

Beyond initial adoption of generative AI: the role of AI performance and comfort expectancy in driving ChatGPT continuance among students at Indonesian universities

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Abstract

Purpose – This study examines the continuance usage intention of ChatGPT among Indonesian university students. Considering the limitations of traditional TAM constructs for generative AI technology, this study developed an integrated generative-AI response adoption framework (GRAF) with two new constructs: AI relevant performance and AI comfort expectancy.

Design/methodology/approach – This study employs a quantitative approach with purposive sampling. Data were collected from 688 university students who used ChatGPT in higher-education institutions on the island of Java, Indonesia. Two new constructs – AI relevant performance and AI comfort expectancy – were developed through four stages of validation and tested using exploratory factor analysis. Hypothesis testing was conducted using partial least squares structural equation modeling (PLS-SEM).

Findings – The findings reveal that information quality and system quality do not directly affect continuance usage intention but are fully mediated by AI-relevant performance and AI comfort expectancy. Satisfaction is the strongest predictor of continuance intention. However, satisfaction did not mediate the relationship between system quality and continuance intention, indicating that ChatGPT users developed a direct evaluation pathway through AI-specific factors.

Research limitations/implications – This study did not include the factors of ethical concerns and privacy-related impacts, nor did it differentiate adoption patterns across disciplines. Theoretically, this research broadens the understanding that generative AI technology requires a more contextual evaluation construct than the traditional TAM.

Practical implications – Higher education institutions must integrate AI relevance assessment into curriculum design, provide contextual prompt engineering training, and create safe spaces for AI exploration to enhance users' psychological comfort.

Originality/value – This study contributes to the literature by developing two new constructs (AI relevant performance and AI comfort expectancy) that are empirically validated, as well as identifying a full mediation mechanism, which indicates that the evaluation of generative AI technology requires a different cognitive pathway than conventional technology.

Keywords ChatGPT, Technology acceptance model, Continuance usage, AI relevant performance, AI comfort expectancy, Indonesian higher education

Paper type Research article

1. Introduction

Generative artificial intelligence (AI) refers to AI systems capable of producing new content—including text, images, and code—based on patterns learned from large datasets (Hagos *et al.*,



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2024). Unlike conventional AI, which only processes data without generating new content, ChatGPT offers natural conversational interactions that allow users to acquire information and learn adaptively (Wolf and Maier, 2024). This application has attracted a diverse range of users in the global higher education sector, as evidenced by a comprehensive study of 23,218 students from 109 countries who utilized ChatGPT for brainstorming, summarizing texts, and finding research articles (Ravšelj *et al.*, 2025). Countries in the Asia-Pacific region, including Indonesia, have shown much greater optimism toward generative AI, along with higher adoption rates (Rainer, 2023). However, the success of technology platforms depends on sustained use (Bhattacharjee, 2001), while the use of AI in Indonesian higher education is still in its early stages and requires further research (Helmiatin *et al.*, 2024).

Research highlights user satisfaction as a key determinant of the sustainability of technology use. The Expectation-Confirmation Model (ECM) developed by Bhattacharjee (2001) posits that satisfaction is the primary predictor of continuance intention in the context of information systems. This model has been widely applied across various technology contexts (Ashfaq *et al.*, 2020; Liu *et al.*, 2023); however, its application to generative AI technology remains limited, particularly regarding the specific factors that influence continued usage. The Technology Acceptance Model (TAM), featuring the constructs of Perceived Usefulness and Perceived Ease of Use, has also become a dominant theoretical framework in studies of technology adoption (Al-Nuaimi and Al-Emran, 2021; Davis, 1989). Compared to the Theory of Planned Behavior (TPB) and the Unified Theory of Acceptance and Use of Technology (UTAUT), TAM offers a more parsimonious framework with two main constructs (Nnaji *et al.*, 2023) and has proven robust in explaining technology acceptance (Kruger and Steyn, 2024). Therefore, TAM was chosen as the theoretical anchor for this study. However, despite its robustness, the standard TAM may oversimplify the complexities of the technology adoption process in rapidly evolving contexts such as generative AI (Kruger and Steyn, 2024; Pramanik and Jana, 2025). Specifically, Perceived Usefulness and Perceived Ease of Use demonstrate dual functions in generative AI, thus requiring more contextualized constructs (Wolf and Maier, 2024).

