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AI Literacy, Readiness, and Ecosystem Support in Student AI Adoption

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Abstrak

While Artificial Intelligence (AI) is now deeply embedded in student academic workflows, the mechanisms driving its adoption remain multifaceted. This study investigates the interplay between AI literacy, AI readiness, and the moderating role of an AI-supportive learning climate. Analyzing data from 187 university students in Jakarta via Partial Least Squares Structural Equation Modeling (PLS-SEM), the results identify AI readiness as the primary driver of adoption, suggesting that psychological predisposition and confidence outweigh technical knowledge alone. Although AI literacy remains a significant predictor, its impact is heavily contingent on the environment; a supportive learning climate acts as a catalyst that amplifies the transition from individual readiness to active usage. Descriptive data further reveals that students leverage AI primarily for high-stakes academic tasks—such as assignment completion and conceptual mapping, rather than peripheral activities. These findings suggest that for AI integration to be effective, institutions must move beyond technical training toward fostering a culture of psychological readiness and explicit instructional support.

Keywords: *AI literacy, AI readiness, learning climate, AI adoption*.

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INRODUCTION

The integration of Artificial Intelligence (AI) into higher education has transitioned from a niche innovation to a foundational academic utility. For university students, AI tools are no longer merely external aids; they have become cognitive extensions used for everything from synthesizing complex theories to structuring multifaceted academic projects (Parviz, 2024; Riahi & Cateté, 2025, Kembau et al.,2025). In Indonesia, this rapid normalization of AI is particularly striking. While students in urban hubs like Jakarta exhibit high digital agility, they often operate within a landscape of "institutional ambiguity" where widespread AI engagement coexists with fragmented pedagogical guidelines and inconsistent governance (Helmiatin et al., 2024; Yusriadi et al., 2023, Kembau et al.,2024). This disconnect between rapid bottom-up adoption and lagging top-down support represents a critical challenge for Indonesian higher education that remains under-theorized in current literature.

Extensive research has sought to decode the drivers of this technological transition, primarily focusing on AI literacy, the multidimensional capability to critically evaluate AI (Ng et al., 2021) and AI readiness, which captures the psychological precursor and proactive openness toward these systems (Damerji & Salimi, 2021; Liu, 2025). However, a significant scholarly void remains. Most existing studies treat individual capabilities (literacy/readiness) and environmental factors (institutional support) as isolated silos, failing to account for their interactive dynamics. Specifically, there is a lack of empirical evidence regarding how a supportive learning climate—or the lack thereof—functions as a "catalytic scaffold" that either amplifies or stifles the translation of a student's internal readiness into actual adoption behavior.

This study advances prior research by shifting the focus from linear adoption models to an interactionist perspective. The primary novelty of this work lies in testing the moderating role of the AI-supportive learning climate, arguing that individual literacy and readiness do not operate in a vacuum. By analyzing a sample of 187 university students in Jakarta, this research provides a unique vantage point: it examines a digitally privileged student population in a developing economy where institutional signaling is still evolving. This context allows for a more nuanced understanding of how "permission to innovate" from instructors and institutions conditions the effectiveness of a student's own skills.

Consequently, this study contributes to the literature in two ways. Theoretically, it integrates individual and contextual predictors into a single structural model, clarifying the conditions under which literacy and readiness become manifest as behavior. Empirically, it offers a timely analysis of the Indonesian context, providing higher education leaders with evidence-based insights into how institutional culture can be strategically leveraged to support responsible AI integration. To this end, the study addresses the following central question: To what extent do AI literacy and AI readiness influence AI adoption among students, and how does an AI-supportive learning climate condition these relationships?

