effect of the level of RTC on attitude towards AI was found to be negative and significant ($\beta = -0.3466$; $p < 0.001$). However, when this effect is examined indirectly through AIL, it weakens significantly compared to the direct effect. Not only is the direct effect ($\beta = -0.1754$; $p < 0.001$) significant, but the mediation path (indirect effect = – 0.1712; BootCI 95% [– 0.2190, – 0.1252]) is also statistically significant. The findings suggest that AIL functions as a partial mediator in the association between RTC and students' AIA. The path coefficients and effects analyzed within the scope of the SEM are summarized in ▶**Table 5**.

Table 2. Summary descriptives for RTC, AIL, and AIA

	mean	s.d	min	Q1	median	Q3	max	Skewness	Kurtosis
RTC	3.59	0.92	1.25	3.13	3.75	4.25	5	– 0.79	– 0.28
AIL	3.81	0.86	1.4	3.2	4	4.4	5	– 0.7	– 0.4
AIA	3.81	0.88	1	3.33	4	4.67	5	– 0.59	– 0.01

Table 3. Factor-analytic summary (EFA) and CFA model fit

	Total Variance explained	χ^2	df	χ^2/df	GFI	AGFI	CFI	TLI	Rmsea
Value	63.96	277.93	97	2.87	0.94	0.916	0.968	0.96	0.058

Table 4. Pearson correlations among AI literacy, attitudes toward AI, and resistance to change

	AIL	AIA	RTC
AIL	1.00		
AIA	0.501	1.00	
RTC	– 0.421	– 0.361	1.00

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All paths in the model are statistically significant and consistent with previous theoretical expectations. These findings suggest that students' level of RTC affects their attitudes towards AI both directly and indirectly, and that AIL plays a critical mediating role in the indirect path.

The test results of the four main hypotheses within the scope of the study are summarized in ▶Table 6.

From a practical standpoint, the partial mediation indicates that strengthening AI literacy can mitigate the adverse influence of resistance to change on students' evaluations of AI in learning contexts. Instructors and program designers can operationalize this by embedding short, hands-on AI literacy activities that clarify capabilities and limits, offering low-stakes practice with timely feedback, and foregrounding transparency and ethics to foster knowledge-based trust and perceived control. Such supports are likely to yield more favorable attitudes while leaving room to address residual resistance through complementary psychosocial approaches, for example brief anxiety-reduction or change-readiness interventions for subgroups with elevated RTC.

4. Discussion

In this discussion, the relationships among the study's three focal constructs—resistance to change (RTC), AI literacy (AIL), and attitudes toward AI (AIA)—are considered within the scope of H1–H4 and RQ1–RQ3. It is shown that RTC exerts negative effects on both AIL and AIA, that AIL exerts a positive effect on AIA, and that AIL serves as a partial mediator in the RTC–AIA link. Descriptive results provide the sample profile and variable distributions, and the bivariate associations are observed to support the hypothesized directions.

4.1. Effects of Resistance to Change on AIL and AIA

In view of the relationships stated in H1 and H2 and the findings obtained from the analyses conducted in the study, AIL is observed to be dampened and AIA lowered at higher levels of RTC (Oreg, 2003; Frick et al., 2021; Li et al., 2023; Amin et al., 2025; Shahid et al., 2024). As learning-intensive practices are avoided and familiar routines are retained, opportunities through which AIL would be built are reduced; in parallel, uncertainty in assessment and feedback processes is increased. In practice, delays or abandonment of AI-supported writing feedback tools, reluctance toward AI-assisted coding tutors, and underuse of analytics dashboards have been noted. Through this behavioral pattern, resistance-based cognitive and affective reservations are inferred to generate cumulative negative effects on AIA.

4.2. The Mediating Role of AI Literacy

Consistent with the expectations of H3 and H4 and based on the structural model results, AIL is shown to function as a partial mediating mechanism between RTC and AIA. When the capabilities and limits of AI are understood, outputs are subjected to critical evaluation, and ethical awareness is strengthened, perceived control is increased and ambiguity is reduced (Long & Magerko, 2020; Wang, Rau, & Yuan, 2023; Kong et al., 2021; Laupichler et al., 2022; Chiu et al., 2024; Alamäki et al., 2024). It is further underscored that the ethical strand of AIL—encompassing privacy literacy, data governance, and algorithmic fairness—constitutes a principal antecedent of knowledge-based trust. When data flows can be traced, model limitations articulated, and

Table 5. Structural Model and Mediation Analysis Results

Path	β	SE	t	p	%95 CI (LL–UL)
RTC → AIL (AI literacy)	–.3957	.0360	–11.01	<.001	[–.4664, –.3251]
AIL → AIA (Attitude)	.4327	.0404	10.72	<.001	[.3534, .5120]
RTC → AIA (Direct effect)	–.1754	.0379	–4.62	<.001	[–.2499, –.1009]
RTC → AIL → AIA (Indirect effect via AIL)	–.1712	.0240	–	–	[–.2190, –.1252]
RTC → AIA (Total effect)	–.3466	.0377	–9.19	<.001	[–.4208, –.2725]

Table 6. Test Results of Hypotheses

Hypothesis	Hypothesis Description	Results
H1	RTC negatively affects attitude towards AI.	Supported
H2	RTC negatively affects AI literacy.	Supported
H3	AI literacy positively affects attitude towards AI.	Supported
H4	AI literacy mediates the relationship between RTC and AI attitude.	Supported

bias mechanisms identified, dispositional resistance is less likely to be generalized into globally negative attitudes. In this manner, the mediation pathway posited in H4 is reinforced through ethics-informed comprehension that converts ambiguity into perceived control. As the ethics-privacy-bias components of AIL are internalized, knowledge-based trust is established via improved understandability and transparency; because data handling practices, model generalization, and potential error/bias sources are rendered intelligible, the appraisal channel by which RTC would otherwise depress AIA is attenuated.

