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Article

Extending the UTAUT framework: the role of security, privacy, and trust in generative AI adoption among indonesian university students

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ABSTRACT

The rapid expansion of Generative AI adoption in higher education has not been matched by sufficient understanding of how security, privacy, and trust shape its use, leaving a research gap regarding how risks and trust are formed in academic settings. This study examines the effects of security, privacy, and trust on students' behavioral intention and actual use of Generative AI by extending the UTAUT framework through the integration of these constructs. A quantitative survey was administered to 450 students at Bina Nusantara University using purposive convenience sampling, and the data were analyzed with PLS-SEM (SmartPLS 3.0). The results show that Performance Expectancy (β = 0.247; t = 4.355; $p < 0.001$), Effort Expectancy (β = 0.213; t = 3.597; $p < 0.001$), and Social Influence (β = 0.186; t = 3.564; $p < 0.001$) significantly shape Behavioral Intention, while Behavioral Intention strongly predicts Use Behavior (β = 0.368; t = 6.700; $p < 0.001$). Facilitating Conditions also exert a direct influence on Use Behavior (β = 0.228; t = 5.511; $p < 0.001$). Among the risk-related variables, Security affects Behavioral Intention (β = 0.150; t = 2.981; p = 0.003) but not actual behavior, and Privacy is not significant for either dependent variable ($p > 0.05$). Trust consistently predicts both intention and behavior (β = 0.108; p = 0.010; β = 0.148; p = 0.002). These findings extend UTAUT by underscoring the mediating role of trust in Generative AI adoption and offer policy implications for improving data security transparency and institutional trust-building strategies.

Keywords:

Generative AI Adoption,
Security,
Privacy,
Trust,
UTAUT Model,
Higher Education

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Introduction

The development of artificial intelligence (AI) technology in recent years has shown extremely rapid acceleration, especially with the emergence of Generative AI (GenAI), which is capable of automatically producing text, images, code, and even complex analyses (Helmiatin et al., 2024; Rana et al., 2024; Yakubu et al., 2025). This technology is no longer merely a supporting tool but has evolved into an ecosystem that shapes the way people learn, work, and interact in the digital era (Baharin et al., 2024; Chukwuere, 2025; Elnaem et al., 2025). In higher education, GenAI tools such as ChatGPT, Gemini, Copilot, and Claude have become part of everyday academic practices, from summarizing learning materials and assisting with programming to enhancing information literacy and supporting research (Pasaribu et al., 2025; Sadewo et al., 2025; Whyte & Dewi, 2025). This phenomenon marks a paradigm shift in learning, where students are no longer just consumers of information but also co-creators with the help of intelligent technologies.

The adoption of GenAI among Indonesian university students has increased significantly, in line with improved internet access, greater digital device penetration, and increasingly complex academic demands. The 2024–2025 Global Student Survey reported that 95% of Indonesian students use GenAI in their learning processes, with 86% using AI to complete academic tasks (Yonatan, 2025). Early studies indicate that most students use GenAI to enhance conceptual understanding, save time, and improve the quality of learning outcomes (Borah et al., 2024; Fayaza et al., 2025; Gu & Yan, 2025). However, the adoption of new technology is never driven solely by its functional benefits (Utama et al., 2025). In the context of GenAI, growing concerns have emerged regarding data security, personal information privacy, potential algorithmic bias, and the reliability of AI-generated output. These concerns are particularly relevant for students who interact daily with digital platforms and often need to input personal data or sensitive academic content into AI systems.

Most research on technology acceptance in education relies on the Unified Theory of Acceptance and Use of Technology (UTAUT), which explains that technology intention and use are influenced by four key constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions (Andrews et al., 2021; Fang et al., 2025; Rahi et al., 2019). Although the UTAUT framework has proven robust in explaining the adoption of various digital technologies, critics argue that it does not fully capture modern digital risk dimensions, particularly those related to security, privacy, and user trust. These aspects become critically important when the object of study is a technology that processes data and produces outputs automatically based on complex probabilistic models.