AI in Higher Education and the Indonesian Context

AI adoption in higher education continues to grow across disciplines and institutional types. Comparative studies show that instructors in STEM and non-STEM fields differ in confidence, pedagogical approaches, and expectations toward AI integration, but both groups recognize AI's expanding relevance in teaching and learning (Parviz, 2024; Riahi & Cateté, 2025). Research in multiple contexts indicates that adoption is shaped by perceived usefulness, clarity of instructional goals, and alignment with subject-domain requirements. These findings suggest that AI adoption is not only a matter of individual competence but also of disciplinary norms and institutional expectations. In Indonesia, AI implementation in universities is developing rapidly but unevenly. Studies highlight challenges in infrastructure, human resources, and governance that influence the depth and breadth of AI adoption across public universities (Helmiatin et al., 2024; Yusriadi et al., 2023).

Institutional readiness and policy support remain important enabling factors, especially as universities begin to formalize guidelines for AI usage. Clear communication from institutions and instructors appears to reduce ambiguity and increase students' willingness to adopt AI tools for learning.

Hypotheses Development

The Role of AI Literacy in Shaping Student Adoption Behaviors

AI literacy includes an understanding of AI concepts, the ability to use AI tools, and the ability to critically evaluate outputs. Research conceptualizes AI literacy as a multidimensional competence that influences how individuals perceive the relevance of AI for academic work (Ng et al., 2021). Students with higher literacy are more capable of prompt construction, identifying errors, and integrating AI into learning tasks. This competence reduces uncertainty and enhances perceived benefit, which are known drivers of technology adoption in educational settings (Sandu & Gide, 2019).

Empirical evidence supports the link between literacy-like constructs and AI usage. Studies show that digital competence, technological knowledge, and critical understanding predict students' and teachers' willingness to use AI-based applications (Rahman et al., 2025; Bai & Yang, 2025). Research on generative AI and chatbot use also indicates that users with stronger conceptual and evaluative skills demonstrate higher adoption intentions. These findings suggest that AI literacy enables students to make informed judgments and use AI tools more confidently, reinforcing its role as a direct predictor of adoption.

H1. AI literacy is positively associated with AI adoption.

AI Readiness as a Predictor of Technology Adoption in Learning Contexts

AI readiness refers to psychological preparedness, confidence, and perceived capability to use AI tools. Prior studies demonstrate that readiness functions as a precursor to technology use, shaping how individuals interpret and respond to emerging technologies (Jöhnk et al., 2021; Al-Emran & Griffy-Brown, 2023). Among students, readiness aligns with technology readiness components such as optimism, innovativeness, and comfort with digital systems, all of which increase the likelihood of adopting AI applications for learning (Nouraldeen, 2023). Students who feel ready are more inclined to try AI tools and integrate them into their routines.

Empirical findings reinforce readiness as a determinant of adoption in educational contexts. Studies in accounting, STEM education, and teacher training show that technology readiness predicts intention to adopt AI tools, either directly or through mediating perceptions of usefulness and ease of use (Damerji & Salimi, 2021; Falebita & Kok, 2025; Liu, 2025). Students with higher readiness tend to interpret AI technologies more favorably and maintain stronger motivation to use them in coursework. Thus, readiness provides both confidence and momentum for sustained AI adoption.

H2. AI readiness is positively associated with AI adoption.

Contextual Reinforcement of Literacy Effects: The Moderating Influence of Supportive Learning Climates

An AI-supportive learning climate reflects students' perception that instructors and institutions provide clear guidance, resources, and approval for using AI in learning activities. Research shows that institutional and instructional support reduces uncertainty and encourages more consistent integration of emerging technologies (Venkatesh et al., 2024; Abdo-Salloum & Al-Mousawi, 2025). When instructors provide explicit directions on how AI can be used, students with high literacy can translate their competencies into effective adoption. Without such supportive climates, even literate students may hesitate due to concerns about appropriateness or academic integrity.