In addition to satisfaction and technology acceptance, the quality of information systems is an important factor influencing user behavior. The D&M Information System Success Model introduces the constructs of Information Quality and System Quality as predictors of information system success (DeLone and McLean, 2003). These two constructs have proven effective in predicting continuance intention across various technology contexts (Khan and Saleh, 2023; Veeramootoo *et al.*, 2018). However, research findings reveal inconsistencies—Information Quality does not significantly affect continuance intention in the context of e-filing (Veeramootoo *et al.*, 2018), while System Quality is not significant in the e-government context (Gupta and Maurya, 2020). These findings indicate that the influence of IQ and SQ may vary depending on the characteristics of the technology, and the mechanisms through which system quality affects continuance intention in the context of generative AI have yet to be extensively explored. Specifically, this study develops two new, contextually relevant constructs for generative AI. AI Relevant performance integrates performance expectancy (Venkatesh *et al.*, 2012) with job relevance (Dwivedi *et al.*, 2020) to measure the relevance and usefulness of ChatGPT in improving academic task performance. Meanwhile, AI Comfort Expectancy combines perceived comfort (Wu *et al.*, 2021) with effort expectancy (Siyal *et al.*, 2021) to measure users' comfort in adopting AI technology. This study argues that IQ and SQ influence continuance intention through the mediation of these two AI-specific constructs—a mechanism that has not been examined in previous literature.

This study addresses this gap by integrating the D&M ISS, TAM, and ECM to investigate the mechanisms influencing the continuance intention of ChatGPT. This study focuses on ChatGPT users within higher education institutions on the island of Java, Indonesia, with the majority of respondents being undergraduate students—an area that houses 47% of the nation's total higher education institutions (Annur, 2023). Unlike developed countries, which have more established technological infrastructure and AI guidelines, AI adoption in

Indonesian higher education is still in its early stages. Globally, less than 10% of schools and universities have formal guidelines on generative AI (UNESCO, 2023), and language barriers and infrastructure limitations pose unique challenges for ChatGPT users in Indonesia (Hamamah *et al.*, 2023). The proposed integrated hypothetical model combines the D&M Information System Success Model (DeLone and McLean, 2003), the development of TAM constructs (Davis, 1989), and the Expectation-Confirmation Model (Bhattacharjee, 2001) to predict the continuance intention to use ChatGPT. Integrating these models is important because it provides a holistic understanding of technology adoption behavior (Suhartanto *et al.*, 2020).

2. Theoretical framework and development of hypotheses

2.1 Extended technology acceptance model to Generative-AI Response Adoption Framework (GRAF)

Continuance intention reflects the likelihood that individuals will continue using a technology after initial adoption (Bhattacharjee, 2001). In the context of ChatGPT, continuance intention refers to users' intention to keep using this generative AI tool for academic activities such as research, writing, and learning (Saxena and Doleck, 2023). Unlike one-time initial adoption, continuance intention determines the long-term success of a technology, as its true value lies in continuous use (Bhattacharjee, 2001). Studies confirm that continuance intention reliably predicts the sustainability of technology adoption (Ashfaq *et al.*, 2020; Liu *et al.*, 2023)—including in the educational context (Saxena and Doleck, 2023). Scholars emphasize the need to explore factors that influence continuance intention for generative AI technologies (Al-kairy, 2024; Pramanik and Jana, 2025). The Technology Acceptance Model (TAM) by Davis (1989) explains that technology acceptance is shaped by Perceived Usefulness and Perceived Ease of Use, which in turn influence attitudes and usage intentions. TAM has shown strong predictive power across various technology contexts (Al-Nuaimi and Al-Emran, 2021); however, it has been criticized for oversimplifying the complexity of the adoption process in rapidly evolving technologies such as generative AI (Kruger and Steyn, 2024). Nevertheless, compared to the Theory of Planned Behavior (Ajzen, 1991) and the Unified Theory of Acceptance and Use of Technology (Venkatesh *et al.*, 2012), TAM offers a more parsimonious framework with two main constructs while still maintaining robust explanatory power (Nnaji *et al.*, 2023); thus, it was chosen as the theoretical anchor for this research.

Given the unique characteristics of generative AI technology, which offers natural conversational interactions and adaptive responses (Bansal *et al.*, 2024), the traditional TAM may not fully capture the complexities of adopting ChatGPT (Pramanik and Jana, 2025). Wolf and Maier (2024), stated that Perceived Usefulness and Perceived Ease of Use in generative AI display dual functions—as both enablers and barriers to adoption—necessitating the development of more contextual constructs. In response to these limitations, this study expands TAM by developing two new constructs and integrating the D&M Information System Success Model (DeLone and McLean, 2003) and the Expectation-Confirmation Model (Bhattacharjee, 2001). AI Relevant Performance (AI-RP) integrates performance expectancy (Venkatesh *et al.*, 2012) with job relevance (Dwivedi *et al.*, 2020; Mayer and Girwidz, 2019) to assess the relevance and usefulness of ChatGPT in improving academic task performance. AI Comfort Expectancy (AI-CE) combines perceived comfort (Wu *et al.*, 2021) with effort expectancy (Siyal *et al.*, 2021) to measure the level of comfort and ease users experience when adopting AI technology. The development of AI-RP and AI-CE is based on the argument that traditional TAM constructs—Perceived Usefulness and Perceived Ease of Use—are too general to capture the specific nuances of generative AI technology. AI-RP explicitly measures the relevance of AI to users' academic tasks rather than general perceptions of usefulness. Meanwhile, AI-CE captures the psychological comfort of interacting with AI, going beyond mere technical ease of use.

