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Can AI Self-Efficacy Explain Students' AI Adoption? The Mediating Role of Attitude

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Abstrak

Artificial Intelligence (AI) has become an integral part of students' academic activities, yet the mechanisms driving its adoption remain insufficiently explained. This study examines how perceived usefulness and AI self-efficacy influence AI adoption, with attitude toward AI as a mediating variable. Using a quantitative approach, data were collected from 187 university students in Jakarta and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The results indicate that both perceived usefulness and AI self-efficacy have significant positive effects on attitude toward AI, while attitude strongly predicts AI adoption. Mediation analysis confirms that attitude plays a central role in translating students' evaluations and confidence into actual usage behavior. These findings suggest that AI adoption is not directly driven by perception or capability alone, but by how these factors shape students' overall evaluation of AI. The study contributes to the literature by offering a mediation-based perspective that integrates cognitive, belief-based, and affective dimensions into a unified framework. Practically, the results highlight the importance of fostering positive attitudes and user confidence, rather than focusing solely on technical skills, to support effective AI integration in higher education.

Keywords: *perceived usefulness, AI self-efficacy, attitude toward AI, AI adoption, higher education*.

Abstract

Artificial Intelligence (AI) telah menjadi bagian integral dalam aktivitas akademik mahasiswa, namun mekanisme yang mendorong adopsinya masih belum sepenuhnya dipahami. Penelitian ini bertujuan untuk menganalisis pengaruh perceived usefulness dan AI self-efficacy terhadap AI adoption dengan attitude toward AI sebagai variabel mediasi. Penelitian ini menggunakan pendekatan kuantitatif dengan data yang dikumpulkan dari 187 mahasiswa perguruan tinggi di Jakarta dan dianalisis menggunakan Partial Least Squares Structural Equation Modeling (PLS-SEM). Hasil penelitian menunjukkan bahwa perceived usefulness dan AI self-efficacy memiliki pengaruh positif signifikan terhadap attitude toward AI, sementara attitude terbukti berperan kuat dalam mendorong AI adoption. Analisis mediasi mengonfirmasi bahwa attitude menjadi mekanisme utama yang menjembatani pengaruh evaluasi dan kepercayaan diri mahasiswa terhadap perilaku penggunaan AI. Temuan ini menunjukkan bahwa adopsi AI tidak semata-mata didorong oleh persepsi manfaat atau kemampuan, tetapi oleh bagaimana kedua faktor tersebut membentuk evaluasi keseluruhan mahasiswa terhadap AI. Penelitian ini memberikan kontribusi teoretis dengan menawarkan perspektif berbasis mediasi yang mengintegrasikan dimensi kognitif, keyakinan, dan afektif dalam satu kerangka konseptual. Secara praktis, hasil penelitian ini menekankan pentingnya membangun sikap positif dan kepercayaan diri pengguna, bukan hanya peningkatan keterampilan teknis, dalam mendukung integrasi AI yang efektif di pendidikan tinggi.

Kata Kunci: perceived usefulness, AI self-efficacy, attitude toward AI, adopsi AI, pendidikan tinggi

INRODUCTION

Artificial Intelligence (AI) is no longer a peripheral tool in higher education, it has become part of how students think, learn, and complete academic work. From generating ideas to structuring assignments, AI systems are increasingly embedded in everyday learning activities (Bergdahl & Sjöberg, 2025; Kembau et al.,2026). What is striking, however, is not just how often students use AI, but how naturally it fits into their workflow. In contexts such as Indonesia, where students are highly adaptive to digital tools, AI adoption has grown rapidly even in the absence of clear institutional guidelines (Helmiatin et al., 2024; Yusriadi et al., 2023). This suggests that adoption is not solely driven by formal instruction or technical training. Instead, students appear to rely on their own judgment—how useful they believe AI is and how confident they feel in using it—to decide whether and how to engage with these tools (Rahman et al., 2025; Wang et al., 2021). As a result, AI adoption is increasingly shaped by perception and belief rather than access alone.

