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Benefits, Convenience, Ethics, and Anxiety Shaping Indonesian Students' Intentions to Adopt Generative Artificial Intelligence

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ABSTRACT

Purpose – This study examines Indonesian university students' behavioral intention to adopt generative artificial intelligence by extending the technology acceptance model with ethical concern and artificial intelligence anxiety. It evaluates how perceived usefulness, perceived ease of use, ethical concern, and artificial intelligence anxiety jointly shape adoption intention in higher education.

Design/methods/approach – A quantitative cross-sectional survey was administered to 96 active undergraduate students at a public university in Indonesia. The extended model was analyzed using partial least squares structural equation modeling to estimate the predictive power and the significance of structural relationships among constructs.

Findings – The structural model explained 64.5% of the variance in behavioral intention. Perceived usefulness was the strongest predictor, followed by ethical concern and perceived ease of use. Artificial intelligence anxiety did not significantly influence behavioral intention, suggesting that functional value and ethical awareness outweighed affective apprehension among experienced users.

Research implications/limitations - Institutions should prioritize practical integration and clear ethical guidance for generative artificial intelligence use rather than focusing primarily on reducing anxiety. Generalizability is limited by the cross-sectional design, small sample size, and a sample dominated by science and technology disciplines.

Originality/value - This study provides empirical evidence that ethical concern functions as a regulatory facilitator rather than a barrier in generative artificial intelligence acceptance, offering a refined lens for responsible adoption policies in Indonesian higher education.

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INTRODUCTION

The rapid development of Artificial Intelligence (AI) technology has catalyzed transformative shifts across global higher education ecosystems. Recent systematic analyses demonstrate AI's substantial potential in enhancing learning quality through intelligent tutoring systems, adaptive learning pathways, and conversational educational agents (Ocen et al., 2025). This technological integration extends beyond pedagogy into institutional governance and administrative optimization, reflecting UNESCO's strategic emphasis on holistic digital transformation in educational systems (Mochizuki et al., 2025). Empirical evidence from cross-national student surveys reveals striking adoption patterns, with contemporary studies reporting that over 85% of higher education students actively utilizing AI tools for academic tasks, though institutional support frameworks remain inconsistent (Sergeeva et al., 2025).

In Indonesia, the adoption of AI in higher education is evolving, though empirical evidence suggests significant challenges remain. Recent research indicates that AI literacy among Indonesian higher-education students remains at a concerningly low level, with particular gaps in understanding ethical implications and technical capabilities (Sari et al., 2025). Studies examining student perspectives reveal limited awareness regarding how AI systems function and the potential ethical dilemmas they may present (Sari et al., 2025). While AI tools show promise for enhancing educational processes, their implementation faces barriers including infrastructure limitations, digital literacy gaps, and the need for comprehensive policy frameworks (Sutrisno et al., 2025).

To understand the acceptance of AI technology, this study uses the Technology Acceptance Model (TAM), which makes Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as the main predictors of intention to use technology (Chen et al., 2025; Ibrahim et al., 2024). Various studies show that these two factors consistently influence the adoption of AI in higher education, including the use of ChatGPT and similar AI applications Several other studies have also revealed that PU and PEOU play a dominant role in technology adoption behavior (Sustaningrum & Haldaka, 2025; Wang & Fan, 2025). However, some studies have found that the power of influence of these two constructs can vary according to the context and features of the technology used (Grassini et al., 2025). This suggests that acceptance of AI-based applications may not be entirely explained by functional factors alone.

Furthermore, while TAM is often used in AI acceptance, there are still some gaps to be aware of. Most studies have not quantitatively explored the ethical dimension **of** the TAM model, and are more often discussed conceptually, even though ethical issues are increasingly relevant today (Ghosh, 2025; Guleria et al., 2023; Zhou et al., 2024). On the other hand, research on AI Anxiety (AIA) is more developed in the context of work and automation; therefore, it does not reflect students' experiences as AI users in learning. Some studies in the field of education have indeed begun to examine AIA, but generally the focus is limited to aspects of learning behavior or AI literacy (Wu & Li, 2025). In addition, until now there has been no research that has tested PU, PEOU, EC, and AIA simultaneously in a single predictive model, especially in the context of Indonesia, which is accelerating digital transformation in education (Ramadini & Pratiwi, 2025).