Research on the use of artificial intelligence in education has generally focused on earlier generations of AI technologies such as intelligent tutoring systems, adaptive learning, and automated assessment. Studies by Huang et al. (2023), Kaswan et al. (2024) and Silva et al. (2024) show that AI can improve learning outcomes through personalized instruction. However, the technologies examined in those studies consist of deterministic AI operating based on predefined rules, not Generative AI that autonomously produces new content. Meanwhile, more recent research has begun to explore Generative AI in educational contexts, including educators' perceptions of pedagogical changes and the ability of models such as ChatGPT to answer exam questions (Baidoo-anu & Owusu Ansah, 2023; Kadaruddin, 2023; Mittal et al., 2024). However, these studies tend to emphasize the technical performance of the systems or pedagogical implications rather than students' adoption behavior as direct users.

In the domain of technology adoption, UTAUT has become one of the most widely used theoretical frameworks for understanding intention and usage behavior. UTAUT-based research has been conducted on various technologies, such as educational chatbots (Tian et al., 2024), AI in human resource recruitment (Tanantong & Wongras, 2024), and other digital technologies in the business sector. Nevertheless, most of these studies do not focus on the three increasingly relevant variables in the context of Generative AI: security, privacy, and trust.

Across the body of literature, several research gaps become evident. First, there is a lack of studies specifically examining the adoption behavior of Generative AI among Indonesian university students, even though the use of such technologies is becoming increasingly widespread on campuses. Second, although security, privacy, and trust are central issues in public discussions on AI, these three variables have not been systematically tested as primary determinants in UTAUT-based models of Generative AI adoption. Third, there is a theoretical gap regarding where these risk-related variables should be positioned within the UTAUT framework—whether as external factors influencing intention or as risk components moderating the relationships among core constructs. Fourth, most existing data on Generative AI usage come from corporate reports or institutional surveys whose methodologies are not always transparent, indicating the need for independent empirical research using standardized instruments and more rigorous analytical techniques such as SEM-PLS.

The novelty of this study lies in its effort to integrate three risk-related variables—security, privacy, and trust—into the UTAUT framework to explain the adoption of Generative AI among Indonesian university students. This approach differs from previous studies, which generally focused only on technical aspects or educators' perceptions. In addition, this research offers a conceptual contribution by asserting that Generative AI cannot be equated with earlier generations of AI due to fundamental differences in their working mechanisms, the types of data they use, and the potential risks they pose. Another contribution emerges from the empirical findings showing that privacy does not have a significant influence on student adoption, which contrasts with findings in other digital services. This result is significant because it illustrates the behavioral dynamics of Indonesia's younger digital generation, who tend to prioritize functional benefits over privacy concerns.

The urgency of this study becomes increasingly evident as the use of Generative AI on campuses continues to rise without sufficient education regarding data security and ethical use. Higher education institutions require strong empirical foundations to design policies, academic guidelines, and AI integration strategies that can protect students while supporting the learning process. Without a deep understanding of trust and security factors, the implementation of Generative AI risks causing data breaches, misinformation, and a decline in learning quality. Therefore, understanding the factors that influence student adoption is essential for both policymakers and technology developers.

This study aims to analyze the influence of security, privacy, and trust on the intention and behavior of Generative AI use among students at Bina Nusantara University. The study also seeks to identify which factors exert the strongest influence on technology adoption, thereby offering theoretical contributions to the development of an extended UTAUT model and practical contributions for educational institutions in designing implementation strategies for Generative AI that are safe, trustworthy, and centered on user needs.

Methods

This study uses a quantitative approach with a cross-sectional design to analyze the influence of security, privacy, and trust on the adoption of Generative AI among students at Bina Nusantara University. This approach is appropriate for mapping students' perceptions of security, privacy, and trust in the use of Generative AI (Zhao et al., 2024). However, consistent with the characteristics of a cross-sectional design, this study cannot identify causal relationships; it can only demonstrate statistical associations between variables. Therefore, the interpretation of the findings is limited to correlational relationships rather than assumptions of cause and effect.

This study employed a purposive convenience sampling technique, selecting respondents based on ease of access while still meeting specific criteria, namely active students of Bina Nusantara University. The research population consists of all active students at Bina Nusantara University, while the number of samples successfully collected was 450 respondents. The respondent criteria include: (1) being an active student, (2) having used or been exposed to Generative AI, and (3) being willing to complete the questionnaire in full. To minimize potential bias, the survey system was configured to allow only one response per email account, thereby reducing the possibility of duplicate data.