However, most existing research still explains AI adoption through capability-based perspectives. Studies have consistently highlighted the role of AI literacy, digital competence, and technology readiness in influencing whether students adopt AI tools (Ng et al., 2021; Damerji & Salimi, 2021; Falebita & Kok, 2025). While these factors are important, they primarily address whether students can use AI, not how they decide to use it. More recent work has begun to consider perception-related variables such as perceived usefulness and ease of use, but these are often treated as direct predictors of adoption without examining the psychological process that connects evaluation to behavior (Bai & Yang, 2025; Wang et al.,2024; Venkatesh, 2022). This creates a conceptual gap. If students already have access and basic capability, what actually drives them to integrate AI into their academic routines? The answer likely lies in how their perceptions and self-beliefs are translated into a favorable or unfavorable attitude toward AI.

To address this issue, this study proposes a model that focuses on the internal decision-making process behind AI adoption. Specifically, it examines how perceived usefulness and AI self-efficacy influence students' attitudes toward AI, and how these attitudes, in turn, drive actual adoption behavior. By positioning attitude as a mediating variable, this study shifts the focus from direct relationships to a more explanatory pathway that reflects how students evaluate and internalize technology before using it. This approach is aligned with recent developments in technology adoption research that emphasize the role of psychological and affective factors in shaping behavior (Bai & Yang, 2025; Venkatesh, 2022). Using data from university students in Jakarta, this study also provides empirical insight into a rapidly evolving educational environment where AI use is widespread but not yet fully structured. In doing so, it contributes to a more nuanced understanding of AI adoption, one that goes beyond skills and readiness to capture how students form intentions and translate them into action

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LITERATURE REVIEW

Recent research on AI adoption in education has gradually shifted from focusing purely on technical capability toward understanding how individuals evaluate and respond to AI systems. Early studies emphasized constructs such as digital competence, AI literacy, and technology readiness as primary drivers of adoption (Ng et al., 2021; Damerji & Salimi, 2021). These constructs explain whether users possess the necessary knowledge and preparedness to engage with AI. However, as AI tools become more accessible and user-friendly, especially in student contexts, the role of subjective evaluation becomes more prominent. Studies now show that perceived usefulness, how much a user believes AI improves their performance, plays a central role in shaping adoption decisions (Wang et al., 2021; Wang et al., 2024; Rahman et al., 2025). This aligns with broader technology adoption frameworks such as UTAUT, which highlight performance expectancy as a key determinant of use behavior (Venkatesh, 2022; Kembau et al.,2025).

At the same time, belief-related constructs such as self-efficacy have gained attention as critical factors influencing how individuals approach new technologies. AI self-efficacy reflects a user's confidence in their ability to effectively use AI tools, and it has been shown to influence both motivation and behavioral intention (Falebita & Kok, 2025; Liu, 2025). Beyond cognitive evaluation and capability, recent models increasingly recognize the role of attitude as a central psychological mechanism that connects perception and behavior. In models such as AIDUA, attitude represents an overall affective evaluation that mediates how users translate beliefs and perceptions into actual usage (Bai & Yang, 2025). Despite this development, many studies still treat these constructs in isolation or as direct predictors, leaving a gap in understanding how perceived usefulness and self-efficacy jointly shape attitudes and ultimately influence AI adoption.

Hypotheses Development

The Role of Perceived Usefulness in Shaping Attitude Toward AI

Students tend to adopt technologies that they perceive as beneficial to their academic performance. When AI is seen as a tool that can simplify tasks, improve efficiency, or enhance learning outcomes, students are more likely to develop a positive evaluation of its use. This perception is particularly relevant in academic settings where time pressure and cognitive demands are high. Empirical studies have consistently shown that perceived usefulness is a strong predictor of positive attitudes toward technology, as users are more inclined to favor tools that offer clear and tangible value (Wang et al., 2021; Rahman et al., 2025). Within the context of AI, this means that students who recognize the practical advantages of AI are more likely to form a favorable attitude toward its integration into their learning process.