Given the limitations of each model when used separately—TAM, which assumes perception as constant (Davis, 1989), D&M ISS, which relies on subjective measures (Petter et al., 2008), and ECM, which does not provide a complete understanding of satisfaction (Bhattacharjee, 2001)—as well as the limitations of integrating only two models, which do not encompass all relevant factors (Nguyen et al., 2021; Tseng et al., 2022; Tyagi et al., 2022), this study integrates TAM, D&M ISS, and ECM into a single complementary framework. In this integrated framework, Information Quality and System Quality from D&M ISS functions as an antecedent influencing user perceptions, while AI-RP and AI-CE bridge the relationship between system quality and continuance intention, with Satisfaction from ECM acting as a mediator. By integrating these elements, this study developed GRAF (Generative-AI Response Adoption Framework) (Figure 1), which consists of six constructs: IQ, SQ, AI-RP, AI-CE, Satisfaction, and Continuance Usage Intention.

2.2 Information quality

Information Quality refers to users’ evaluation of the quality of information provided by a system in terms of accuracy, completeness, and relevance (DeLone and McLean, 2003). In the context of ChatGPT, Information Quality encompasses the ability to provide factual, comprehensive, and easily understood answers in academic activities. Empirical studies show the influence of Information Quality on continuance intention across various technology contexts (Kaium et al., 2020; Khan and Saleh, 2023). Information Quality has also been shown to affect user satisfaction in various information system contexts (Almusfar, 2025), where high-quality information increases positive user evaluations of the system. The quality of information generated by ChatGPT greatly influences users’ perceptions of AI systems’ relevance and performance. When the information provided is accurate and relevant to academic tasks, users perceive AI as a valuable tool for enhancing performance (Ahmed et al., 2024). Research shows that information quality is related to users’ comfort levels when dealing with uncertainty (Ilgen et al., 2019). This finding is confirmed in the context of AI, where systematic literature reviews indicate that clear and easy-to-understand information increases users’ comfort when interacting with AI technologies (Laato et al., 2022). Accordingly, the following hypotheses are proposed:

H1a. Information quality has a positive effect on continuance usage intention.

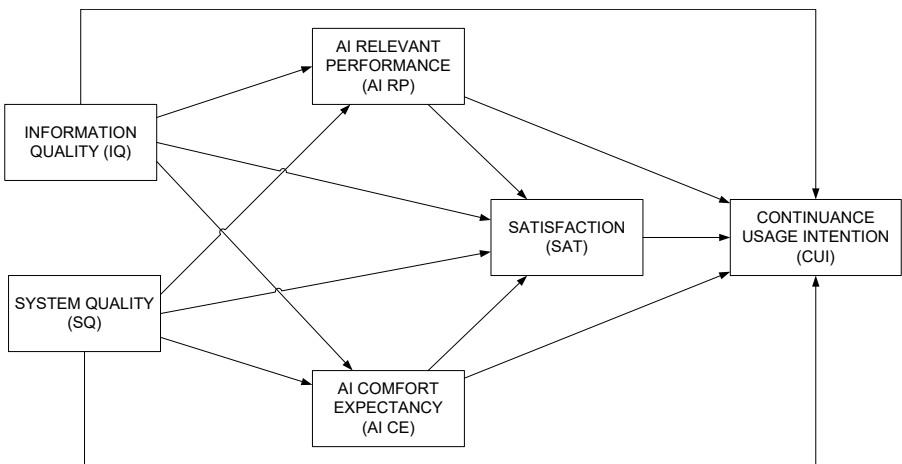


Figure 1. Proposed research model. Source(s): Adapted from Davis (1989) into the GRAF (Generative-AI Response Adoption Framework)

- H1b.* Information quality has a positive effect on satisfaction.
- H1c.* Information quality has a positive effect on AI relevant performance.
- H1d.* Information quality has a positive effect on AI comfort expectancy.