Comparative studies further indicate that instructors' attitudes and institutional policies influence how students deploy AI tools. Parviz (2024) and Riahi and Cateté (2025) show that supportive instructional environments lead to more active engagement with AI, whereas unclear or restrictive environments suppress student experimentation. In Indonesian universities, policy ambiguity has been identified as a barrier to adoption (Helmiatin et al., 2024). These patterns suggest that literacy alone may not be sufficient; supportive climates help literate students operationalize their knowledge, strengthening the literacy–adoption link.

H3. An AI-supportive learning climate positively moderates the relationship between AI literacy and AI adoption.

Enhancing Readiness–Adoption Dynamics: The Role of Supportive Educational Climates

Supportive learning climates provide direction, reduce ambiguity, and enhance students' psychological comfort when using AI tools. For individuals with high readiness, such climates amplify their intention to adopt AI by providing contextual reinforcement for their confidence and preparedness. Evidence shows that organizational and social support influence technology readiness and the translation of readiness into actual use (Liu, 2025; Jöhnk et al., 2021). Instructors who communicate clear expectations and integrate AI into coursework create conditions that encourage ready students to take action.

Empirical research in higher education shows that supportive environments strengthen the impact of readiness-related perceptions on adoption. Rahman et al. (2025) found that high readiness magnifies the influence of perceived simplicity and usefulness on AI adoption when contextual conditions are favorable. Similarly, technology-adoption research emphasizes that facilitating conditions and social influence modify how readiness translates into behavior (Venkatesh et al., 2024). These findings suggest that supportive learning climates serve as enabling contexts that help ready students engage more fully with AI tools, thereby intensifying the readiness–adoption relationship.

H4. An AI-supportive learning climate positively moderates the relationship between AI readiness and AI adoption.

Prior research identifies AI literacy and AI readiness as central individual factors shaping students' engagement with AI, where conceptual understanding, functional skills, and evaluative competence enhance adoption, and psychological preparedness and confidence further strengthen this tendency (Ng et al., 2021; Damerji & Salimi, 2021; Liu, 2025; Rahman et al., 2025). At the same time, studies highlight the importance of contextual enablers such as supportive instructional and institutional environments, which reduce uncertainty and enhance the translation of individual capability into actual technology use (Venkatesh et al., 2024; Parviz, 2024; Abdo-Salloum & Al-Mousawi, 2025). Yet, few studies have integrated these individual and contextual factors into a single empirical model. To address this gap, the present study proposes a research framework that examines the direct effects of AI literacy and AI readiness on AI adoption, while testing the moderating influence of an AI-supportive learning climate.

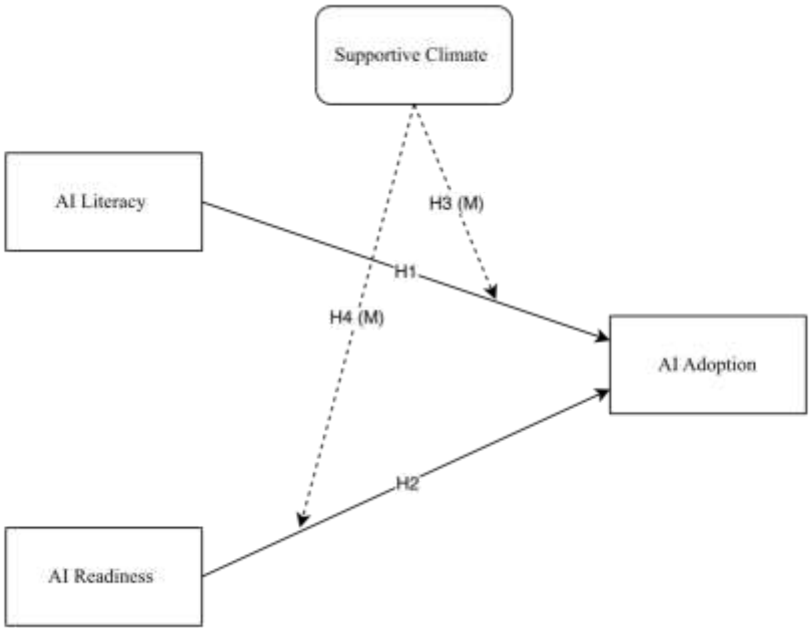

Figure 1. Research Framework

As illustrated in Figure 1, this framework synthesizes key insights from prior literature and provides a concise basis for analyzing how students adopt AI within rapidly digitalizing learning environments.