H1. Perceived usefulness positively influences attitude toward AI.

The Role of AI Self-Efficacy in Shaping Attitude Toward AI

Confidence plays a crucial role in how students approach new technologies. Even when a system is perceived as useful, a lack of confidence can limit engagement and reduce willingness to explore its capabilities. AI self-efficacy reflects an individual's belief in their ability to effectively use AI tools, including their ability to navigate features, interpret outputs, and apply them to academic tasks (Wang et al.,2024; Bergdahl & Sjöberg, 2025). Prior research indicates that individuals with higher self-efficacy are more likely to experience positive emotions and lower anxiety when interacting with technology, which in turn fosters a more favorable attitude (Falebita & Kok, 2025; Liu, 2025). In the context of AI adoption, students who feel capable of using AI are not only more willing to try it but are also more likely to develop a positive overall evaluation of its usefulness in their academic work.

H2. AI self-efficacy positively influences attitude toward AI.

The Role of Attitude in Driving AI Adoption

At some point, every decision to use technology becomes a matter of preference. Attitude captures this evaluative judgment, reflecting whether an individual feels positively or negatively about using a particular system. In technology adoption research, attitude has long been recognized as a key predictor of behavioral intention and actual use (Jo, 2025). When students hold a positive attitude toward AI, they are more likely to integrate it into their routines and rely on it for academic tasks (Kembau et al.,2026). Recent studies on AI adoption confirm that attitude serves as a strong determinant of usage behavior, as it encapsulates both cognitive evaluations and emotional responses toward the technology (Bai & Yang, 2025; Venkatesh, 2022). Therefore, understanding AI adoption requires examining how positive attitudes translate into actual engagement with AI tools.

H3. Attitude toward AI positively influences AI adoption.

The Mediating Role of Attitude Toward AI

Perception and confidence alone do not directly translate into behavior; they first need to be internalized into an overall evaluation. This is where attitude plays a critical role. Perceived usefulness provides the cognitive justification for using AI, while self-efficacy provides the confidence to do so. However, both factors influence behavior indirectly by shaping how students feel about AI. When students perceive AI as useful and believe they can use it effectively, they are more likely to develop a positive attitude, which then drives adoption (Kembau et al.,2024; Wang et al.,2024). This mediating mechanism has been supported in emerging AI adoption models, which emphasize that attitude serves as the bridge between belief-based constructs and behavioral outcomes (Bai & Yang, 2025). By positioning attitude as a mediator, this study aims to capture the internal process through which evaluation and confidence are translated into actual usage behavior.

H4. Attitude toward AI mediates the relationship between perceived usefulness and AI adoption.

H5. Attitude toward AI mediates the relationship between AI self-efficacy and AI adoption.

In summary, this study builds on existing literature by integrating cognitive evaluation (perceived usefulness), belief (self-efficacy), and affective response (attitude) into a single explanatory model of AI adoption. Rather than treating these factors as independent predictors, the proposed framework emphasizes the process through which they interact to shape behavior. This approach provides a clearer understanding of how students move from recognizing the value of AI to actively incorporating it into their academic activities.