2.3 System quality

System Quality refers to the desired technical characteristics of a system that focus on system usability and performance (DeLone and McLean, 2003). In the context of ChatGPT, System Quality includes fast response times, system stability, ease of navigating the interface, and minimal technical errors. Empirical studies have shown the influence of System Quality on continuance intention in various technology contexts (Veeramootoo *et al.*, 2018; Zhang *et al.*, 2023). System Quality has also been shown to affect user satisfaction in various information system contexts (Almusfar, 2025; Tang *et al.*, 2024), where high system quality enhances users' positive evaluations of their experience using the system. Good system quality—such as responsive speed and reliability—affects users' perceptions of AI system relevance and performance (Bandi *et al.*, 2023; Kim and Kim, 2025). When the system functions well and is responsive, users perceive AI as a reliable tool for enhancing their academic task performance. Studies have shown that system quality is related to the level of comfort and ease with which users adopt technology (Saputra *et al.*, 2023; Siyal *et al.*, 2021; Wu *et al.*, 2021). A stable and user-friendly system increases the comfort of users interacting with AI technology. Accordingly, the following hypotheses are proposed:

- H2a.* System quality has a positive effect on continuance usage intention.
- H2b.* System quality has a positive effect on satisfaction.
- H2c.* System quality has a positive effect on AI relevant performance.
- H2d.* System quality has a positive effect on AI comfort expectancy.

2.4 AI relevant performance

AI Relevant Performance (AI-RP) is a new construct developed in this study through the synthesis of two complementary concepts. The first concept is personal job relevance, which originates from the evolution of perceived usefulness in TAM. Perceived usefulness was initially developed in TAM 2 (Venkatesh and Davis, 2000), then expanded with the concepts of personal and organizational utility (Slatten, 2012), and subsequently contextualized as personal job relevance in the educational context (Mayer and Girwidz, 2019). The second concept is performance expectancy from UTAUT (Venkatesh *et al.*, 2003), contextualized with the aspect of compatibility—the alignment of technology with work, values, and user experience (Dwivedi *et al.*, 2020). The synthesis of these two concepts is based on the argument that Perceived Usefulness in traditional TAM is too general to capture the specific nuances of generative AI technology (Wolf and Maier, 2024). In the context of ChatGPT, AI-RP measures how relevant and useful ChatGPT is in enhancing users' performance and productivity in their academic tasks—not just a general perception of usefulness, but its relevance to users' specific tasks. Empirical studies indicate that performance expectancy has a significant positive impact on continuance intention (Abdelazim *et al.*, 2025; Alkhwaldi, 2023; Ooi *et al.*, 2025). Moreover, the relevance and performance of AI have been shown to influence user satisfaction in the context of generative AI technology (Ahmed *et al.*, 2024; Pramanik and Jana, 2025). The following hypotheses are proposed:

- H3a.* AI relevant performance has a positive effect on continuance usage intention.
- H3b.* AI relevant performance has a positive effect on satisfaction.

2.5 AI comfort expectancy

AI Comfort Expectancy (AI-CE) is a new construct developed in this study through the synthesis of two complementary concepts. The first concept is perceived comfort, which originates from the evolution of the perceived ease of use in TAM. Perceived ease of use was initially developed in TAM 3 (Venkatesh and Bala, 2008), then expanded with the concepts of perceived aesthetics (Hwang *et al.*, 2016) and perceived fees (Wang *et al.*, 2019), and subsequently contextualized as perceived comfort in the context of digital technology adoption (Wu *et al.*, 2021). The second concept is effort expectancy from UTAUT (Venkatesh *et al.*, 2012), which describes the perception of ease of use of technology. The integration of these two concepts is based on the argument that Perceived Ease of Use in traditional TAM is overly technical and does not capture the psychological comfort aspect of users when interacting with AI technology (Wolf and Maier, 2024). In the context of ChatGPT, AI-CE measures the level of user comfort and ease in adopting and interacting with AI technology—not just technical ease, but also psychological comfort in using a system with a high degree of autonomy. Empirical studies indicate that effort expectancy has a significant positive impact on continuance intention (Siyal *et al.*, 2021; Tyagi and Krishankumar, 2023). In addition, psychological comfort influences user satisfaction in the context of AI technology (Gao *et al.*, 2022; Xiaowen *et al.*, 2025). Accordingly, the following hypotheses are proposed:

H4a. AI comfort expectancy has a positive effect on continuance usage intention.

H4b. AI comfort expectancy has a positive effect on satisfaction.

2.6 Satisfaction

Satisfaction refers to a user's feeling of contentment with their experience of using an information system (Bhattacharjee, 2001). In the context of ChatGPT, satisfaction encompasses users' contentment with the quality of responses provided, ease of use, and how well the system meets their expectations. Empirical studies consistently demonstrate the central role of satisfaction in information system success models, where Bhattacharjee (2001) in ECM shows that satisfaction is the primary predictor of continuance intention. (Khayer and Bao, 2020; Liu *et al.*, 2023; Taghizadeh *et al.*, 2022) have demonstrated that satisfaction significantly influences continuance usage intention in various contexts. Accordingly, the following hypothesis is proposed:

H5. Satisfaction has a positive effect on continuance usage intention.