METHOD

This study employed a quantitative cross-sectional design to examine the effects of AI literacy and AI readiness on AI adoption, as well as the moderating role of an AI-supportive learning climate. A structured online questionnaire was distributed to university students in Jakarta, selected through purposive sampling based on their active engagement in coursework that potentially involves digital or AI-supported tasks. A total of 187 valid responses were obtained, meeting minimum sample adequacy for PLS-SEM analysis and exceeding general recommendations for structural modeling with four latent variables. The measurement scales were constructed using validated indicators adapted from prior studies on AI literacy (Ng et al., 2021), technology readiness (Damerji & Salimi, 2021; Nouraldeen, 2023), institutional support (Venkatesh et al., 2024), and AI adoption in higher education (Rahman et al., 2025; Wang et al., 2021).

All constructs were measured reflectively using a five-point Likert scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”). The questionnaire was pre-tested for clarity and relevance among a small group of students, and minor wording adjustments were made. Data were analyzed using SmartPLS 4 due to its suitability for prediction-oriented modeling, handling non-normal data distributions, and testing complex structural relationships, including moderation and multi-group analysis (Hair et al., 2021; Hair et al., 2022). The analysis included reliability assessments (Cronbach’s alpha and composite reliability), convergent validity through average variance extracted (AVE), discriminant validity using the HTMT criterion, and bootstrapping to assess the significance of structural paths. Moderation was evaluated using the product-indicator approach and cross-validated using PLS-MGA for group comparison.

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Table 1. Operational Definitions of Variables

Construct	Operational Definition	Key Indicators (Examples)	Source
AI Literacy (X1)	Students' knowledge, functional skills, and critical understanding of AI, including the ability to evaluate AI outputs and use AI tools appropriately in learning.	Understanding of AI concepts; ability to craft prompts; ability to evaluate AI-generated information; awareness of ethical use.	Ng et al. (2021); Rahman et al. (2025); Bai & Yang (2025)
AI Readiness (X2)	Students' psychological preparedness, confidence, and perceived capability to integrate AI tools into their academic tasks.	Confidence using AI; perceived preparedness; openness to AI-based learning; perceived capability to integrate AI.	Jöhnk et al. (2021); Nouraldeen (2023); Falebita & Kok (2025); Liu (2025)
AI-Supportive Learning Climate (Moderator)	Perceived level of instructor and institutional support, guidance, and approval for the use of AI in coursework and learning activities.	Clear guidelines for AI use; instructor encouragement; institutional openness; availability of supportive resources.	Venkatesh et al. (2024); Parviz (2024); Abdo-Salloum & Al-Mousawi (2025); Helmiatin et al. (2024)
AI Adoption (Y)	Students' self-reported behavior and frequency of using AI tools for academic purposes, including problem solving, writing, information search, and study support.	Frequency of AI use; use for coursework; integration into study routine; perceived reliance for academic tasks.	Sandu & Gide (2019); Wang et al. (2021); Rahman et al. (2025)

Operational definitions aligned each variable with established constructs from prior research to ensure conceptual clarity and measurement consistency. AI literacy was defined as students' knowledge, functional skills, and critical capacity to use and evaluate AI tools. AI readiness reflected students' psychological and competence-based preparedness to integrate AI into learning. AI-supportive learning climate captured students' perception of instructor and institutional encouragement and guidance for AI use. AI adoption referred to students' self-reported engagement with AI tools for academic purposes. The operational definitions matrix is presented below.