Based on these gaps, this study expands the TAM by adding Ethical Concern (EC) and AI Anxiety (AIA) as external variables to form the Extended TAM model. This approach is consistent with the theory that TAM can be customized based on the characteristics of the technology being studied. In this context, students' decisions to use AI are influenced not only by benefits and convenience, but also by moral considerations and emotional responses (Karahan & Bilgili, 2025; Katsantonis & Katsantonis, 2024; Mohamed et al., 2025). Therefore, EC was added to reflect ethical considerations, and AIA represented AI-related anxiety and uncertainty. This integration provides a stronger theoretical foundation for understanding the acceptance of AI in the context of learning (B. D. Lund et al., 2024; Zhou et al., 2024).

Based on this framework, this study makes a theoretical contribution by expanding TAM through the integration of EC and AIA, which has not been widely discussed before. The resulting model offers a sophisticated blueprint for future research that wishes to examine disruptive technologies in sensitive environments, such as education. This contribution is important because the resulting model combines functional, psychological, and ethical factors. This demonstrates that utility does not operate in a vacuum and that high usefulness can be negated by high ethical dissonance or anxiety.

In terms of practical applications, the results of this study are expected to assist higher-education institutions in designing safe, ethical, and effective AI-use policies to maintain academic integrity. Policies that only ban or mandate AI without addressing students underlying anxieties or ethical confusion are likely to fail; understanding the drivers of behavior allows for more nuanced guidelines. In addition, this study provides empirical insights into the readiness of Indonesian students to use generative AI in academic activities. It serves as a status check on the nation's educational health in the face of the Fourth Industrial Revolution. Thus, this study supports a more systematic direction for digital transformation in higher education in Indonesia.

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This study aimed to analyze the factors that affect students' intentions to utilize generative AI in the learning process. The focus is strictly on the antecedents of behavioral intention, viewing it as an immediate precursor to actual usage behavior. In particular, this study examines the influence of PU, PEOU, EC, and AIA as an extension of the applied TAM. The goal is to address the empirical and conceptual gaps identified in the existing literature. This study posits that by mapping these four dimensions, a clearer path to responsible AI integration can be charted. Based on these objectives, this study formulated research questions that focused on the relationship between each construct and Behavioral Intention (BI). The research questions are comprehensive and seek to isolate the individual contribution of each variable. The first inquiry is defined as RQ1, which asks how PEOU affects students' BI in the use of AI applications. Following this, functional utility was queried in RQ2, asking how PU affects student BI in the use of AI applications. Moving to the added variables, RQ3 explored how EC affects students' BI in the use of AI applications. Finally, the emotional dimension is scrutinized in RQ4, which asks how AIA affects students' BI in the use of AI applications. Collectively, these questions provide a rigorous interrogation of the factors driving the AI revolution in Indonesian classrooms.

METHOD

Research Design:

This study uses a quantitative approach with a cross-sectional survey design, which photographs the phenomenon over a period to allow the assessment of influential factors without repeated observations (Creswell & Creswell, 2017) . This design effectively describes the relationship between variables at one time, so that it is suitable for assessing the influence of Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Ethical Concern (EC), and AI Anxiety (AIA) in the Extended TAM model on students' behavioral intention (BI) using AI-based applications in learning (Setia, 2016).

Participants:

The participants in this study were active undergraduate students at Makassar State University from various faculties. They were chosen because they are quite familiar with the use of AI-based applications such as ChatGPT, Grammarly, and Canva, or similar tools that are commonly used to help in learning activities. The selected respondents were active students for at least one semester and had used AI-based tools for academic activities.

Population and Sampling Method:
The research population included all active students of the State University of Makassar who had used AI applications in learning. Sampling used purposive sampling because this technique selects respondents based on certain characteristics and is able to produce an 'information-rich' sample, that is, those who understand the research topic best so that they can provide the most relevant information. The sample criteria included: (1) students who had been active for at least one semester, (2) had used AI in learning, and (3) were willing to fill out questionnaires online.