2.7 Mechanism of the indirect effects of AI relevant performance, AI comfort expectancy, and satisfaction

Previous studies have shown inconsistent results regarding the direct influence of Information Quality and System Quality on continuance intention—Information Quality was not significant in the context of e-filing (Veeramootoo *et al.*, 2018), while System Quality was not significant in the context of e-government (Gupta and Maurya, 2020). This inconsistency indicates that the relationship between system quality and continuance intention may be indirect, mediated by other factors such as user perceptions and satisfaction. According to the mediation mechanism proposed by Baron and Kenny (1986), this study examines the roles of AI-RP, AI-CE, and Satisfaction as mediators in the relationship between IQ and SQ with CI. Empirical studies have demonstrated that Information Quality influences perceptions of the relevance and performance of AI technology (Ahmed *et al.*, 2024) as well as the level of user comfort in dealing with uncertainty (Ilgen *et al.*, 2019; Laato *et al.*, 2022). Similarly, System Quality affects users' perceptions of system performance (Bandi *et al.*, 2023) and comfort (Saputra *et al.*, 2023). Based on this theoretical foundation, this study argues that AI-RP and AI-CE—as new constructs integrating these concepts—can serve as mediators in the

relationship between system quality and continuance intention. Furthermore, performance and effort expectancy—the components forming AI-RP and AI-CE—have been shown to affect user satisfaction (Xiaowen *et al.*, 2025), which in turn influences continuance intention (Bhattacharjee, 2001). Based on these arguments, the following hypotheses are proposed:

- H6a. AI relevant performance mediates the relationship between information quality and continuance usage intention.
- H6b. AI comfort expectancy mediates the relationship between information quality and continuance usage intention.
- H6c. Satisfaction mediates the relationship between information quality and continuance usage intention.
- H7a. AI relevant performance mediates the relationship between system quality and continuance usage intention.
- H7b. AI comfort expectancy mediates the relationship between system quality and continuance usage intention.
- H7c. Satisfaction mediates the relationship between system quality and continuance usage intention.
- H8a. Satisfaction mediates the relationship between AI relevant performance and continuance usage intention.
- H8b. Satisfaction mediates the relationship between AI comfort expectancy and continuance usage intention.

3. Research methodology

To develop and refine the measurements for AI Relevant Performance and AI Comfort Expectancy, this study follows four stages of scale development and validation (Hair *et al.*, 2019). The AI-RP indicators were synthesized from performance expectancy (Dwivedi *et al.*, 2022) and personal job relevance (Mayer and Girwidz, 2019), while the AI-CE indicators were derived from perceived comfort (Wu *et al.*, 2021) and effort expectancy (Siyal *et al.*, 2021). In the second stage, face validation was conducted through expert review by three experts to assess the relevance of the content and clarity of the items. In the third stage, semantic validation ensured the suitability of item wording to the context of generative AI. In the fourth stage, the refined indicators were empirically validated through Exploratory Factor Analysis (Table 1). Four items were validated for AI Relevant Performance and four items for measuring AI Comfort Expectancy. For the constructs of information quality and system quality, established measurements were used (DeLone and McLean, 2003), while satisfaction and continuance usage intention were adopted from Bhattacharjee (2001).

Table 1. Empirical validation constructs

Criteria	AI relevant performance	AI comfort expectancy	Threshold
KMO	0.831	0.791	≥0.6
Bartlett's Test (χ^2)	254.580***	208.218***	$p < 0.05$
Variance explained	75.83%	69.85%	≥60%
Factor loading range	0.795–0.908	0.789–0.891	≥0.5
Factors extracted	1	1	–

Note(s): *** $p < 0.001$

A cross-sectional approach was used to examine the proposed theoretical model. This study employed a non-probability sampling technique (convenience sampling) because of the absence of a well-defined sampling frame for ChatGPT users in Indonesian universities. The minimum sample size was calculated following the procedure of Hair *et al.* (2021), which recommends 5–10 times the number of items, totaling 24 items. All variables were measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). A preliminary test was conducted with 20 students to ensure the clarity and comprehensibility of the survey items (Tenenhaus *et al.*, 2005). This approach is useful in the context of evolving AI technologies, where accessing a fully representative sample is challenging (Saunders *et al.*, 2023). Hypothesis testing in this study utilized the structural equation modeling (SEM) approach. Respondents were identified as (1) all ChatGPT 3.5 users, (2) active students (both undergraduate and postgraduate), (3) individuals who had used ChatGPT 3.5 in the past 3 months to reduce response bias, and (4) universities located on Java Island, which is the focus of digital transformation through the National AI Strategy 2020–2045 (BPPT, 2020) and the National Research Master Plan 2017–2045 (Kementerian and Teknologi, 2017). Respondents were reached through Google Forms and direct distribution of questionnaires. CMB was tested using the procedure of Podsakoff *et al.* (2003), resulting in a variance of 42.018% (<50%), confirming that the study is free from significant CMB (see Table 2). This study involved 688 respondents, 53% male and 47% female, with 62% aged between 20–23 years, that is, undergraduate students. Of the respondents, 547 (79%) were undergraduates and 141 (21%) were postgraduates.

