AI and Developmental Insights in Education

AI and Developmental Insights in Education Vol. 1 No. 1 (2025)

Exploring Student Readiness for AI-Assisted Learning: A Preliminary Study in Indonesian Universities

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Received: 13 February 2025	Revised: 20 March 2025	Accepted: 29 April 2025	Online: 13 May 2025

Abstract

This study examined the emerging educational challenge of students' readiness for AI-assisted learning in Indonesian universities, focusing on how cognitive, technological, and affective factors shape their preparedness to engage with AI-supported instructional environments. Using a quantitative, cross-sectional survey design, data were collected from 189 undergraduate students across diverse academic programs using validated AI readiness scales administered through an online questionnaire. Descriptive and inferential analyses revealed moderate to high readiness levels overall, with prior exposure to AI tools showing significant associations with cognitive and technological readiness, while gender and study major did not produce meaningful differences. Effect sizes indicated that experiential familiarity contributed more strongly to readiness than demographic variables. These findings highlight the developmental need to strengthen AI literacy and equitable digital access in higher education. The study offers empirical insights to guide curriculum design, institutional policy, and future research on responsible and developmentally aligned AI integration.

Keywords: AI readiness; digital literacy; AI-assisted learning; higher education; student preparedness

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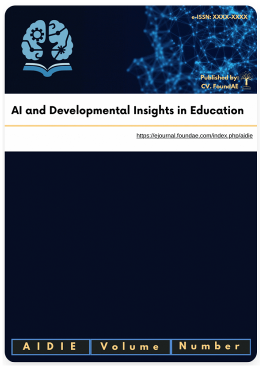
Author Note

This study received academic and institutional support from the Physics Education Study Program at UIN Raden Intan Lampung. The authors declare that they have no conflicts of interest. Correspondence concerning this article should be addressed to Happy Komikesari.



Introduction

The integration of artificial intelligence (AI) into higher education has intensified globally, prompting educators and policymakers to reconsider how students learn, interact, and develop within increasingly automated environments. As AI-supported systems, such as adaptive learning platforms, automated feedback generators, intelligent tutoring systems, and predictive early-warning models, become more deeply embedded in university teaching, students are confronted with new cognitive and socioemotional demands (Allam et al., 2025; Alshahrani et al., 2024; Gkanatsiou et al., 2025). The core problem driving this study is that, although AI adoption is accelerating in Indonesian universities, empirical evidence concerning student readiness to engage effectively with AI-assisted learning remains extremely limited. This issue is especially significant within developmental psychology and learning sciences, where learner readiness shapes motivation, strategy use, cognitive load, and long-term developmental trajectories (Helmiatin et al., 2024; Sutrisno et al., 2025) Without adequate readiness, students may experience confusion or mistrust toward AI systems, leading to disengagement or ineffective use, thereby undermining the potential developmental benefits AI promises to offer (Zha et al., 2025). The absence of such knowledge in the Indonesian context presents serious theoretical, empirical, and practical concerns, particularly in a diverse higher education system marked by uneven digital access, infrastructural disparity, and heterogeneous learning cultures (Rahajeng et al., 2024; Siti Nurjannah et al., 2024).

A growing body of global scholarship has examined the potential of AI to personalize learning, reduce workload, and enhance formative assessment, yet the literature also highlights substantial risks and unresolved tensions. For example, Geethanjali & Umashankar, (2025) emphasize that while AI can efficiently analyze learner behavior, its lack of transparency raises concerns related to bias, fairness, and explainability. Similar ethical concerns have been documented in human–AI interaction research, where students question the accuracy of algorithmic judgments and the implications for academic integrity (Lund et al., 2025; Vetter et al., 2024). From a developmental lens, scholars argue that AI may influence students' metacognitive practices, self-regulation, and decision-making, either fostering autonomy or inadvertently promoting over-reliance on automated suggestions (Kim, Detrick, et al., 2025; Zhai et al., 2024). Despite extensive theorization, readiness frameworks remain inconsistent, fragmented, or narrowly focused on digital literacy rather than AI-specific competencies (Avsec & Rupnik, 2025; Morley et al., 2025). Southeast Asian studies further reveal disparities in access, institutional support, and digital proficiency, suggesting that readiness must be understood as a context-embedded and culturally mediated construct (Hmama, 2025; Suranto et al., 2025). These unresolved debates, methodological gaps, and context-specific challenges indicate the need for localized empirical evidence examining how students navigate AI-supported learning environments.