The research model was developed based on a modification of the UTAUT (Unified Theory of Acceptance and Use of Technology) framework with the addition of three external variables, namely security, privacy, and trust. More specifically, it integrates UTAUT variables consisting of Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI), and Use Behavior (UB) with three additional variables that are the main focus of the study consisting of Security, Privacy, and Trust.

Data collection was conducted using a structured questionnaire with a 6-point Likert scale. It was used to reduce respondents' tendency to automatically choose neutral answers. This forced-choice approach is supported by Rokeman (2024), who found that even-numbered scales can reduce central tendency bias and improve response clarity.

For the UTAUT variables (PE, EE, SI, FC, BI, UB), the instrument from Venkatesh (2022) was used. The Security variable adapted instruments from Al-Emran et al. (2020). The Trust variable used instruments from Rana et al. (2024). The Privacy variable adapted instruments from Rana et al. (2024). This research instrument underwent a series of adaptation procedures to ensure content validity. The adaptation process was carried out through translation and back-translation by two independent translators to maintain consistency of meaning. Subsequently, the instrument was validated by two experts in educational technology and user behavior to assess construct appropriateness, item clarity, and contextual relevance. The revised instrument was then pilot-tested on 30 students to ensure readability and initial reliability.

Each variable was measured using multiple indicators with a total of 30 questions. Performance Expectancy was measured with 4 indicators covering the perception of the usefulness of Generative AI in academic tasks, increased efficiency, productivity, and academic ability. Effort Expectancy was measured with 4 indicators covering ease of interaction, mastery of technology, ease of use, and ease of learning. Social Influence was measured using 3 indicators covering the influence of important people, people who influence behavior, and people whose opinions are considered important. Facilitating Conditions were measured using 3 indicators covering resource availability, system compatibility, and perceived importance of use. Behavioral Intention is measured using three indicators, including intention, prediction, and plan of use. Use Behavior is measured using four indicators, including the frequency of Generative AI use, duration of use per session, types of academic activities involving AI, and the intensity of using it for completing assignments.

Security is measured by five indicators, including data security mechanisms, security awareness, technical resources, protection from interception, and technical capacity for protection from piracy. Trust is measured using four indicators, including effectiveness and security as designed, user freedom, trust in other users, and credibility of the developer organization. Privacy is measured using three indicators, including respect for privacy, restrictions on information collection, and protection from sharing with third parties.

In addition to the main research variables, the questionnaire also collected respondents' demographic information, including age, gender, study program, academic level, as well as their experiences and contexts of using Generative AI in academic activities. This information was used to describe the sample profile and identify potential characteristic differences that may function as covariates.

The analysis was conducted using PLS-SEM through SmartPLS 3.0 because this method is capable of handling complex models and data distributions that are not fully normal, making it suitable for the characteristics of this study. The analysis stages included evaluation of the measurement model and structural model. Measurement model evaluation included convergent validity testing through outer loading values (> 0.7), Average Variance Extracted/AVE (> 0.5), and reliability testing through Composite Reliability (> 0.7) and Cronbach's Alpha (> 0.6). Discriminant validity testing was conducted using the Fornell-Larcker criteria and cross loading.

Structural model evaluation includes assessment of collinearity (VIF < 5), coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2). Hypothesis testing is performed through a bootstrapping procedure with 5,000 subsamples to obtain t-statistics and p-values. The hypothesis is accepted if the t-statistics value is > 1.96 and the p-value is < 0.05 at a 5% significance level.

This study tested eleven hypotheses describing the relationship between variables in the model. Hypotheses H1-H5 tested the relationship of classic UTAUT variables, where PE, EE, and SI had a positive effect on BI, FC had a positive effect on UB, and BI had a positive effect on UB. Hypotheses H6-H11 test the influence of additional variables, where Security, Privacy, and Trust each have a positive effect on BI and UB. This research model is expected to provide a comprehensive understanding of the factors that influence the adoption of Generative AI in the context of higher education in Indonesia.