Instrument:
The research instrument was a closed questionnaire based on the TAM model with the addition of AI Anxiety (AIA) and Ethical Concern (EC) constructs. The entire item uses a 4-point Likert scale from 'Strongly disagree' to 'Strongly agree', which was chosen to quantitatively measure perception and avoid central tendency bias (the tendency to choose a middle answer)(Douven, 2018). Once the items of each construct were compiled, the questionnaire was validated by experts using the Index of Item Congruence (IOC) to ensure the clarity and suitability of the items.

Table 1. Construct Research

Construct	Description	Source
Perceived Ease Of Use (PEOU)	Students' perception that AI-based applications are easy to use and do not require much effort and are comfortable to use in learning activities	(Ebadi & Raygan, 2023)
Perceived Usefulness (PU)	Students' perception that the use of AI can provide real benefits in increasing learning effectiveness, assignment quality, and academic achievement.	(Ebadi & Raygan, 2023)
Ethical Concern (EC)	Students' concerns are related to the ethical impact of AI use such as privacy, information accuracy, academic integrity, and the potential for overdependenc	(Hu et al., 2025; Zuo et al., 2025)
AI Anxiety (AIA)	Students' levels of anxiety about the development of AI, including concerns about the future of work, the reliability of AI, and changes in social interactions.	(Pan et al., 2025)
Behvaioral Intention (BI)	Readiness, interest. and students' tendency to use AI in an ongoing manner in learning.	(Zuo et al., 2025)

Procedures:
The procedure of this study followed the standards of quantitative methodology and PLS-SEM. Figure 1 below shows the research flow from problem formulation to drawing conclusions based on empirical results

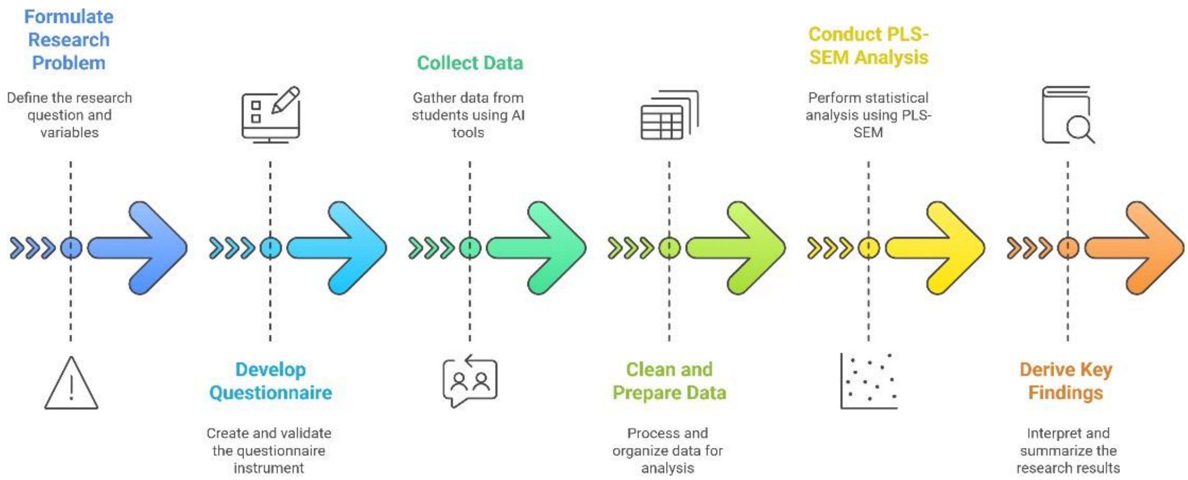

Figure 1. Research Procedure

The research procedure began with formulating the problem and assigning variables based on the Extended TAM to ensure the suitability of the construct with the research objectives. The questionnaire was developed based on the relevant literature and validated by experts to guarantee clarity and appropriateness. Once declared eligible, the data were collected from AI user students and cleaned to ensure the quality and completeness of the data. The analysis was conducted using PLS-SEM through SmartPLS, including the evaluation of the outer model (validity and reliability) and the inner model (R^2, f^2, and path significance), which are suitable for predictive models and medium-sized sample sizes. The final stage is the withdrawal of findings through the interpretation of the analysis results to answer the research objectives empirically.