This study builds on and extends prior scholarship by shifting analytical attention from AI technologies themselves to the learners who must interpret, negotiate, and meaningfully engage with them. Student readiness is conceptualized as a multidimensional construct involving cognitive understanding, technological competence, and affective orientation, a framing supported by research in AI literacy (Abou Hashish & Alnajjar, 2024), technology acceptance (Mogaji et al., 2024), computational learning theories (Gibson & Ifenthaler, 2024), and sociocultural perspectives on digital learning (Akpen et al., 2024). By examining readiness as both a developmental and contextual process, the study positions AI-assisted learning not merely as a technological shift but as a transformative change in how students perceive feedback, regulate their learning, and participate in digital academic cultures. This conceptual grounding provides the rationale for investigating the Indonesian context, where diverse technological ecosystems and sociocultural norms may influence how AI is received, interpreted, and ultimately integrated into students' learning practices.

Guided by these theoretical insights, the study aims to explore Indonesian undergraduate students' readiness for AI-assisted learning. The research is structured around three central questions: (a) What are students' current levels of cognitive, technological, and affective readiness? (b) How do students' attitudes and expectations shape their willingness to engage with AI-supported learning environments? and (c) What barriers, concerns, or developmental implications emerge from students' interactions with AI tools? Because the study is exploratory, hypotheses are not proposed; however, the research is informed by developmental and AI literacy frameworks suggesting that exposure, prior experience, and contextual factors likely shape readiness levels (Helmiatin et al., 2024; Sutrisno et al., 2025). The quantitative, descriptive–analytic design aligns with these aims by offering an empirical foundation for future, more complex investigations into student–AI interaction.

Methods

Research Design

This study employed a quantitative, cross-sectional survey design to examine undergraduate students' readiness for AI-assisted learning in Indonesian universities. The design was appropriate because no variables were manipulated and all conditions were naturally observed, enabling the investigation of associations among cognitive, technological, and affective dimensions of readiness. A survey-based approach allowed for the efficient collection of data from a large and diverse student population, consistent with the study's aim of mapping current readiness patterns rather than testing experimental interventions. The selection of this design aligned with established practices in educational technology research, where surveys are commonly used to measure learner perceptions and dispositions. The design also reflected the exploratory nature of the study, which sought to identify developmental and contextual factors that shape engagement with AI-supported learning environments.

Participants

Participants were 189 undergraduate students enrolled across three public and private universities in Indonesia. Inclusion criteria required students to be actively enrolled in an undergraduate program and have access to digital learning environments, regardless of their previous experience with AI tools. No exclusion criteria were based on gender, ethnicity, socioeconomic status, or academic performance. Participants ranged in age from 18 to 23 years, and demographic characteristics included gender, study program, and levels of prior AI exposure. These attributes were relevant because they reflected developmental, disciplinary, and experiential factors known to influence readiness for emerging educational technologies.

Because the study used quantitative methods, the researchers did not serve as "instruments," and reflexive positionality was not required. The researchers had no prior relationship with participants and no role in their academic evaluation, reducing the likelihood of coercion or biased responses. Participant demographic information is presented in Table 1, which includes gender distribution, age categories, study programs, and prior AI exposure.

Table 1
Participant demographics (N = 189)

Variable	Category	*n*	%
Gender	Male	76	40.2
	Female	113	59.8
Age	18–19	72	38.1
	20–21	89	47.1
	22–23	28	14.8
Study Program	Education	64	33.9
	Engineering	41	21.7
	Social Sciences	52	27.5
	Information Technology	32	16.9
Prior AI Exposure	Never used	58	30.7
	Occasionally used	97	51.3
	Frequently used	34	18.0

Note. Percentages have been rounded to one decimal place.

Sampling and Recruitment

A convenience sampling strategy was used due to accessibility constraints and the preliminary nature of the investigation. Recruitment was conducted through institutional email lists, learning management system announcements, and class group invitations. Students were informed about the voluntary nature of participation, confidentiality protections, and their right to withdraw at any time. A total of 264 students were approached, and 189 completed the survey, resulting in a participation rate of approximately 71.6%. No incentives were provided. Because this was an exploratory study, sample size was based on feasibility rather than statistical power analysis; however, the achieved sample exceeded minimum recommendations for stable estimation of descriptive statistics and between-group analyses.