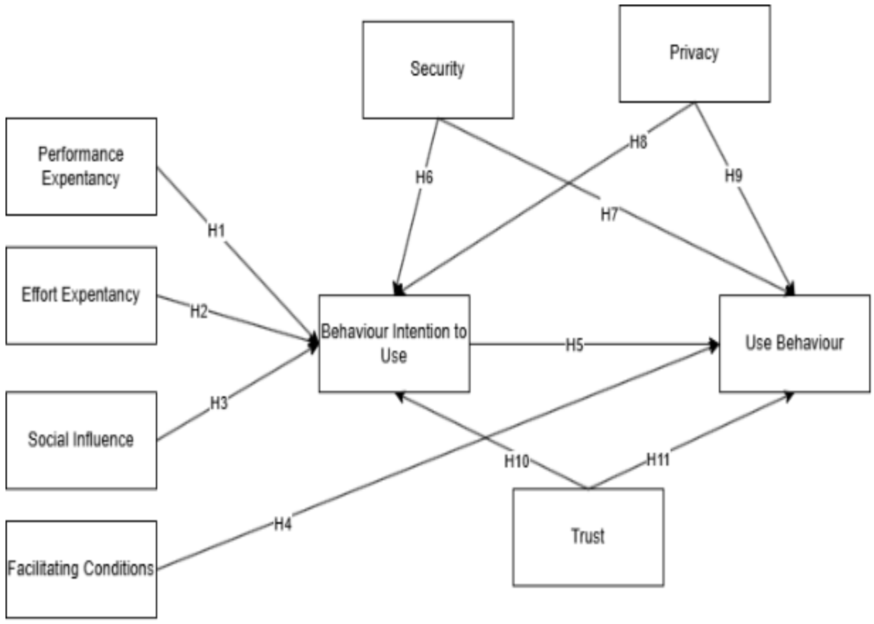

Figure 1. The Model of the Present Study

This study received institutional ethical approval, and all respondents provided informed consent before completing the questionnaire. Data were collected anonymously without any personal identifying information and were stored securely. Protecting respondent privacy was a priority, given that the research topic relates to security and trust in AI technology.

Results and Discussion

Table 1. Descriptive Profile Results

Characteristic	Category	Frequency (n)	Percentage (%)
Gender	Male	277	61,4%
	Female	173	38,6%
Level of Study	Diploma (D3/D4)	61	13,5%
	Bachelor's (S1)	372	82,7%
	Magister/Doctoral	17	3,8%
Generative AI Applications Used	ChatGPT	288	64,1%
	Bard/Gemini	59	13,1%
	Lainnya (Bing AI, Claude, Copilot, BlackBox)	±45	<10%
	CopyAI	0	0%
Duration of Generative AI Use	< 6 months	130	28,8%
	6 months – 1 year	116	25,7%
	1 – 2 years	120	26,6%
	2 – 3 years	68	15,0%
	> 3 years	±16	<5%

Source: Data Processed (2025)

Table 1 shows that the respondents in this study were predominantly male students (61.4%) and undergraduate students (82.7%), reflecting the characteristics of the BINUS student population, which is relatively similar in gender distribution and educational level. ChatGPT emerged as the most widely used Generative AI application (64.1%), indicating the dominance of this platform as the primary tool supporting academic activities. In addition, the duration of Generative AI use varied, but most respondents (approximately 81.1%) had been using this technology for less than six months to two years, suggesting that although the technology is relatively new, its penetration and adoption rate among students is quite high. These findings indicate that students have strong exposure to Generative AI, possess diverse usage experiences, and are in an active adoption phase.

Outer Model Test Results

Table 2 shows that all indicators have loading values above 0.70, which means each indicator strongly reflects the latent construct it measures. Loading values ranging from 0.802 to 0.918 indicate that these indicators make substantial contributions to their respective variables, consistent with Hair Jr (2020) criteria for convergent validity. This demonstrates that all measurement items possess adequate internal consistency and are able to explain construct variance optimally, allowing the conclusion that the measurement model has good convergent validity quality.

Table 3 shows that the Composite Reliability (CR) values for all constructs are above 0.85, indicating very good internal reliability and consistency in accordance with the recommendations of Hair Jr (2020). In addition, all Average Variance Extracted (AVE) values exceed the minimum threshold of 0.50, demonstrating that each construct is able to explain more than half of the variance of its indicators. With high CR values and AVE ranging from 0.680 to 0.835, the model meets the criteria for reliability and convergent validity, meaning that the instrument can be considered stable and capable of accurately measuring the constructs within the context of research on Generative AI use.