Analysis Plan:

Descriptive Analysis

Descriptive analysis is used to describe respondent characteristics and patterns of AI use through tables, percentages, or averages, so that the data archetypes can be clearly understood (Stöhr et al., 2024). In this study, the analysis was carried out using Jamovi to present information such as gender, age, major, generation, semester, and patterns of AI use to ensure the suitability of the sample for the purpose of the study.

Inferential Analysis

Inferential analysis utilized PLS-SEM via SmartPLS 4 to assess relationships within the Extended TAM, specifically examining the influence of PEOU, PU, EC, and AIA on Behavioral Intention. This approach was selected for its efficacy in handling complex predictive models with medium-sized samples (Hair et al., 2021; Koteczki & Balassa, 2025). The process begins with an outer model evaluation to ensure construct validity and reliability through convergent validity, requiring outer loadings above 0.70 and an AVE exceeding 0.50, alongside discriminant validity via HTMT values below 0.90. Additionally, internal consistency was verified using Cronbach's Alpha and Composite Reliability thresholds greater than 0.70 (Hair et al., 2021). Subsequently, the inner model evaluation analyzes structural predictability and significance through R2 classification, f2 effect sizes, and bootstrapping path coefficients. The relationship significance is determined by t-values exceeding 1.96 or p-values below 0.05, while β values indicate the direction and strength of influence (Hair et al., 2021). These combined metrics confirm the robustness of the model regarding the relationships presented in Figure 2.

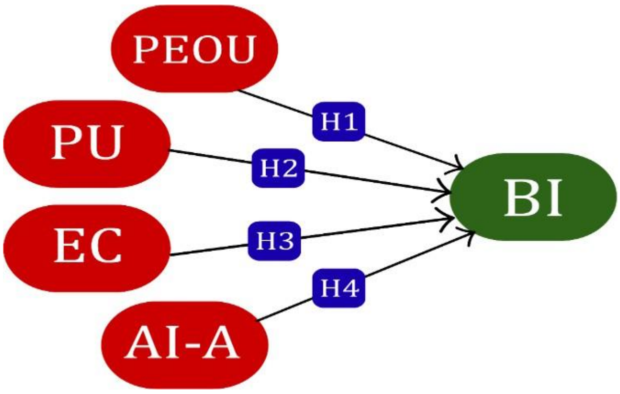

Figure 2. Construct Relationship Model

H1: Perceived Ease of Use (PEOU) positively affects students' Behavioral Intention (BI) to use AI applications.

H2: Perceived Usefulness (PU) has a positive effect on students' Behavioral Intention (BI) to use AI applications.

H3: Ethical Concern (EC) affects students' Behavioral Intention (BI) to use AI applications.

H4: AI Anxiety (AIA) affects students' Behavioral Intention (BI) in the use AI applications.

RESULTS AND DISCUSSION

RESULT

Analysis Descriptive

Table 2 presents the profile of respondents and patterns of AI application use, including basic characteristics such as gender, age, study program, generation, semester, and frequency and type of applications used. This information provides the initial context regarding the research sample and the trends in the use of AI before further analysis is conducted.

Table 2. Respondent Demographics and AI Use Patterns

Category	Sub Category	Sum	Total
Gender	Man	39	40.6%
	Woman	57	59.4%
Age	17	1	1.0%
	18	25	26.0%
	19	54	56.3%
	20	12	12.5%
	21	2	2.1%
	22	2	2.1%
Major	NON STEM	18	18.8%
	STEM	78	81.3%
Force	2021	1	1.0%
	2023	2	2.1%
	2024	68	70.8%
	2025	25	25.0%
Semester	I	25	25.0%
	III	68	70.8%
	V	1	1.0%
	IX	2	2.1%
Frequency of AI Use	1-2 times a week	9	9.4%
	3-5 times a week	32	33.3%
	Infrequently	7	7.3%
	Every day	48	50.0%
Types of AI used	ChatGPT	77	80.2%
	Gemini	54	56.3%
	Canva	45	46.9%
	Perplexity AI	27	28.1%

Based on Table 2, of the 96 respondents in this study, the majority were female (59.4%) and 19 years old (56.3%). Most of them came from STEM study programs (81.3%), were third-year students (70.8 %), and were from the class of 2024 (70.8%). The use of AI was relatively high, with 50% of respondents using AI daily and 33.3% using it 3–5 times a week. ChatGPT was the most used application (80.2%), followed by Gemini (56.3%), Canva (46.9%), and Perplexity AI (28.1%). These findings show that the respondents were young students with STEM backgrounds who actively utilized various AI applications in academic activities.