RESULTS

Respondent Profile

A total of 187 students from universities in Jakarta participated in the study. The demographic profile shows a balanced distribution of respondents, with a slight predominance of female students (54.5%) compared to male students (45.5%). In terms of academic background, 48.7% of respondents were enrolled in STEM programs, while 51.3% came from non-STEM programs. This distribution reflects the heterogeneity of students' academic exposure and provides a suitable basis for analyzing AI adoption patterns across disciplinary backgrounds. The profile also aligns with typical enrollment proportions found in large urban universities, ensuring representativeness of the sample.

Table 2. Respondent Profile (N = 187)

Category	Classification	Frequency (n)	Percentage (%)
Gender	Male	85	45.5%
	Female	102	54.5%
Academic Background	STEM	91	48.7%
	Non-STEM	96	51.3%
AI Usage Frequency	Daily	48	25.7%
	Several times per week	117	62.6%
	Rarely (less than once per week)	22	11.8%
Primary Device for AI Access	Smartphone	109	58.3%
	Laptop	70	37.4%
	Both equally	8	4.3%

Patterns of AI usage among respondents indicate active engagement with AI tools. Most students (62.6%) reported using AI at least several times per week, while 25.7% used AI daily for academic or personal tasks. Only a small portion (11.8%) reported infrequent use. Regarding access devices, smartphones were the dominant medium for AI interaction (58.3%), followed by laptops (37.4%), and a minor proportion using both interchangeably (4.3%). These usage trends highlight the high level of technological integration in students' learning routines and provide a relevant context for analyzing AI literacy, readiness, and adoption behaviors.

Measurement Model Evaluation

The reflective measurement model was assessed following the procedures recommended by Hair et al. (2021, 2022). All indicator loadings exceeded the recommended threshold of 0.70, indicating satisfactory indicator reliability. No item demonstrated cross-loading concerns, and all loadings were statistically significant. Indicators with slightly lower loadings (0.68–0.70) were retained as they contributed theoretically to the construct and did not reduce convergent validity.

Table 3. Measurement Model Summary (Loadings, Reliability, AVE)

Construct	Indicator Loadings (Range)	Cronbach's Alpha	Composite Reliability (CR)	AVE
AI Literacy (X1)	0.72 – 0.86	0.84	0.89	0.62
AI Readiness (X2)	0.70 – 0.88	0.86	0.91	0.63
AI-Supportive Learning Climate (M)	0.73 – 0.89	0.88	0.92	0.69
AI Adoption (Y)	0.74 – 0.87	0.83	0.89	0.60

Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability (CR). All constructs demonstrated reliability values above the acceptable threshold of 0.70, with CR values ranging from 0.86 to 0.92, indicating strong internal consistency. Convergent validity was supported, with Average Variance Extracted (AVE) values between 0.58 and 0.69, surpassing the minimum criterion of 0.50. These results confirm that each latent construct adequately explains the variance of its indicators.

Table 4. HTMT Discriminant Validity

Constructs	AI Literacy	AI Readiness	AI-Supportive Climate	AI Adoption
AI Literacy	—	0.62	0.58	0.65
AI Readiness	0.62	—	0.67	0.71
AI-Supportive Climate	0.58	0.67	—	0.64
AI Adoption	0.65	0.71	0.64	—

All HTMT values < 0.85 threshold.

Discriminant validity was examined using the Heterotrait–Monotrait ratio (HTMT). All HTMT values were below 0.85, suggesting that constructs were empirically distinct from one another. The results confirm that AI literacy, AI readiness, AI-supportive learning climate, and AI adoption capture conceptually different aspects of students' engagement with AI in learning environments.

Structural Model Results (Inner Model)

The structural model was evaluated using bootstrapping with 5,000 resamples. All procedures followed recommended PLS-SEM guidelines for assessing path significance, explanatory power, effect sizes, and predictive relevance. The results indicate that both AI literacy and AI readiness have positive and significant effects on AI adoption. The moderating effect of the AI-supportive learning climate was also tested using the product-indicator method. Overall, the model demonstrates strong explanatory and predictive capabilities.