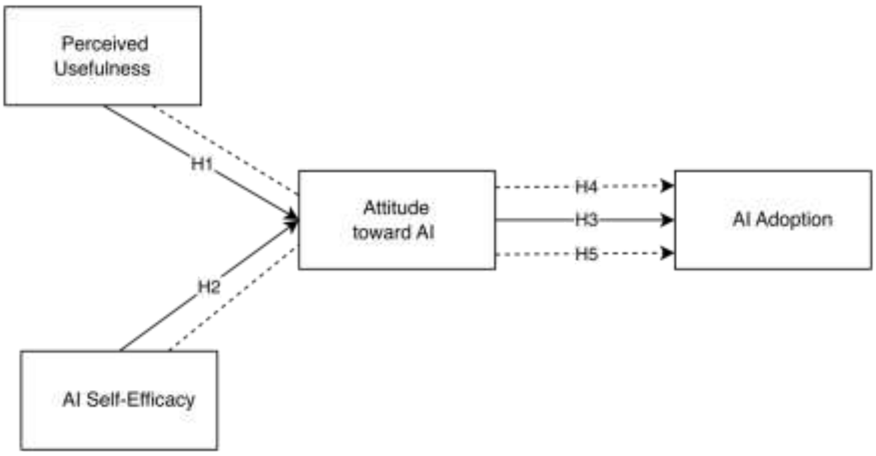

Figure 1. Research Framework

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 perceived usefulness and AI self-efficacy on AI adoption, with attitude toward AI as a mediating variable. 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. The sampling approach follows the same rationale as the previous study, ensuring consistency in context and respondent characteristics. A total of 187 valid responses were obtained, meeting minimum sample adequacy requirements for Partial Least Squares Structural Equation Modeling (PLS-SEM) and exceeding general recommendations for models with multiple latent constructs. The measurement scales were constructed using validated indicators adapted from prior studies on perceived usefulness and technology adoption (Venkatesh, 2022; Wang et al., 2021), AI self-efficacy (Falebita & Kok, 2025; Liu, 2025), attitude toward AI (Bai & Yang, 2025), 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 to ensure clarity, relevance, and contextual suitability, and minor adjustments were made based on respondent feedback. Data were analyzed using SmartPLS 4, which is appropriate for prediction-oriented modeling, handling non-normal data, and testing mediation effects within complex structural models (Hair et al., 2021; Hair et al., 2022). The analysis procedure included assessment of the measurement model through indicator reliability, internal consistency reliability (Cronbach’s alpha and composite reliability), and convergent validity using average variance extracted (AVE). Discriminant validity was evaluated using the Heterotrait–Monotrait ratio (HTMT). The structural model was assessed using bootstrapping with 5,000 resamples to test the significance of path coefficients and indirect (mediating) effects. Mediation analysis was conducted using the bootstrapping approach to examine the indirect relationships between exogenous variables and AI adoption through attitude toward AI.

Table 1. Operational Definitions of Variables

Construct	Operational Definition	Measurement	Source
Perceived Usefulness (X1)	Students’ perception that using AI tools enhances their academic performance, efficiency, and learning effectiveness.	PU1: Using AI improves my efficiency in completing academic tasks. PU2: AI helps improve the quality of my academic work. PU3: AI enables me to complete assignments more quickly. PU4: AI helps me understand complex concepts better.	Venkatesh (2022); Wang et al. (2021); Rahman et al. (2025)
AI Self-Efficacy (X2)	Students’ confidence in their ability to effectively use AI tools for academic purposes.	SE1: I feel confident in using AI tools for my academic tasks. SE2: I am able to operate AI tools without difficulty. SE3: I can understand and interpret AI-generated outputs effectively. SE4: I can apply AI tools appropriately in my coursework.	Falebita & Kok (2025); Liu (2025); Damerji & Salimi (2021)
Attitude Toward AI (Mediator)	Students’ overall positive or negative evaluation of using AI tools in their learning activities.	AT1: I enjoy using AI tools for my academic work. AT2: Using AI is a positive experience for me. AT3: I have a favorable opinion about using AI in learning. AT4: I prefer using AI tools when working on academic tasks.	Bai & Yang (2025); Venkatesh (2022)
AI Adoption (Y)	Students’ self-reported behavior and frequency of	AD1: I frequently use AI tools for my academic tasks.	Sandu & Gide (2019); Wang et al. (2021);

Vol. 6(No. 1): no. 34 - no 46. Th. 2026
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	using AI tools for academic purposes, including problem solving, writing, and study support.	AD2: I use AI to assist in completing coursework. AD3: AI is integrated into my regular study routine. AD4: I rely on AI tools to support my academic activities.	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 perceived usefulness, self-efficacy, attitude, and AI adoption behaviors