Measurement Model (outer model)

Convergent Validity

The following table 3 presents the results of outer loadings and AVE from the constructs of AI Anxiety (AIA), Ethical Concern (EC), Perceived Ease Of Use (PEOU), Perceved Usefulness (PU) and Behavioral Intention (BI).

Table 3. Outer Loadings dan AVE

Construct	Item	Outer Loadings	Average variance extracted (AVE)
AI Anxiety	AIA1	0.743	0.548
	AIA2	0.755	
	AIA3	0.727	
	AIA4	0.737	
Behavioral Intention	BI1	0.852	0.729
	BI2	0.872	
	BI3	0.807	
	BI4	0.865	
	BI5	0.871	
Ethical Concern	EC1	0.807	0.728
	EC2	0.853	
	EC3	0.879	
	EC4	0.871	
Perceived Ease of Use	PEOU1	0.876	0.7
	PEOU2	0.844	
	PEOU3	0.786	
	PEOU4	0.786	
	PEOU5	0.885	
Perceived Usefulness	PU1	0.795	0.677
	PU2	0.793	
	PU3	0.835	
	PU4	0.846	
	PU5	0.843	

The results of the convergent validity test in Table 3 show that all indicators have outer loadings > 0.70, with ranges for AI Anxiety (0.727–0.755), Behavioral Intention (0.807– 0.872), Ethical Concern (0.807–0.879), Perceived Ease of Use (0.786–0.885), and Perceived Usefulness (0.793–0.846). The AVE value was above 0.50 (0.548–0.729), indicating that each construct could explain more than 50% of the variance of the indicator. Thus, the entire construct meets convergent validity, and its indicators represent consistently measured concepts.

Construct Realibility

The results of construct reliability, which include Cronbach's Alpha and Composite Reliability (CR) values of each construct, are presented in Table 4.

Table 4. Construct Realibility dan Validity

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
AIA	0.741	0.754	0.829

BI	0.907	0.907	0.931
EC	0.875	0.875	0.914
PEOU	0.892	0.899	0.921
PU	0.88	0.881	0.913

The results of the reliability test in Table 4 show that the entire construct has Cronbach's Alpha and Composite Reliability (CR) values above 0.70, as recommended. Cronbach's alpha was in the range of 0.741–0.907, and CR was 0.829–0.931, signifying strong internal consistency and a stable indicator of measuring variables. Thus, all constructs were declared reliable and suitable for use in subsequent analyses.

Discriminant Validity

Discriminant validity is used to ensure that each construct in the study is completely different from the others, which is tested using the Heterotrait–Monotrait Ratio (HTMT). Table 5 shows that the HTMT value is in the range of 0.409–0.835, below the 0.90 threshold. This result confirms that the validity of the discriminator is fulfilled and that each construct, namely AIA, BI, EC, PEOU, and PU, is different and does not overlap, so that each variable captures the concept according to its theoretical definition.

Table 5. Heterotrait-Monotrait Ratio (HTMT)

	AIA	BI	EC	PEOU	PU
AIA					
BI	0.442				
EC	0.58	0.622			
PEOU	0.494	0.769	0.645		
PU	0.409	0.835	0.477	0.809	

Overall, the results of the evaluation of the outer model show that the research instrument has an excellent measurement quality. All indicators were valid and reliable, and each construct was clearly distinguished from the others. Therefore, the measurement model in this study is feasible for continuing the analysis at the inner stage of the model and hypothesis testing.

Structural Model (Inner Model) R Square (R2)

The evaluation of the structural model begins by examining the R-squared value for the endogenous constructs. This grade provides an initial overview of the power of models in explaining students' behavior when using AI. The results of the calculation are presented in Table 6.

Table 6. R-Square (R2)

	R-square	R-square adjusted
BI	0.645	0.629

The R-squared results in Table 6 show that Behavioral Intention (BI) has a value of R^2 = 0.645, which means that PU, PEOU, EC, and AIA can explain 64.5% of BI variations. This score is relatively strong and reflects a model with good predictive ability; therefore, cognitive, ethical, and emotional factors are proven to contribute significantly shape students' intentions to use AI.