Table 2. Outer Loading

Construct	Indicator	Outer Loading
Performance Expectancy (PE)	PE1	0.842
	PE2	0.873
	PE3	0.861
	PE4	0.825
Effort Expectancy (EE)	EE1	0.802
	EE2	0.879
	EE3	0.918
	EE4	0.866
Social Influence (SI)	SI1	0.840
	SI2	0.874
	SI3	0.857
Facilitating Conditions (FC)	FC1	0.884
	FC2	0.865
	FC3	0.802
Behavioral Intention (BI)	BI1	0.893
	BI2	0.884
	BI3	0.902
Trust (T)	T1	0.835
	T2	0.871
	T3	0.852
	T4	0.868
Security (S)	S1	0.828
	S2	0.847
	S3	0.860
	S4	0.802
	S5	0.835
Privacy (PV)	PV1	0.890
	PV2	0.835
	PV3	0.867

Source: Data Processed (2025)

Table 3. Composite Reliability (CR) and AVE

Construct	Composite Reliability (CR)	AVE
Performance Expectancy	0.912	0.722
Effort Expectancy	0.931	0.774
Social Influence	0.904	0.758
Facilitating Conditions	0.889	0.728
Behavioral Intention	0.954	0.835
Trust	0.907	0.709
Security	0.908	0.681
Privacy	0.865	0.680

Source: Data Processed (2025)

Table 4 shows that the square root of the AVE (displayed on the diagonal) is higher than the correlations between constructs in each corresponding row and column, indicating that the Fornell–Larcker criterion is satisfied. This demonstrates that each construct has a clear conceptual identity and can be distinguished from other constructs in the model. Accordingly, there is no indication that variables such as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Behavioral Intention, Trust, Security, and Privacy excessively overlap with one another. The fulfillment of discriminant validity indicates that the measurement model has a solid construct structure and can be reliably used for further structural analysis.

Table 4. Discriminant Validity - Fornell–Larcker

Construct	PE	EE	SI	FC	BI	T	S	PV
PE	0.849							
EE	0.612	0.880						
SI	0.554	0.571	0.870					
FC	0.498	0.541	0.513	0.853				
BI	0.612	0.634	0.588	0.503	0.914			
T	0.532	0.560	0.507	0.497	0.611	0.842		
S	0.511	0.518	0.490	0.471	0.589	0.603	0.825	
PV	0.467	0.498	0.452	0.420	0.548	0.579	0.561	0.825

Source: Data Processed (2025)

Table 5. Discriminant Validity – HTMT (Heterotrait–Monotrait Ratio)

Construct	PE	EE	SI	FC	BI	T	S	PV
PE	—							
EE	0.684	—						
SI	0.633	0.649	—					
FC	0.572	0.614	0.590	—				
BI	0.676	0.698	0.655	0.569	—			
T	0.610	0.640	0.588	0.564	0.691	—		
S	0.588	0.606	0.573	0.539	0.667	0.689	—	
PV	0.545	0.587	0.525	0.498	0.629	0.678	0.613	—

Source: Data Processed (2025)

Table 5 shows that all HTMT ratios fall below the 0.90 threshold, and most are even below 0.85, indicating strong discriminant validity. This confirms that each construct in the model has clear conceptual distinctions and that no overlap occurs between one construct and another. Accordingly, variables such as Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Behavioral Intention, Trust, Security, and Privacy truly measure different concepts, ensuring that the measurement model is stable and suitable for use in subsequent structural analyses.

Inner Model Test Results

Table 6. Q^2 (Predictive Relevance)

Construct	Q^2
Behavioral Intention	0.379
Trust	0.314
Use Behavior	0.167

Source: Data Processed (2025)

Table 7. Effect Size (F2)

Relationship	f^2	Description
PE → BI	0.112	Medium
EE → BI	0.087	Small
SI → BI	0.052	Small
FC → BI	0.034	Small
T → BI	0.098	Medium
S → T	0.215	Medium
PV → T	0.188	Medium
BI → UB	0.281	Medium–Large

Source: Data Processed (2025)

Table 6 shows that all endogenous constructs have Q^2 values greater than zero, indicating that the model possesses good predictive relevance. The Behavioral Intention construct has a Q^2 value of 0.379, demonstrating strong predictive ability; Trust has a value of 0.314, indicating moderate predictive power; and Use Behavior has a value of 0.167, which still reflects predictive relevance, although at a weaker level. Overall, these findings confirm that the structural model is capable of predicting the endogenous variables effectively and meets the criteria for predictive adequacy.