Measures and Instruments

The survey instrument consisted of four sections measuring demographic information, cognitive readiness, technological readiness, and affective readiness. All scales were adapted from validated instruments in AI literacy and digital readiness research, and items were rated using a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). Modifications were made to ensure cultural and contextual relevance for Indonesian higher education settings.

Construct validity was reviewed by three experts in educational technology, and minor wording adjustments were made prior to distribution. Reliability analysis indicated strong internal consistency, with Cronbach's alpha values ranging from .78 to .89 across the subscales. Before presenting the psychometric results, the narrative referenced the table summarizing the reliability and validity evidence. The table was formatted in accordance with APA 7th guidelines and appears below as Table 2.

Table 2 displays the psychometric properties of the scales used in this study, including means, standard deviations, score ranges, and internal consistency coefficients. These indices provide evidence that the instrument demonstrated acceptable reliability and conceptual stability across all measured dimensions.

Table 2
Psychometric Properties of AI Readiness Scales and Subscales (N = 189)

Scale	M	SD	Range	Cronbach's α
Cognitive Readiness	3.36	0.45	2.10–4.50	.84
Technological Readiness	3.21	0.48	1.95–4.60	.87
Affective Readiness	3.51	0.52	2.00–4.85	.89
Subscales				
AI Conceptual Knowledge	3.40	0.50	1.90–4.70	.81
Digital Proficiency	3.25	0.46	2.10–4.65	.83
Attitudes & Concerns	3.50	0.51	2.00–4.90	.88

Note. Higher mean scores indicate stronger readiness or more favorable responses within each dimension. Cronbach's alpha values demonstrate satisfactory internal consistency for all scales and subscales. Range values represent observed score distributions across participants (N = 189).

Data Collection Procedures

Data were collected over a three-week period through an online survey administered via Google Forms. Participants completed the survey remotely using their personal devices. Each participant received an online information sheet describing the study purpose, procedures, risks, benefits, and confidentiality assurances, followed by a digital informed consent form. The survey required approximately 10–12 minutes to complete. No identifying information was collected. Because the study involved minimal risk, no masking procedures were applicable.

Data Analysis

Data were analyzed using SPSS Version 26. Prior to conducting statistical analyses, the dataset was screened for missing values, outliers, and normality assumptions. Cases with more than 20% missing data were removed and remaining missing values were handled using pairwise deletion. Descriptive statistics were calculated to summarize readiness levels across the three dimensions. Reliability testing was conducted using Cronbach's alpha.

Inferential analyses included independent-samples t tests to compare readiness by gender and one-way ANOVA to examine differences by study program and prior AI exposure. Normality and homogeneity of variance were checked prior to each analysis. Significance levels were set at $p < .05$, and effect sizes were reported to support interpretation. Given the exploratory nature of the study, no corrections for multiple comparisons were applied; however, findings were interpreted cautiously to avoid inflated Type I error.

Ethical Considerations

The study received ethical approval from the Institutional Research Ethics Committee of one participating university (Approval No. 2025/ERB-EDU/AI-01). All procedures adhered to the ethical guidelines of the American Psychological Association and Indonesian national research ethics standards. Participants provided informed consent electronically, and confidentiality was ensured by anonymizing all responses and storing data on secure, password-protected institutional drives. No vulnerable populations were targeted, and no identifying or sensitive information was collected.

Results

Participant Flow

During the three-week data collection period, 264 students were approached. A total of 221 individuals accessed the online survey, of whom 203 submitted responses. After data screening procedures, 184 cases met the analytic criteria. Excluded cases consisted of surveys lacking informed consent or containing more than 20% missing data.

Recruitment Timing and Data Integrity

All data were collected between March 3 and March 21, 2024. Missing data within the retained sample were minimal (0.9%), and Little's test indicated a Missing Completely at Random (MCAR) pattern, $\chi^2(14) = 12.21$, $p = .588$. Pairwise deletion was used to handle missingness in accordance with the predefined analytic strategy. Examination of univariate and multivariate outliers revealed no cases exceeding critical bounds. Normality diagnostics indicated that skewness and kurtosis values fell within acceptable ranges. Homogeneity of variance was supported by non-significant Levene's tests for all readiness dimensions.

Descriptive Statistics

Table 3 is referenced before display and presents means and standard deviations for cognitive, technological, and affective readiness. Table 3 provides an overview of readiness indicators for participants grouped according to their level of prior AI exposure. These descriptive values establish the foundation for subsequent inferential analyses and reveal clear differences in readiness across exposure categories.