Effect Size (f2)

Effect size (f^2) analysis was performed to assess the contribution of each exogenous variable to Behavioral Intention (BI). This test helps to determine the extent to which each construct exerts a real influence on the structural model.

Table 7. Effect Size (f2)

	AIA	BI	EC	PEOU	PU
AIA					
BI		0.003			
EC		0.076			
PEOU		0.042			
PU		0.338			

The results in Table 7 show that Perceived Usefulness (PU) has the largest effect size (f^2 = 0.338) and is the most dominant predictor of BI. Ethical Concern (EC) (f^2 = 0.076) and Perceived Ease of Use (PEOU) (f^2 = 0.042) exert a small but significant effect, while AI Anxiety (AIA) has a very small effect size (f^2 = 0.003), and thus, has almost no effect on BI in this model.

Test Hypotheses and Path Coefficients

Table 8 presents the results of the hypothesis test to determine whether the relationship proposed in the hypothesis is statistically significant, as well as the direction and strength of the influence of each variable. The value of the path coefficient (β), t-statistics, and p-value became the basis for assessing the empirical support for the formulated hypothesis.

Table 8. Hypothesis Testing Results

Hipotesis	Path Coefficients	T statistics	P values	Status
H1 AIA -> BI	0.038	0.471	0.319	Positive and Insignificant
H2 EC -> BI	0.213	2.156	0.016	Positive and Significant
H3 PEOU -> BI	0.196	1.902	0.029	Positive and Significant
H4 PU -> BI	0.502	4.465	0	Positive and Significant

Based on Table 8, three hypotheses (H2, H3, and H4) are supported because they have a $p < 0.05$, so the relationship tested was positive and significant. Perceived Usefulness (PU), Perceived Ease of Use (PEOU), and Ethical Concern (EC) contributed to increasing students' intention to use AI, with PU being the strongest predictor (β = 0.502). However, H1 was rejected because AI Anxiety (AIA) had values of t and p that were far below the minimum limit; therefore, this variable was not proven to affect the intention to use AI in this study.

Overall, the results of the internal model evaluation show that PU, PEOU, and EC significantly contributed to explaining the intention to use AI, whereas AIA had no significant influence. The combination of a strong R^2 value, prominent f^2 on PU, and clear path significance provides a comprehensive picture of the main factors of AI acceptance among students.

DISCUSSION

The findings of this study provide a comprehensive overview of the factors influencing the acceptance of Gen AI in higher education. Overall, the results confirm the relevance of Extended TAM, where cognitive and ethical factors have been shown to be more dominant than emotional factors. These findings broaden our understanding of how students evaluate and utilize AI in their academic activities. H1 was accepted in this study, indicating that PEOU has a significant and positive effect on BI. These findings are consistent with the TAM theory, which places convenience as one of the main factors of intention to use technology. This consistency is also seen in some studies where students use and accept AI because of its ease of operation, as that it does not require much effort (Albayati, 2024; Brandhofer & Tengler, 2025). Thus, PEOU in the context of this research is useful as an enabler for students that allows it to more easily access and learn the benefits of AI without significant technical barriers. This switch shows that using AI not only supports technical experience but also prepares students to integrate AI into their learning process.

In line with PEOU, H2 is also accepted, where PU has the strongest influence on BI. These findings emphasize that college students are more motivated to use AI because of the functional value they perceive. Several studies also show a similar pattern, where students who feel the real benefits of AI such as improving the quality of assignments and achievements, being able to provide a deep understanding of the material, and improving grammar, are strong reasons for students to use and accept AI in learning (Dogaru et al., 2025; Schmidt et al., 2025). Thus, PU not only encourages intent to use, but also serves as a logical justification for why students view AI as a suitable tool to support and improve their academic productivity. This shift suggests that in the context of AI-driven applications, benefit-oriented remains the primary foundation of decision-making.