Table 7 presents the magnitude of each predictor variable's contribution to the endogenous constructs. The results show that the effects of Performance Expectancy and Trust on Behavioral Intention fall into the medium category, indicating that both variables make a moderate yet meaningful contribution to shaping usage intention. Effort Expectancy, Social Influence, and Facilitating Conditions have small f^2 values, but still provide significant contributions to the model. The effects of Security and Privacy on Trust are categorized as medium, reinforcing the crucial role of perceived security and data protection in building user trust. Meanwhile, Behavioral Intention exerts a medium–large effect on Use Behavior, demonstrating that intention is a key determinant of actual behavior. Overall, the f^2 values confirm the relevance of each pathway in the model, even though the effect sizes vary.

Table 8. R^2 (Coefficient of Determination)

	R^2	Category
Behavioral Intention	0.642	Substantial
Trust	0.552	Moderate
Use Behavior	0.268	Weak–Moderate

Source: Data Processed (2025)

Table 8 shows the strength of the model in explaining the variance of the endogenous constructs. Behavioral Intention has an R^2 value of 0.642, categorized as substantial, indicating that more than 64% of the variance in usage intention can be explained by exogenous variables such as Performance Expectancy, Effort Expectancy, Social Influence, Trust, and Facilitating Conditions. The construct of Trust has an R^2 of 0.552, which falls into the moderate category, suggesting that perceptions of security and privacy play a significant role in shaping user trust. Meanwhile, Use Behavior has an R^2 of 0.268, categorized as weak–moderate, yet still demonstrating that Behavioral Intention makes a meaningful contribution to actual usage behavior. Overall, the R^2 values indicate that the model possesses strong explanatory power for the key constructs under investigation.

Table 9. Path Coefficient

Relationship Between Variables	Path Coefficient	t-Statistic	p-Value	Description
Performance Expectancy → Behavioral Intention	0.247	4.355	0.001	Significant
Effort Expectancy → Behavioral Intention	0.213	3.597	0.001	Significant
Social Influence → Behavioral Intention	0.186	3.564	0.001	Significant
Facilitating Conditions → Use Behavior	0.288	5.511	0.001	Significant
Behavioral Intention → Use Behavior	0.368	6.700	0.001	Significant
Security → Behavioral Intention	0.150	2.981	0.003	Significant
Trust → Behavioral Intention	0.108	2.578	0.010	Significant
Trust → Use Behavior	0.148	3.070	0.002	Significant
Privacy → Behavioral Intention	0.041	0.872	0.383	Not Significant
Privacy → Use Behavior	0.010	0.190	0.850	Not Significant
Security → Use Behavior	0.064	1.302	0.193	Not Significant

Source: Data Processed (2025)

The accepted hypotheses include the effect of Performance Expectancy on Behavioral Intention (β=0.247; t=4.355; p<0.001), Effort Expectancy on Behavioral Intention (β=0.213; t=3.597; p<0.001), Social Influence on Behavioral Intention (β=0.186; t=3.564; p<0.001), Facilitating Conditions on Use Behavior (β=0.228; t=5.511; p<0.001), and Behavioral Intention on Use Behavior (β=0.368; t=6.700; p<0.001), Security on Behavioral Intention (β=0.150; t=2.981; p=0.003), Trust on Behavioral Intention (β=0.108; t=2.578; p=0.010), and Trust on Use Behavior (β=0.148; t=3.070; p=0.002).

The three rejected hypotheses were Privacy on Behavioral Intention (β=0.041; t=0.872; p=0.383), Privacy on Use Behavior (β=0.010; t=0.190; p=0.850), and Security on Use Behavior (β=0.064; t=1.302; p=0.193). These findings reveal an interesting pattern where the factor of trust has a consistent influence on both dependent variables, security only influences the intention to use but has no effect on actual behavior, while privacy shows no significant influence at all.