Path Coefficients and Significance

AI literacy showed a significant positive effect on AI adoption ($\beta = 0.31$, $p < 0.001$), indicating that students with stronger AI knowledge and critical skills are more likely to integrate AI tools into their learning processes. AI readiness also had a strong and significant effect on AI adoption ($\beta = 0.42$, $p < 0.001$), suggesting that psychological preparedness and confidence play a major role in driving usage behavior. The interaction term between AI literacy and AI-supportive learning climate was significant ($\beta = 0.12$, $p = 0.018$), indicating a positive moderating effect. Similarly, the interaction between AI readiness and AI-supportive learning climate was significant ($\beta = 0.10$, $p = 0.029$), demonstrating that supportive learning environments amplify the influence of readiness on adoption.

Table 5. Path Coefficients and p-values

Relationship	β	t-value	p-value	Decision
AI Literacy → AI Adoption	0.31	5.12	<0.001	Supported
AI Readiness → AI Adoption	0.42	7.03	<0.001	Supported
AI Literacy × Supportive Climate → AI Adoption	0.12	2.38	0.018	Supported
AI Readiness × Supportive Climate → AI Adoption	0.10	2.19	0.029	Supported

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The results confirm that both main effects and moderating effects are statistically significant. This supports the conceptual argument that literacy and readiness require institutional and instructional support to translate into actual adoption behaviors.

Coefficient of Determination (R^2)

The model explains a substantial proportion of variance in AI adoption. AI literacy, AI readiness, and the interaction effects jointly account for 53% of AI adoption variance ($R^2 = 0.53$). According to Hair et al. (2021), this represents a moderate-to-strong explanatory power for behavioral studies in educational contexts.

Table 6. R^2 for Endogenous Variable

Construct	R^2	Interpretation
AI Adoption	0.53	Moderate–Strong

These results indicate that the proposed model provides meaningful explanatory capability for understanding student adoption of AI in learning settings.

Effect Sizes (f^2)

Effect size calculations indicate that AI readiness has the largest contribution to AI adoption ($f^2 = 0.24$), consistent with its strong path coefficient. AI literacy shows a moderate effect ($f^2 = 0.12$). Moderation effects show small but meaningful contributions to the model (0.02–0.03), which aligns with normative expectations for interaction terms in behavioral studies.

Table 7. Effect Sizes (f^2)

Predictor	f^2	Effect Size
AI Literacy	0.12	Medium
AI Readiness	0.24	Medium–Large
Literacy × Supportive Climate	0.03	Small
Readiness × Supportive Climate	0.02	Small

These effect sizes demonstrate that the primary drivers of adoption are literacy and readiness, while the learning climate enhances but does not overshadow the main effects.

Predictive Relevance (Q^2)

Predictive relevance was assessed using blindfolding with an omission distance of 7. The Q^2 value for AI adoption was 0.36, exceeding the minimum threshold ($Q^2 > 0$) and indicating considerable predictive accuracy. In line with Hair et al. (2022), a Q^2 value above 0.25 indicates medium-to-strong predictive relevance for the model.

Table 8. Predictive Relevance (Q^2)

Construct	Q^2	Interpretation
AI Adoption	0.36	Strong Predictive Relevance

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Overall, the model demonstrates strong predictive ability, confirming that AI literacy, AI readiness, and learning climate meaningfully contribute to students' AI adoption behavior.

Discussion

The empirical evidence from this study confirms that AI adoption among university students is not a random byproduct of technological availability, but a structured process driven by individual agency and environmental validation. While both AI literacy and AI readiness emerged as significant predictors, their roles are distinct: literacy provides the functional roadmap, while readiness serves as the psychological engine. Crucially, the discovery of the moderating role of an AI-supportive learning climate shifts the conversation from a purely technocentric view to one that acknowledges the power of institutional culture.