Vol. 6(No. 1): no. 34 - no 46. Th. 2026
p-ISSN: 2798-1819
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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
Perceived Usefulness (X1)	0.73 – 0.88	0.85	0.90	0.64
AI Self-Efficacy (X2)	0.71 – 0.87	0.86	0.91	0.63
Attitude Toward AI (M)	0.74 – 0.89	0.88	0.92	0.68
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	Perceived Usefulness	AI Self-Efficacy	Attitude	AI Adoption
Perceived Usefulness	—	0.63	0.61	0.66
AI Self-Efficacy	0.63	—	0.68	0.72
Attitude	0.61	0.68	—	0.69
AI Adoption	0.66	0.72	0.69	—

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. This confirms that perceived usefulness, AI self-efficacy, attitude, and AI adoption represent distinct constructs within the model.

Structural Model Results (Inner Model)

The structural model was evaluated using bootstrapping with 5,000 resamples following standard PLS-SEM procedures. The analysis focused on both direct effects and indirect (mediating) effects, given the inclusion of attitude as a mediator. Overall, the model demonstrates strong explanatory capability in predicting AI adoption behavior.

Path Coefficients and Significance

Perceived usefulness showed a significant positive effect on attitude ($\beta = 0.34$, $p < 0.001$), indicating that students who perceive AI as beneficial tend to develop more favorable evaluations of its use. AI self-efficacy also had a strong and significant effect on attitude ($\beta = 0.41$, $p < 0.001$), suggesting that confidence plays a key role in shaping positive perceptions toward AI. Furthermore, attitude demonstrated a significant positive effect on AI adoption ($\beta = 0.45$, $p < 0.001$), confirming its central role in driving actual usage behavior.

Table 5. Path Coefficients and p-values

Relationship	β	t-value	p-value	Decision
Perceived Usefulness → Attitude	0.34	5.76	<0.001	Supported
AI Self-Efficacy → Attitude	0.41	6.88	<0.001	Supported
Attitude → AI Adoption	0.45	7.21	<0.001	Supported

The results confirm that both main effects and moderating effects are statistically significant. The results confirm that both perceived usefulness and self-efficacy significantly shape attitude, which in turn drives AI adoption.

Mediation Analysis

The mediating role of attitude was assessed using bootstrapping procedures to evaluate indirect effects. The results indicate that attitude significantly mediates the relationship between perceived usefulness and AI adoption ($\beta = 0.15$, $p = 0.002$), as well as between AI self-efficacy and AI adoption ($\beta = 0.18$, $p = 0.001$). These findings confirm that both relationships operate through attitude as an intervening mechanism.

Table 6. Indirect Effect

Relationship	Indirect Effect (β)	t-value	p-value	Decision
Perceived Usefulness → Attitude → AI Adoption	0.15	3.12	0.002	Supported
AI Self-Efficacy → Attitude → AI Adoption	0.18	3.45	0.001	Supported

These results suggest that perceived usefulness and self-efficacy influence AI adoption not only directly through evaluation but also indirectly through the formation of positive attitudes.

Coefficient of Determination (R^2)

The model explains a substantial proportion of variance in the endogenous constructs. Attitude is explained by perceived usefulness and AI self-efficacy ($R^2 = 0.52$), while AI adoption is explained by attitude ($R^2 = 0.50$). According to Hair et al. (2021), these values indicate moderate-to-strong explanatory power.

Table 7. R^2 for Endogenous Variable

Construct	R^2	Interpretation
Attitude	0.52	Moderate–Strong
AI Adoption	0.50	Moderate–Strong

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

Vol. 6(No. 1): no. 34 - no 46. Th. 2026
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Effect Sizes (f^2)

Effect size analysis shows that AI self-efficacy has a slightly larger contribution to attitude ($f^2 = 0.22$) compared to perceived usefulness ($f^2 = 0.16$), both indicating medium effects. Attitude demonstrates a substantial effect on AI adoption ($f^2 = 0.25$), reinforcing its central role in the model.