The results of this study are consistent with the UTAUT theory, which indicates that Performance Expectancy, Effort Expectancy, and Social Influence have a positive effect on the intention to adopt technology (Cheng et al., 2022; Jain et al., 2022; Kbaier et al., 2025; Mozie et al., 2025; Su et al., 2025). Performance Expectancy is the strongest predictor, showing that students adopt Generative AI mainly because of the perceived benefits in improving their academic performance (Rana et al., 2024). The significant Effort Expectancy indicates that the ease of use of Generative AI is an important factor in encouraging adoption. The significant influence of Social Influence shows the importance of social factors in the context of Indonesia's collectivist culture. This confirms that recommendations and influence from peers, lecturers, or academic authority figures play an important role in students' decisions to adopt Generative AI. Facilitating Conditions, which have a significant effect on Use Behavior, indicate that the availability of adequate technological infrastructure is an important prerequisite for the actual implementation of Generative AI in academic activities.

The consistent influence of Trust on both dependent variables confirms the importance of trust factors in AI technology adoption, especially in contexts involving sensitive data (Ghimire et al., 2024; Hosseini, 2025; Masrek et al., 2025). Students tend to use Generative AI when they believe that the technology is safe, reliable, and developed by credible organizations. In the context of Generative AI, trust encompasses the belief that the system operates accurately, safely, and is developed by credible organizations. When students feel confident that the technology is reliable and poses no harmful risks, they not only intend to use it but also actually apply it in their academic activities. This reinforces the notion that trust functions as a psychological mechanism that bridges risk perceptions and perceived benefits, and serves as a key component in extending the UTAUT framework to intelligent technologies that rely on autonomous data processing.

Conversely, the influence of Security, which is only significant on Behavioral Intention (Tran & Nguyen, 2024; Valle et al., 2024; Zaman et al., 2025) but not on Use Behavior, indicates that perceptions of security play a greater role in the early stages of adoption (intention formation) but have less influence on actual usage behavior. In other words, students take into account system protection, data integrity, and cybersecurity aspects when forming their intention to use Generative AI. However, once they begin using the technology, their actual usage decisions appear to be more strongly influenced by other functional and situational factors such as ease of use, effectiveness, or academic demands. This reinforces the argument that security functions as a gateway factor—important for establishing users' psychological readiness but not always decisive in determining continued usage behavior. These findings also imply that AI service providers need to emphasize security aspects particularly during the early stages of technology introduction.

The most interesting finding is the insignificance of the influence of Privacy, which contradicts the initial expectations of the study. This can be explained from several perspectives. First, the demographic characteristics of the respondents, who were predominantly young students, may have relatively low privacy awareness compared to a more mature population. Second, in the context of academic use, students may not consider data shared with Generative AI to be highly sensitive information. Third, the perceived functional benefits may outweigh privacy concerns in the decision to use the technology (Rana et al., 2024). Theoretically, these results indicate that privacy may not be a primary determinant in the educational context and should be examined further through research that considers cultural dimensions, levels of digital literacy, and differences in AI usage domains.

Conclusion

This study shows that security and trust play a central role in shaping students' intentions and behaviors in using Generative AI, while privacy does not exhibit a significant direct effect. These findings not only confirm the relevance of several UTAUT constructs but also reveal the importance of trust and security as increasingly critical theoretical extensions in the context of data-driven technologies such as Generative AI. The non-significance of privacy indicates that students tend to view data protection as an inherent component of general security perceptions rather than as a standalone construct, offering new insights into how young users interpret risks and data protection in the era of generative AI. These results enrich the UTAUT model by affirming that the use of highly autonomous technologies requires attention to trust and security as strong conceptual mediators, which have previously been underexplored in studies of educational technology adoption.

Theoretically, this study extends technology adoption models by demonstrating that trust serves as the central linkage between security factors and usage intention, clarifying the psychological mechanism that bridges risk perception and technology adoption. Practically, the findings provide strategic guidance for educational institutions and AI developers to emphasize algorithmic transparency, data protection, and effective communication regarding system security to enhance the acceptance of Generative AI. However, this study has several limitations, including the use of a cross-sectional design, non-probability sampling techniques, and reliance on perceptual data that may be influenced by social bias or technological usage trends. Therefore, future research should consider longitudinal designs to capture behavioral changes over time, broaden population coverage, and examine additional variables such as perceived risk or the trustworthiness of AI providers to provide a more comprehensive understanding of Generative AI adoption. Overall, this study contributes to theoretical and practical advancements in Generative AI acceptance by offering an integrative synthesis that highlights the role of security and trust as foundational elements in the adoption of intelligent technologies in higher education.

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