4.3. Theoretical Integration and the Role of Descriptive Findings

When the descriptive findings reported under RQ1–RQ3 are considered together with the structural relations examined under H1–H4, the demographic profile and baseline levels of the focal variables are found to provide reference points for AIL and AIA, while the directions and magnitudes of the pairwise associations are observed to align with the hypothesized paths. This integration indicates that the RTC → AIL → AIA sequence captures shared variance across predisposition (RTC), knowledge (AIL), and attitudinal outcome (AIA). At the theoretical level, it is supported that AIL should be conceptualized not only as a knowledge-and-skills set but also as a conversion mechanism through which ambiguity arising from RTC is transformed into perceived control, thereby shaping AIA upward via cognitive clarity and value-informed appraisal.

4.4. Practical Implications and Program Design

In light of the implications of the relationships confirmed under H1–H4 for educational settings, the positioning of AIL as a strategic lever is warranted to strengthen AIA and to dilute the effect of RTC. To this end, it is suggested that AIL components be embedded across courses; that "how AI works," "limits and failure modes," and "ethics–privacy–bias" be addressed in an integrated manner; and that student participation in tool selection and usage principles be ensured so that low-stakes experimentation can be expanded gradually. It is further indicated that brief "why this suggestion?" panels and clear data-use notices paired with AI-supported feedback can be employed to enhance transparency and consolidate knowledge-based trust. Where usage boundaries are defined, reflective and self-regulatory practices are encouraged, and access to support resources is provided, resistance-related negative affect is expected to be reduced. Through interdisciplinary delivery and authentic datasets, the technical, ethical, and critical dimensions of AIL can be reinforced jointly. Within this framework, the demonstrated mediation dynamic is considered readily transferable to program design and therefore suitable for scalable interventions in institutional digital transformation.

5. Conclusions

This study revealed that RTC is a significant psychological barrier to positive AI adoption attitudes. However, increasing the level of AIL partially removes this barrier by enabling students to better understand and engage with AI technologies. An original contribution is provided through the articulation of an integrated RTC → AIL → AIA pathway in which AIL, as a developable competence, partially mediates the adverse influence of RTC on attitudes. The findings suggest that educational institutions and organizations seeking to implement AI-based systems should prioritize not only technical infrastructure but also the psychological and cognitive readiness of their stakeholders. In practical terms, this priority is to be operationalized by embedding AIL across coursework, coupling foundations with ethics–privacy–bias content and explainability-oriented feedback, and enabling low-stakes, participatory experimentation and self-regulation supports so that knowledge-based trust is consolidated and resistance-related frictions are reduced.

By proving the partial mediating role of AIL, the study adds a new perspective to the literature and calls for integrating AIL into digital transformation strategies. This perspective further specifies AIL not only as knowledge and skills but also as a conversion mechanism that transforms ambiguity into perceived control, rendering the mediation mechanism design-addressable in educational settings.

Overall, AIL stands out as a critical leverage point to support constructive attitudes and reduce psychological friction in AI integration processes. When embedded curricula, transparency practices, and structured self-regulation supports are employed, improvements in AIA are expected while the influence of RTC is diluted.

This research is a cross-sectional study conducted on a homogeneous sample of university students. Therefore, generalization of the findings is limited. In addition, it was limited to quantitative data only; it did not include interviews, focus group discussions or case studies that could add qualitative depth. In future studies, it is recommended to conduct more comprehensive analyses using a hybrid method with different demographic groups (e.g. professional adults, faculty members). In addition, longitudinal or staged quasi-experimental designs are

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recommended so that change in AIL and AIA can be tracked as programs are rolled out, and multi-group, cross-cultural analyses are encouraged to examine stability and measurement invariance. Mixed-methods work is further expected to integrate qualitative components (e.g., interviews, focus groups, case vignettes) and process indicators (e.g., voluntary tool uptake, help-seeking) alongside pre/post AIL and AIA measures. The model may also be extended by examining adjacent constructs (e.g., trust in technology, perceived usefulness, organizational culture) as potential moderators or mediators to delineate conditions under which the RTC → AIL → AIA sequence is amplified or weakened.

Research Ethics

Ethical approval for this study was obtained from the Usak University Social and Human Sciences Scientific Research and Publication Ethics Committee, with the decision dated 15/04/2025 and numbered 116.

Artificial Intelligence Use

The author(s) declare that no generative artificial intelligence (e.g., ChatGPT, Gemini, Copilot, etc.) was used in any part of this study.

Author Contributions

The author(s) have (has) accepted responsibility for the entire content of this manuscript and approved its submission.

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The author(s) state(s) no conflict of interest.

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Data Availability

The raw data can be obtained on request from the corresponding author.

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