4. Result

4.1 Measurement model assessment

Based on Table 3, all construct items show factor loadings above 0.6, in accordance with the recommended standards, demonstrating convergent validity. Construct reliability was confirmed through CRA and CR values, all of which exceeded the minimum threshold of 0.7, while AVE values above 0.5 indicated that the scale successfully extracted sufficient variance from each item. Discriminant validity was evidenced by the use of the heterotrait-monotrait method, with all values falling below the recommended threshold of 0.9. Since all reliability and validity requirements have been met, the data is suitable for hypothesis testing (Hair *et al.*, 2014).

4.2 Structural model results

Structural model testing resulted in a goodness-of-fit index of 0.525, indicating a good level of model fit (Tenenhaus *et al.*, 2005). Model feasibility was confirmed by a normal fit index of 0.800 and a standardized root mean square residual of 0.070. For Continuance Usage Intention, an R^2 value of 0.564 was obtained, indicating that Information Quality, System Quality, AI Relevant Performance, AI Comfort Expectancy, and Satisfaction contribute to explaining 54.1% of the variability in Continuance Usage Intention. The model’s predictive ability was also confirmed by all positive Q^2 values (Chin *et al.*, 2008). Figure 2 presents the results of the structural model testing with path coefficients and t -values.

Table 2. CMB test

Component	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% Of variance	Cumulative %	Total	% Of variance	Cumulative %
1	10.084	42.018	42.018	10.084	42.018	42.018

Table 3. Construct reliability and validity

Construct	Factor loading*	CRA	CR	AVE
<i>Information Quality (mean: 3.715; SD: 0.757)</i>				
IQ1	0.730	0.900	0.923	0.667
IQ2	0.825			
IQ3	0.836			
IQ4	0.848			
IQ5	0.830			
IQ6	0.825			
<i>System Quality (mean: 3.974; SD: 0.792)</i>				
SQ1	0.768	0.734	0.821	0.635
SQ2	0.746			
SQ3	0.731			
SQ4	0.760			
<i>AI Relevant Performance (mean: 4.192; SD: 0.757)</i>				
AIRP1	0.886	0.917	0.941	0.801
AIRP2	0.896			
AIRP3	0.900			
AIRP4	0.897			
<i>AI Comfort Expectancy (mean: 4.160; SD: 0.746)</i>				
AICE1	0.883	0.871	0.912	0.723
AICE2	0.870			
AICE3	0.878			
AICE4	0.775			
<i>Satisfaction (mean: 3.760; SD: 0.843)</i>				
SAT1	0.910	0.884	0.928	0.812
SAT2	0.916			
SAT3	0.876			
<i>Continuance Usage Intention (mean: 3.913; SD: 0.920)</i>				
CUI1	0.899	0.833	0.901	0.784
CUI2	0.921			
CUI3	0.777			

Note(s): SD = standard deviation; * significant at $p < 0.01$

Source(s): Table by authors

Based on Table 4, the results of the direct hypothesis testing reveal that IQ does not significantly affect CUI ($b: 0.012, p > 0.05$), leading to the rejection of H1a. However, it had a significant effect on SAT ($b = 0.436, p < 0.05$), AI PR ($b = 0.642, p < 0.05$), and AI CE ($b = 0.438, p < 0.05$), thus supporting H1b, H1c, and H1d. SQ showed a similar pattern, where its effect on CUI and SAT was not significant ($b: -0.054, p > 0.05$ and $b: 0.083, p > 0.05$), leading to the rejection of H2a and H2b. However, it had a significant effect on AI PR ($b: 0.211, p < 0.05$) and AI CE ($b: 0.407, p < 0.05$), supporting H2c and H2d. Furthermore, AI PR had a significant effect on CUI ($b: 0.294, p < 0.05$) and SAT ($b: 0.191, p < 0.05$), confirming H3a and H3b, while AI CE also had a significant effect on CUI ($b: 0.222, p < 0.05$) and SAT ($b: 0.229, p < 0.05$), supporting H4a and H4b. Finally, the effect of SAT on CUI was significant ($b: 0.381, p < 0.05$), confirming H5.