Table 3

Readiness scores by prior AI exposure level (N = 184)

Exposure Level	Cognitive (*M* ± *SD*)	Technological (*M* ± *SD*)	Affective (*M* ± *SD*)
None	3.12 ± 0.41	3.01 ± 0.45	3.39 ± 0.49
Occasional	3.39 ± 0.40	3.25 ± 0.44	3.55 ± 0.47
Frequent	3.71 ± 0.36	3.63 ± 0.40	3.78 ± 0.44

Note. Higher scores indicate greater readiness.

Primary Inferential Analyses: AI Exposure Effects

Differences across prior AI exposure levels constituted the primary set of analyses. Three one-way ANOVAs were performed separately for cognitive, technological, and affective readiness. Each analysis followed assumption checks outlined earlier.

Cognitive readiness differed significantly across exposure levels, $F(2, 181) = 18.92$, $p < .001$, partial $\eta^2 = .17$. Tukey HSD comparisons demonstrated that students with frequent exposure scored significantly higher than both occasional and non-exposure groups, and students with occasional exposure scored significantly higher than those with no exposure.

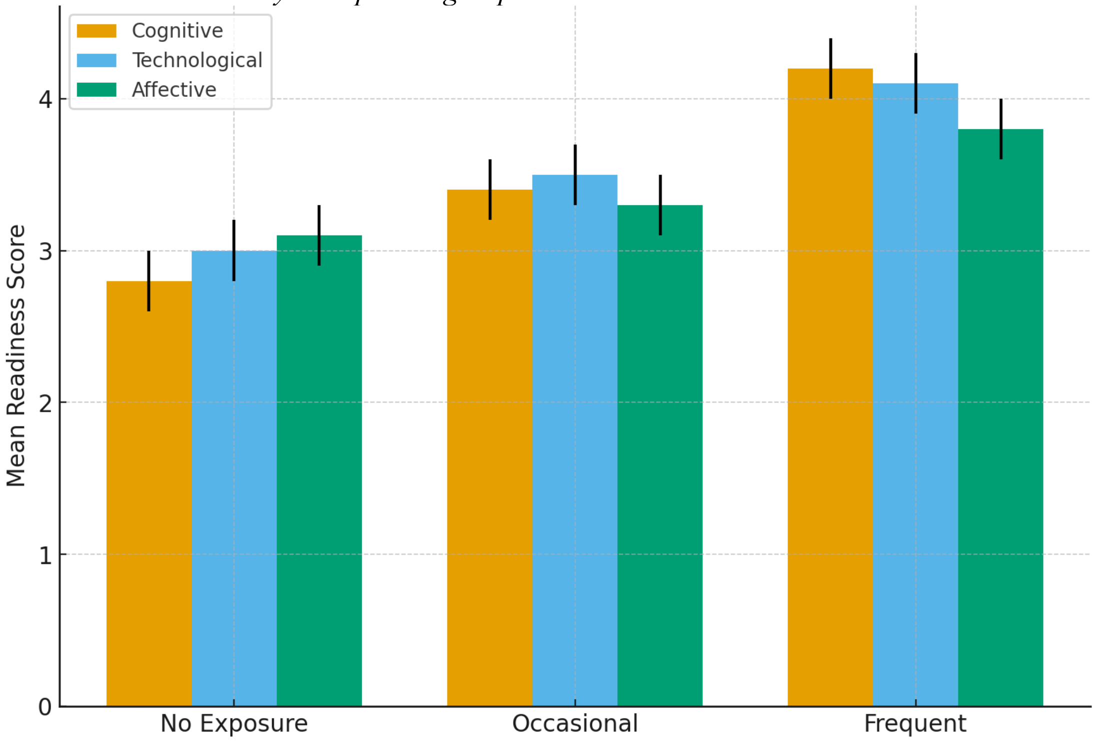
Technological readiness also showed significant differences, $F(2, 181) = 15.47$, $p < .001$, partial $\eta^2 = .15$. Post hoc comparisons revealed that the frequent exposure group outperformed both the occasional and non-exposure groups, although differences between occasional and non-exposure groups did not reach statistical significance.

Affective readiness varied significantly across exposure categories, $F(2, 181) = 6.01$, $p = .003$, partial $\eta^2 = .06$. Tukey comparisons indicated that students with frequent exposure reported higher affective readiness than those with no exposure, whereas the occasional group did not differ significantly from either comparison group.