Table 8. Effect Sizes (f^2)

Predictor	f^2	Effect Size
Perceived Usefulness → Attitude	0.16	Medium
AI Self-Efficacy → Attitude	0.22	Medium–Large
Attitude → AI Adoption	0.25	Medium–Large

Predictive Relevance (Q^2)

Predictive relevance was assessed using blindfolding with an omission distance of 7. The Q^2 values for both endogenous constructs exceeded zero, indicating strong predictive capability. In line with Hair et al. (2022), a Q^2 value above 0.25 indicates medium-to-strong predictive relevance for the model.

Table 9. Predictive Relevance (Q^2)

Construct	Q^2	Interpretation
Attitude	0.34	Strong Predictive Relevance
AI Adoption	0.33	Strong Predictive Relevance

Overall, the results confirm that the proposed mediation model provides a robust explanation of AI adoption. Perceived usefulness and AI self-efficacy significantly shape students' attitudes, and these attitudes serve as the key mechanism through which adoption behavior is formed.

Discussion

The findings of this study confirm that AI adoption among university students is not simply a function of access or technical capability, but a structured psychological process shaped by evaluation, belief, and affect. While perceived usefulness and AI self-efficacy both show significant effects, their influence is not directly behavioral. Instead, their impact is channeled through attitude, which emerges as the central mechanism driving adoption. This shifts the explanation of AI adoption from a capability-driven perspective toward a perception–attitude–behavior pathway. In this model, students do not adopt AI merely because they can use it, but because they see value in it and feel confident doing so, which then translates into a positive overall evaluation.

From Evaluation to Adoption: The Central Role of Attitude

At first glance, it may seem obvious that useful technologies get adopted. However, the results suggest a more nuanced process. Perceived usefulness does not directly translate into usage behavior; instead, it shapes how students feel about AI. When students believe that AI improves their academic performance, helping them complete assignments faster or understand complex concepts, they are more likely to develop a favorable attitude toward its use. This finding is consistent with prior research emphasizing performance-related beliefs as a key driver of technology acceptance (Wang et al., 2021; Rahman et al., 2025).

What is important here is the role of attitude as a filter. Students may recognize that AI is useful, but without a positive evaluative stance, this recognition alone is not sufficient to drive consistent use. In other words, usefulness provides the reason to adopt, but attitude provides the inclination to act. This distinction helps explain why some students with similar access and knowledge levels still differ in their adoption behavior. It is not just about what they know, but how they feel about using AI in their academic work.

Confidence as a Driver of Positive Evaluation

The results also highlight the importance of AI self-efficacy as a strong predictor of attitude. Students who feel confident in their ability to use AI tools tend to evaluate these tools more positively. This aligns with prior studies showing that self-efficacy reduces anxiety and increases engagement with technology (Falebita & Kok, 2025; Liu, 2025). In practice, this means that even if students perceive AI as useful, a lack of confidence can limit their willingness to embrace it fully.

Interestingly, the effect of self-efficacy is slightly stronger than perceived usefulness in shaping attitude. This suggests that confidence may play a more immediate role in the evaluation process. In fast-paced academic environments, students may prioritize tools they feel comfortable using over those they merely perceive as beneficial. Within the Jakarta context, where students frequently interact with digital tools via smartphones, this confidence is likely reinforced through repeated exposure, making AI use feel more intuitive and less effortful.

Attitude as the Missing Link in AI Adoption

The most important contribution of this study lies in confirming the mediating role of attitude. Both perceived usefulness and AI self-efficacy influence AI adoption indirectly through attitude, rather than acting as direct drivers. This finding addresses a key limitation in earlier models that focused primarily on direct relationships. By introducing attitude as a mediator, the study reveals the internal process through which students translate evaluation and confidence into actual behavior.