Mediation effect testing showed that AI PR successfully mediated the relationship between IQ and CUI ($b: 0.189, p < 0.05$), supporting H6a. Similarly, AI CE mediated the relationship between IQ and CUI ($b: 0.100, p < 0.05$), confirming H6b. The SAT also mediated the relationship between IQ and CUI ($b: 0.166, p < 0.05$), thus H6c was accepted. For SQ, AI PR successfully mediated its relationship with CUI ($b: 0.062, p < 0.05$), supporting H7a, while AI CE also mediated the relationship between SQ and CUI ($b: 0.097, p < 0.05$), confirming H7b. However, SAT did not mediate the relationship between SQ and CUI ($b: 0.031, p < 0.05$), so

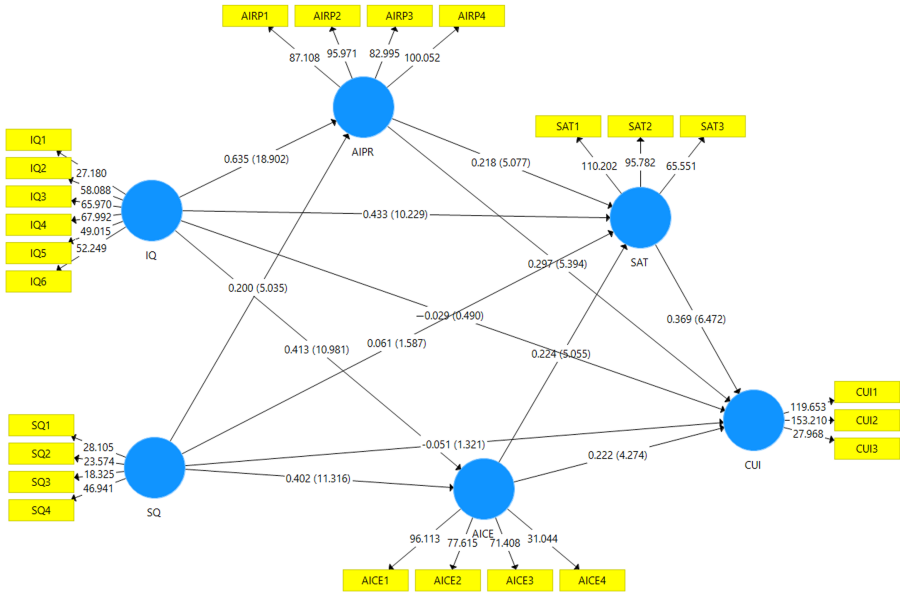


Figure 2. Inner model

Table 4. Results of hypothesis testing

Relationship (hypothesis)	Direct effect		Indirect effect		Total effect		
	B	t-value	B	t-value	B	t-value	
IQ → CUI	H1a	-0.012	0.179 ^{ns}	0.537	10.563*	0.525	10.046 ^{ns}
IQ → SAT	H1b	0.436	7.953*	0.223	5.870**	0.658	17.321**
IQ → AI PR	H1c	0.642	15.852**	-	-	0.642	15.852**
IQ → AI CE	H1d	0.438	10.302**	-	-	0.438	10.302**
SQ → CUI	H2a	-0.054	1.180 ^{ns}	0.235	6.492**	0.181	3.466 ^{ns}
SQ → SAT	H2b	0.083	1.930 ^{ns}	0.133	4.896**	0.216	5.582 ^{ns}
SQ → AI PR	H2c	0.211	4.522**	-	-	0.211	4.522**
SQ → AI CE	H2d	0.407	10.443**	-	-	0.407	10.443**
AI PR → SAT	H3b	0.191	3.998*	-	-	0.191	3.903**
AI PR → CUI	H3a	0.294	4.604*	0.073	3.338**	0.367	5.576**
AI CE → SAT	H4b	0.229	3.998*	-	-	0.229	3.998**
AI CE → CUI	H4a	0.222	3.616*	0.087	3.388**	0.309	4.952**
SAT → CUI	H5	0.381	5.926*	-	-	0.381	5.926**

Note(s): * Significant at $p < 0.05$; ** significant at $p < 0.01$; ns = not significant

Source(s): Table by authors

H7c was rejected. Furthermore, SAT was proven to mediate the relationship between AI PR and CUI (b: 0.073, $p < 0.05$), supporting H8a, and it also mediated the relationship between AI CE and CUI (b: 0.087, $p < 0.05$), confirming H8b.