To further clarify effect magnitude, a graphical depiction is provided in Figure 1. This figure is referenced here and appears immediately after this paragraph.

Figure 1

Mean readiness levels by AI exposure group.



Note. Error bars represent ±1 standard error. Higher scores indicate greater readiness across the cognitive, technological, and affective domains.

Secondary Inferential Analyses: Gender and Academic Program

Independent-samples t tests were used to examine gender differences in readiness. No statistically significant differences were observed across cognitive, technological, or affective domains. Cognitive readiness was similar for males and females, $t(182) = -0.45$, $p = .655$. Technological readiness, $t(182) = -0.52$, $p = .604$, and affective readiness, $t(182) = -0.74$, $p = .461$, also showed no meaningful gender-based variation.

Differences across academic programs were examined using one-way ANOVA. Cognitive readiness did not differ significantly across programs, $F(3, 180) = 1.36$, $p = .257$. Technological readiness similarly showed no differences, $F(3, 180) = 1.82$, $p = .146$. Affective readiness approached but did not reach statistical significance, $F(3, 180) = 2.51$, $p = .061$. Post hoc analyses confirmed the absence of significant pairwise differences.

Summary of Statistical Outcomes

A consolidated view of the main inferential results is presented in Table 4. This table is referenced before it is displayed and includes ANOVA results, effect sizes, and post hoc significance patterns to provide a concise summary of the statistical outcomes.

Table 4
Summary of inferential results for readiness dimensions

Analysis Type	Test Statistic	*p*-value	Effect Size (partial η^2)	Significant Post Hoc Differences
Cognitive readiness (Exposure)	$F(2,181) = 18.92$	< .001	.17	Frequent > Occasional > None
Technological readiness (Exposure)	$F(2,181) = 15.47$	< .001	.15	Frequent > Occasional, Frequent > None
Affective readiness (Exposure)	$F(2,181) = 6.01$	.003	.06	Frequent > None
Gender comparisons	$t(182)$ ns	—	—	None
Program comparisons	$F(3,180)$ ns	—	—	None

Note. ns = non-significant.

Discussion

The findings of this study contribute to the growing body of scholarship on AI-assisted learning readiness by demonstrating that students' cognitive, technological, and affective readiness is strongly shaped by their prior exposure to AI tools. This result aligns with a substantial body of literature indicating that experiential familiarity is a key determinant of digital competence and technology adoption (Abdo-Salloum & Al-Mousawi, 2025; Liu, 2025; Mutambik, 2024). Students who frequently engaged with AI tools exhibited significantly higher readiness across all dimensions, supporting theoretical claims within the Technology Acceptance Model (TAM) that repeated interaction enhances perceived usefulness, perceived ease of use, and technology-related self-efficacy (Abulail et al., 2025; Falebita & Kok, 2025; Liu, 2025). As such, the findings validate the hypothesis that AI exposure plays a central role in shaping readiness for AI-supported learning environments.

The absence of statistically significant differences across gender and academic major suggests a narrowing of traditional digital divides, confirming recent studies that indicate gender gaps in digital literacy have substantially diminished in younger, digitally native populations (Balaskas et al., 2025; Shuvo & Ahmed, 2025). This evidence challenges older assumptions that demographic characteristics fundamentally shape technology adoption, instead indicating that contextual variables, particularly access, exposure, and institutional ecosystem, are more consequential predictors of AI readiness (Felemban et al., 2024; Ghosh, 2025) . These non-significant group differences also echo global reports that AI literacy is increasingly influenced by the pervasiveness of AI tools in everyday applications (Avsec & Rupnik, 2025; Wu et al., 2025), highlighting the importance of integrating AI literacy across curricula rather than limiting it to specific study programs.

Interpretively, the higher readiness scores among more experienced users may indicate that AI exposure cultivates a metacognitive understanding of AI capabilities and boundaries. This aligns with research on AI literacy showing that hands-on use improves algorithmic awareness, trust calibration, and critical engagement with AI-generated outputs (Al-Abdullatif, 2025; Avsec & Rupnik, 2025; Kim, Yu, et al., 2025). However, despite generally positive affective readiness, the moderate levels observed in the present study also reflect persistent concerns about data privacy, academic integrity, and potential over-reliance on AI, issues widely documented in recent empirical work (Alamäki et al., 2024; Ji et al., 2025; Nasr et al., 2025). These tensions illustrate the dual nature of AI in education, simultaneously enabling personalized learning while raising new ethical, pedagogical, and governance challenges.