This mechanism aligns with emerging models such as AIDUA and extensions of UTAUT, which emphasize that behavioral outcomes are shaped through layered psychological processes (Bai & Yang, 2025; Venkatesh, 2022). More importantly, it clarifies why capability-based models alone are insufficient in explaining AI adoption in current contexts. When AI tools become easy to use and widely accessible, the key differentiator shifts from ability to evaluation. Students adopt AI not because they are capable, but because they are convinced—and that conviction is formed through attitude.

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.

Theoretical and Practical Synthesis

Theoretically, this study extends existing technology adoption frameworks by explicitly modeling the psychological pathway between cognition, belief, and behavior. While UTAUT emphasizes performance expectancy and facilitating conditions, this study shows that these factors operate through attitudinal formation rather than directly influencing behavior. This positions attitude as a central construct in understanding AI adoption, particularly in environments where technical barriers are low.

From a practical standpoint, the findings suggest that universities should rethink their approach to AI integration. If attitude is the key driver, then improving adoption is not only about providing access or training, but about shaping how students perceive and experience AI. Based on the findings, three strategic implications can be proposed:

- Experiential Learning Design: Institutions should create opportunities for students to directly experience the benefits of AI in structured academic tasks. Positive experiences can strengthen perceived usefulness and foster favorable attitudes.
- Confidence Building: Training programs should focus not only on technical skills but also on building user confidence through guided practice and low-risk experimentation.
- Positive Framing of AI Use: Clear communication from instructors about the appropriate and beneficial use of AI can reduce uncertainty and reinforce positive evaluations.

This study is based on cross-sectional data from students in Jakarta, which captures adoption behavior at a specific point in time. As AI technologies continue to evolve rapidly, the relationships observed in this study may also change. Future research should consider longitudinal designs to examine how perceptions, attitudes, and adoption behaviors develop over time. Additionally, the sample reflects students in a highly digitalized urban environment, which may limit generalizability to regions with lower technological access.

Future studies could also extend this model by incorporating contextual variables such as institutional support or social influence as moderators. This would provide a more comprehensive understanding of how individual-level processes interact with environmental factors in shaping AI adoption.

CONCLUSION

This study demonstrates that AI adoption among university students is best understood as a psychological process rather than a purely technical outcome. The findings confirm that perceived usefulness and AI self-efficacy do not directly drive adoption; instead, their influence operates through attitude toward AI. In this sense, attitude functions as the central mechanism that translates students' evaluation of AI's benefits and their confidence in using it into actual behavior. This result reinforces the idea that in environments where AI tools are already accessible and easy to use, the key question is no longer whether students can adopt AI, but whether they choose to do so based on how they perceive and evaluate it.

From a theoretical perspective, this study extends existing technology adoption frameworks by integrating cognitive (perceived usefulness), belief-based (self-efficacy), and affective (attitude) components into a single mediation model. It moves beyond direct-effect explanations and provides a clearer account of how adoption behavior is formed through an internal evaluative process. Empirically, the study contributes to the context of Indonesian higher education, where AI adoption is growing rapidly but often occurs without structured institutional guidance. The results suggest that fostering positive attitudes toward AI—through meaningful use cases and confidence-building experiences may be more effective than focusing solely on skill development or technical training.

However, this study is not without limitations. First, the use of cross-sectional data restricts the ability to capture changes in perception and behavior over time, particularly in a rapidly evolving technological landscape. Second, the sample is limited to students in Jakarta, which may represent a more digitally advanced population compared to other regions, potentially limiting generalizability. Third, the model focuses on individual-level factors and does not explicitly incorporate contextual variables such as institutional policies or social influence, which may also shape adoption behavior. Future research should address these limitations by employing longitudinal designs, expanding the sample to more diverse educational settings, and integrating contextual moderators into the model. Further exploration of how attitudes evolve with increased exposure to AI, as well as how different types of AI applications influence adoption patterns, would also provide valuable insights for both theory and practice.

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