5. Discussion and theoretical implication

First, the development of the integrated Generative-AI Response Adoption Framework (GRAF) addresses the gap identified by Wolf and Maier (2024), namely that most previous

studies focused on the traditional TAM, which is inadequate for generative AI technologies. The findings confirm that information and system quality do not directly influence continuance usage intention but rather operate through AI-specific mediators. Through the development of two new constructs—AI Relevant Performance and AI Comfort Expectancy—this study captures a more contextual user evaluation of AI technology. These findings highlight the need to develop context-specific constructs when examining user behavior towards emerging technologies such as ChatGPT, given that traditional models fail to capture the unique characteristics of AI-mediated interactions (Pramanik and Jana, 2025). Second, unlike previous studies that found a significant direct influence of information quality on continuance intention in social media (Khan and Saleh, 2023) and mobile health applications (Kaium *et al.*, 2020), this study reveals a different pattern. This is in line with research on e-filing (Veeramootoo *et al.*, 2018) and e-government services (Gupta and Maurya, 2020), showing that for task-oriented technologies such as ChatGPT in academic settings, users evaluate quality not through traditional system attributes but through the AI's ability to provide relevant performance and comfortable interaction. These findings imply that academic users prioritize how AI assists with their specific tasks, rather than the generic quality attributes emphasized in conventional information systems. Third, the findings indicate that AI-relevant performance and AI comfort expectancy serve as full mediators between quality factors and continuance intention. This implies that traditional quality factors must first be “processed” through AI-specific evaluations before affecting behavioral outcomes. Users do not respond directly to information or system quality; instead, they assess the relevance of AI in assisting their academic tasks and their comfort level in interacting with AI. This mechanism of full mediation confirms that users develop different cognitive pathways when evaluating AI-based systems (Dahri *et al.*, 2024; Xiaowen *et al.*, 2025). Finally, contrary to research suggesting that satisfaction mediates the relationship between system quality and behavioral intention (Ashfaq *et al.*, 2020), this study did not find a significant mediating effect of satisfaction on the system quality–continuance intention pathway. Instead, AI comfort expectancy emerged as the main mediator, indicating that academic ChatGPT users develop a direct evaluation pathway through AI-specific factors rather than through traditional satisfaction mechanisms. Although satisfaction still plays a crucial role in mediating information quality and AI-specific factors toward continuance intention, its influence appears less significant in the system quality pathway, where experiential comfort with AI interaction has a greater impact. These findings expand the ECM framework (Bhattacharjee, 2001), showing that satisfaction-based evaluation in the context of generative AI operates differently from conventional technologies, with users prioritizing AI-specific comfort over traditional system satisfaction.

6. Managerial implication

First, the finding that AI relevant performance is a significant predictor of continuance intention provides practical implications for higher education institutions. Institutions need to integrate AI relevance assessment into curriculum design, for example, by developing assignment assessment rubrics that consider how students use ChatGPT effectively for specific academic tasks. Contextual prompt engineering training is also necessary—not general techniques, but tailored to the needs of each discipline. Developing a repository of validated prompts for various academic tasks in the Indonesian context can help students directly observe the relevance of ChatGPT to their assignments.

Second, the finding that AI comfort expectancy has a significant influence implies the importance of users' psychological comfort. Institutions must create safe spaces for AI exploration through informal workshops where students can experiment with ChatGPT without the pressure of assessment. Clear ethical guidelines regarding the boundaries of ChatGPT use in academic contexts are needed so that students feel comfortable understanding the rules. Educational institutions must maintain traditional quality standards while

developing an evaluation framework that optimizes the transformation of information quality into perceived AI relevance by curating information sources integrated with ChatGPT and developing AI output verification systems to ensure information accuracy in the academic context.

7. Conclusion, limitations and opportunities for future research

In conclusion, this study emphasizes that the intention for continued use of ChatGPT among Indonesian university students is driven by AI-relevant performance and AI comfort expectancy as AI-specific factors, with satisfaction being the strongest predictor. Information and system quality influence continuance usage intention through the mediation of AI-specific factors, indicating that generative AI technologies require a different evaluation approach than conventional technologies. The development of two new constructs—AI Relevant Performance and AI Comfort Expectancy—offers a theoretical contribution by filling the gap in the literature on generative AI technology adoption, where traditional TAM constructs have proven inadequate. Although this study contributes to the understanding of generative AI adoption in the context of higher education in Indonesia, some limitations must be acknowledged. First, this study did not include ethical concerns and privacy-related impacts, which may indirectly influence the intention to continue using generative AI technology (Fernando and Li, 2025). Second, this study did not differentiate adoption patterns across academic disciplines, which may have different needs and perceptions of ChatGPT.

Based on these limitations, several directions for future research are recommended. First, future studies can expand the sample to areas outside Java Island and compare adoption patterns across educational levels (undergraduate vs. postgraduate) to enhance the generalizability of the findings of this study. Second, integrating constructs such as ethical concerns, privacy risks, or AI trust as moderators or mediators in the model could provide a more comprehensive understanding of the factors influencing continuance intention. Third, comparing adoption patterns across disciplines (STEM vs. Social Humanities) may identify whether AI-relevant performance and AI comfort expectancy have different impacts depending on the academic context. Fourth, testing the model on other generative AI platforms can validate whether the constructs of AI-RP and AI-CE are generalizable or platform specific.

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