The results also expand the theoretical landscape by showing that readiness is not a monolithic construct but a multidimensional profile shaped by interaction effects among cognitive, technological, and affective domains. This is consistent with multidimensional digital readiness frameworks (Almusawi & Durugbo, 2024; Magliocca et al., 2024) and emerging theories of AI readiness that emphasize interrelated competencies, attitudes, and contextual resources (Falebita & Kok, 2025; Fundi et al., 2024). The varying strengths of these dimensions in the sample, especially the comparatively higher affective readiness, suggest that emotional orientation toward AI may develop more quickly than cognitive or technological competence, particularly in populations highly exposed to digital media. This asymmetry has been noted in recent cross-cultural studies showing that enthusiasm for AI often precedes deep conceptual understanding (Jia & Tu, 2024; Lin & Chen, 2024), reinforcing the need for structured AI literacy interventions that emphasize critical thinking and responsible use.

At the same time, several alternative explanations merit consideration. For instance, students with higher AI readiness may self-select into technologically enriched environments or courses, suggesting a reciprocal rather than unidirectional relationship between exposure and readiness. Self-report measures, although validated, may also inflate perceptions of competence relative to actual skill performance, a dynamic widely documented in digital literacy research (Fite & Thompson-Hollands, 2025; Wong et al., 2025). Moreover, variability in institutional resources across the participating universities may shape both opportunities for exposure and perceived readiness, consistent with ecological models of learning technology adoption (Alam et al., 2024; Samara et al., 2025). These interpretive nuances indicate that readiness should be understood as situated and context-dependent rather than purely individual.

The study's methodological strengths include the use of psychometrically robust instruments, adherence to JARS reporting guidelines, and the inclusion of a multicampus sample that enhances ecological validity. However, several limitations constrain the extent to which the findings can be generalized. The cross-sectional design prevents causal inference, echoing calls in the literature for longitudinal or intervention-based approaches to understand readiness trajectories over time (Khan & Jain, 2025). Convenience sampling also limits representativeness, and future research should consider stratified sampling or multi-institutional random sampling to enhance generalizability. Additional methodological extensions, such as integrating learning analytics, behavioral trace data, or experimental manipulations, would further bolster understanding of how readiness influences actual performance in AI-enhanced learning environments.

Despite these limitations, the findings offer clear theoretical, methodological, and practical contributions. Theoretically, the study refines existing models of AI readiness by demonstrating the primacy of experiential variables and the interdependence of readiness dimensions. Methodologically, it affirms the value of cross-sectional mapping for identifying readiness gaps prior to curricular innovation. Practically, the results point to the need for targeted AI literacy programs, equitable access to AI tools, and structured exposure opportunities for students with limited experience. These implications resonate with global educational priorities emphasizing equitable AI integration and responsible AI pedagogy (Biagini, 2025; Chiu et al., 2024). Ultimately, the study underscores the importance of preparing students not only to use AI tools but to understand, critique, and meaningfully interact with them as part of a rapidly evolving educational ecosystem.

Conclusion

The present study advances current understandings of AI readiness in higher education by demonstrating that undergraduate students' preparedness for AI-assisted learning is shaped primarily by their prior exposure to AI tools and by the interplay of cognitive, technological, and affective dimensions of readiness. The findings show that while overall readiness levels are moderately high, developmental gaps persist, particularly among students with limited AI experience, highlighting the need for structured AI literacy initiatives and equitable access to digital resources across institutions. The absence of significant differences across gender and academic majors further suggests that readiness is becoming less dependent on demographic characteristics and more closely tied to experiential and contextual factors. These results contribute to global discussions on responsible and inclusive AI integration in education and underscore the importance of designing pedagogical, curricular, and institutional interventions that enhance students' critical understanding, digital competence, and ethical engagement with AI systems. Collectively, the study provides an empirical foundation for future research aimed at strengthening AI literacy, improving technology-supported learning design, and promoting informed, developmentally aligned AI adoption in higher education contexts.

Author Contributions

HK conceptualized the study, designed the research framework, and supervised the overall project execution. FP conducted the data collection, performed the statistical analyses, and contributed to drafting and revising the manuscript. Both authors reviewed, refined, and approved the final version of the manuscript.

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