Another interesting finding is that H3 was positively and significantly received towards BI. This makes an important contribution to the literature because it shows that ethical aspects do not hinder the use of AI, but rather increase the intention to use it responsibly. These findings confirm that ethical concerns often prompt users to adopt practices of using AI that are more cautious and in line with academic values(Arroyo-Machado et al., 2025; Schmidt et al., 2025). Thus, EC in this study acts as an internal regulatory mechanism that directs students to continue using AI while maintaining academic integrity. The transition from PU and PEOU to EC shows that students' acceptance of AI is not solely driven by technical considerations but also by a strong moral orientation.

However, contrary to the initial prediction, H4 was not supported. This indicates that AIA did not significantly affect the BI. These findings can be explained through the user's context. Although some studies show different results, where AI anxiety can reduce students' intentional use of AI (Nigar et al., 2025; Wen et al., 2024). However, the students in this study were intensive users who were accustomed to AI-based applications; therefore, their anxiety was relatively low and not strong enough to influence usage behavior. In addition, the literature on Generation Z shows both positive and negative trends. On the one hand, there are concerns, but on the other hand, the use of AI is needed as a future skill. Outside the educational context, some studies have shown that AIA has a stronger influence on employment than on learning. This comparison makes it clear that AIA may not be precisely positioned as a direct predictor of intent but more realistically as a moderator of other relationships, such as that between perceived risk and trust.

Overall, this study confirms that Indonesian students prioritize cognitive (PU, PEOU) and regulatory (EC) factors over emotional (AIA) factors in determining their intention to use AI-based applications. This reinforces the relevance of the Extended TAM and shows that technology acceptance models must consider the increasingly important ethical dimensions in the era of artificial intelligence. Thus, this study not only supports the previous TAM literature but also expands it by providing empirical evidence regarding the role of EC in facilitating the responsible use of AI.

The findings of this study provide a basis for campuses to formulate policies on the use of AI, as students are more driven by benefits, convenience, and ethical considerations than by emotional factors. Therefore, institutions must provide relevant and user-friendly AI technologies and supplement their use with ethical guidance. For low anxiety levels, education should focus on improving AI literacy and ethics.

From the theoretical perspective, this study expands the TAM by adding EC and AIA as direct predictors of intention to use, showing that ethical and emotional factors also influence students' behavior towards using generative AI. Empirically, this study presents the latest data on the patterns of AI use among Indonesian students, a topic that remains minimally explored in the local context. Methodologically, the use of PLS-SEM in digital-native populations enriches the study of AI technology adoption.

This study has limitations, such as the dominance of respondents from STEM majors, which reduces representativeness, the cross-sectional design that does not capture changes in perception over time, potential self-report bias, and models that do not include other potentially relevant variables. Future studies should use cross-department samples to be more representative, apply longitudinal design to see the dynamics of student perception, and add variables such as trust, perceived risk, AI literacy, and social influence. The mixed-methods approach can also provide a deeper understanding of students' assessments of AI.

CONCLUSION

This study aimed to identify factors that affect students' intention to use AI-based applications through the Extended TAM approach. The results showed that PU, PEOU, and EC had a significant effect on BI, while AIA had no effect, indicating that anxiety was not a major barrier for students who were already accustomed to using AI. These findings show that the model used can illustrate the acceptance of AI in learning. However, the study has limitations, such as a small sample size dominated by STEM students, a cross-sectional design, and potential self-report bias; therefore, the generalization of findings needs to be done carefully. Further research is suggested, involving a more diverse sample, using longitudinal designs, and adding variables such as trust and AI literacy to strengthen technology acceptance models.

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AUTHOR CONTRIBUTION STATEMENT

IH, AA, EN, SA conceptualized the study and developed the research framework. IH led instrument development and data collection. AA performed the structural analysis and model evaluation using partial least squares structural equation modeling. EN supported data cleaning, literature synthesis, and interpretation of findings. IH and SA drafted the manuscript. AA and EN critically reviewed and revised the manuscript for intellectual content. All authors approved the final version and agreed to be accountable for all aspects of the work.

AI DISCLOSURE STATEMENT

The authors used ChatGPT as a language support tool during the preparation of this manuscript, specifically for grammatical refinement, clarity improvement, and structural editing. All substantive scholarly activities, including research design, theoretical development, data collection, statistical analysis, interpretation of results, and formulation of conclusions, were conducted entirely by the authors. The authors critically reviewed and edited all AI-assisted content and took full responsibility for the originality, accuracy, and integrity of the published work.

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