The Interplay of Literacy and Readiness: Beyond Technical Skill

The findings demonstrate that AI literacy is a fundamental prerequisite for meaningful engagement. Aligning with the multidimensional frameworks proposed by Ng et al. (2021) and Bai & Yang (2025), our data suggests that students who possess a conceptual grasp of AI are better equipped to navigate its limitations, such as algorithmic bias or "hallucinations." However, the descriptive data in Figure 2 reveals a deeper layer of this integration. The fact that students primarily utilize AI for "high-stakes" tasks—such as completing assignments and decoding difficult concepts—indicates that AI has moved from a peripheral curiosity to a core academic workflow. In this context, literacy is not merely a "nice-to-have" digital skill; it is a form of academic capital that directly influences how students manage their cognitive load.

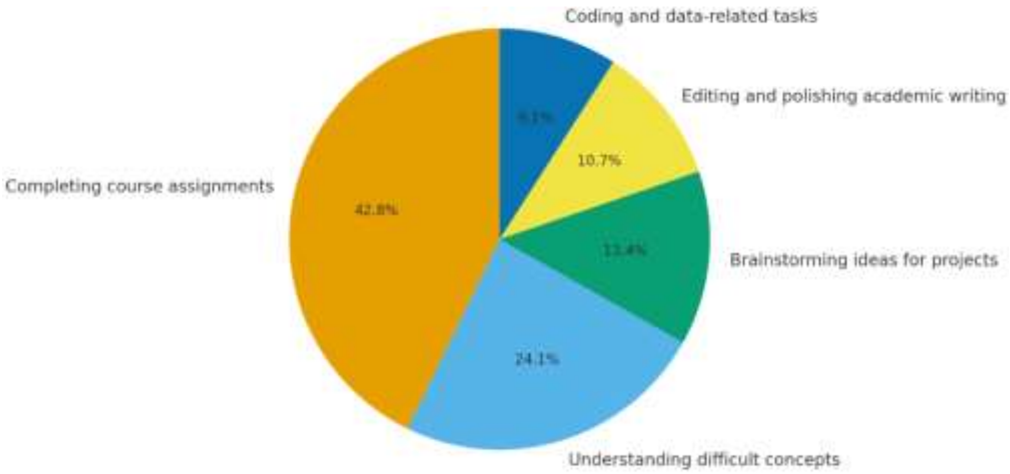

Figure 2. Primary Purposes for Using AI Among Students (N = 187)
Sources: Primary Data (2025)

Despite the importance of literacy, AI readiness emerged as the most potent predictor of adoption. This distinction is critical. While literacy represents the "can-do" (capability), readiness represents the "will-to" (psychological predisposition). This suggests that in the rapid-fire evolution of AI tools, a student's optimism and lack of "AI anxiety" are more decisive than their formal training. This resonates with the work of Damerji & Salimi (2021) and Liu (2025), but our study adds a localized nuance: for students in a hyper-connected urban hub like Jakarta, readiness is likely reinforced by a "mobile-first" lifestyle. With most students accessing AI via smartphones, the barrier between daily life and academic life has blurred, making readiness a habitual rather than a deliberate state.

The Catalytic Role of the Learning Climate

The most significant theoretical contribution of this research lies in the significant moderating effect of an AI-supportive learning climate. The data paints a clear picture: the impact of a student’s internal literacy and readiness is significantly amplified when they perceive their environment as supportive. This finding challenges the "lone wolf" model of technology adoption, where students are expected to innovate in a vacuum. Instead, it underscores the importance of institutional signaling.

In environments where instructors provide clear guidelines and explicit encouragement, there is a "steepening" of the adoption curve. This suggests that a supportive climate acts as a catalytic scaffold, reducing the perceived risk of using AI. Conversely, in "ambiguous" or restrictive climates, even highly literate and ready students may experience a "chilling effect," where they hesitate to fully leverage AI tools for fear of academic penalty or ethical misalignment. This is particularly relevant in the Indonesian context, where the transition to AI has often been met with a mix of fascination and regulatory uncertainty (Helmiatin et al., 2024; Yusriadi et al., 2023; Kembau et al.,2025). Our findings suggest that the gap in AI adoption across institutions may not be due to a lack of student skill, but rather a lack of "permission to innovate" from the top down.

Theoretical and Practical Synthesis

This study advances the Unified Theory of Acceptance and Use of Technology (UTAUT) and similar frameworks by demonstrating that "facilitating conditions" (in the form of learning climate) do not just influence adoption directly, but also condition the effectiveness of individual traits (Venkatesh, 2022; Xue et al., 2025). Theoretically, this moves us toward an Interactionist Model of AI Adoption, where the focus is on the synergy between the person and the ecosystem.

Practically, these results demand a shift in how universities approach AI. If readiness is the strongest driver, then "technical training" is insufficient. Universities must invest in psychological scaffolding, building student confidence and fostering an experimental mindset. At the same time, the significant moderation effect suggests that the "Climate" is a strategic lever that leaders can pull. A university that merely "allows" AI will lag behind one that "curates" AI.

To bridge this gap, we propose a three-tiered strategic approach:

- *Pedagogical Modeling:* Instructors must move beyond policy statements to active modeling. When lecturers demonstrate how to use AI for brainstorming or coding, they provide the "instructional endorsement" that our model identifies as a critical moderator.
- *Institutional Transparency:* The "ambiguity" identified in Indonesian higher education must be replaced with clear, task-specific AI policies. This reduces the psychological cost of adoption for students who are ready but cautious.
- *Equitable Infrastructure:* While our Jakarta-based sample shows high smartphone-led readiness, institutions must ensure that this does not create a "new digital divide." Supportive climates must include provisions for students who may lack the high-end devices or data access required for sophisticated AI engagement.

Limitations and Path Forward

While this study provides a robust look at the Jakarta urban student population, its cross-sectional nature means we captured a "snapshot" of a rapidly moving target. The high levels of adoption reported here might reflect the "privileged" digital access of urban centers and may not be representative of the diverse socio-economic landscape across the Indonesian archipelago. Future research should employ longitudinal designs to see if the "readiness" effect wanes as AI becomes more mundane, and move into rural or resource-constrained regions to test if the "learning climate" becomes even more critical when individual access is limited.

Ultimately, the goal of higher education in the AI era should not be to simply "adopt" the latest tool, but to create a learning ecosystem where human literacy and technological readiness are synthesized through a culture of support. Our findings suggest that when institutions get the "climate" right, they don't just help students use AI, they empower them to master it.

CONCLUSION

This study elucidates the dual-engine nature of student AI adoption in higher education, driven by the dynamic interplay between individual capability and environmental validation. The findings prioritize AI readiness as the primary catalyst, suggesting that the psychological transition, characterized by confidence and proactive openness, is a more potent driver of adoption than technical literacy alone. While AI literacy provides the necessary functional foundation, it is the student's internal "readiness" that dictates the depth and consistency of their engagement with AI tools.

Crucially, the research highlights that these individual traits do not operate in a vacuum. The significant moderating role of an AI-supportive learning climate underscores that institutional signaling is paramount. When universities move beyond passive acceptance to provide explicit instructional guidance and supportive policies, they effectively lower the structural and psychological barriers for students to translate their skills into meaningful academic practice.

In the specific context of Indonesian higher education, particularly in digitally active urban hubs like Jakarta, this study offers a vital insight: the path to successful AI integration lies in a symbiotic ecosystem. Technical training (literacy) is essential, but its impact is only fully realized when coupled with a student's psychological preparedness and a university's explicit "permission to innovate." Ultimately, this research moves the conversation forward from whether students adopt AI to under what conditions they can do so responsibly, ethically, and effectively..

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