



Understanding ChatGPT Use in Supporting Higher Education Learning: Evidence from Malaysia and Indonesia

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Abstract: This study explores the factors influencing the use of ChatGPT to support learning in higher education, particularly in developing countries. Despite the increasing adoption of artificial intelligence (AI) in educational settings, empirical evidence on how students utilize ChatGPT to support learning remains limited. This study aims to identify the determinants of ChatGPT use among university students in Malaysia and Indonesia. A quantitative survey approach based on the Unified Theory of Acceptance and Use of Technology (UTAUT) was used, collecting data from students who had used ChatGPT for academic purposes. The results indicate that ease of use and social influence significantly influence ChatGPT usage intentions, while performance expectations are not a dominant factor. Cross-country differences exist in the relationship between behavioral intentions and actual usage behavior. These findings suggest that ChatGPT use in higher education learning is more influenced by ease of use and social context than by perceived performance benefits. This study contributes to the literature by providing cross-country empirical evidence and emphasizing the importance of integrating AI literacy and pedagogical strategies to support effective and responsible use of ChatGPT.

Keywords: AI Literacy; Artificial Intelligence in Education; ChatGPT; Technology Adoption; UTAUT Model

Recommended citation: Astutik, I., Usman, I., Sanusi, A., Alfian, M., & Nuraini, K. (2026). Understanding ChatGPT Use in Supporting Higher Education Learning: Evidence from Malaysia and Indonesia. *Journal of Innovation in Educational and Cultural Research*, 7(4), 930-940.

INTRODUCTION

The development of digital technology has significantly impacted education (Buzatu et al., 2020; Grassini et al., 2024; Li & Liu, 2024). One such development is the use of artificial intelligence (AI) in learning environments. AI can improve the academic experience and student productivity (R. Chen & Zhao, 2024; Zhong & Kim, 2024). Among AI innovations, ChatGPT is widely used in learning (Al-Ghonmein & Al-Moghrabi, 2024; He et al., 2024). ChatGPT is a language model that can assist students in various academic activities, such as information search, idea generation, and assignment completion (Smith et al., 2023). Therefore, ChatGPT can serve as a learning support tool that encourages a more efficient and flexible learning process (Soehardjo et al., 2024). However, the effective use of ChatGPT in higher education depends not only on the technology's capabilities but also on how students understand, accept, and integrate it into their academic practices.

Despite the increasing use of ChatGPT in educational settings, understanding of student usage behavior in formal learning contexts remains limited (Polyportis, 2024; Sallam et al., 2024; Shishakly et al., 2024). Numerous studies have explored AI in education, including its benefits in improving learning efficiency and information accessibility, as well as challenges such as the risk of dependency, inaccuracy, and ethical issues (Crompton & Burke, 2024; Guleria et al., 2023). However, most research focuses on general perceptions or aspects of the technology, providing little insight into the behavioral factors underlying actual use. Understanding behavioral factors such as perceived ease of use, perceived usefulness, and social influence is crucial to explaining how students adopt ChatGPT in their learning activities.

Several previous studies have applied the UTAUT framework to explain the adoption of educational technology, including ChatGPT use in higher education. These studies generally emphasize factors such as performance expectancy, effort expectancy, and social influence in influencing students' behavioral intentions to use technology. However, these studies tend to focus more on behavioral intentions than actual usage behavior, even though AI technology in education may involve different behavioral dynamics. Specifically, Siddiqui et al. (2025) did not integrate variables such as technology anxiety, enabling conditions, and actual usage behavior into their model. This limitation matters because technology anxiety can reduce students' confidence and intentions to use ChatGPT. However, students may continue to use the technology due to

academic demands, learning needs, and pressures from the educational environment. These findings suggest that technology anxiety may influence behavioral intentions and actual usage behavior differently, but this relationship has not been widely explored in previous research.

Furthermore, previous studies such as [Grassini et al. \(2024\)](#) were conducted in developed country contexts and therefore do not fully represent the conditions of ChatGPT use in developing countries. Differences in digital literacy levels and technological culture between developed and developing countries may influence the factors determining the acceptance and use of ChatGPT. However, cross-national studies such as [Budhathoki et al. \(2024\)](#) still face limitations in the equivalence of research contexts because differences in educational systems and technological readiness can affect the comparability of results. These limitations indicate a research gap, particularly in understanding ChatGPT use in higher education in developing-country contexts. Malaysia and Indonesia, as two countries with relatively similar cultural characteristics and educational systems, provide a relevant context for comparative analysis. However, cross-national empirical studies on students' ChatGPT use remain limited. Without a cross-national perspective, understanding of AI adoption in higher education tends to be fragmented.

Therefore, this study aims to analyze the factors influencing ChatGPT use to support learning in higher education by applying the UTAUT framework and integrating additional variables, including anxiety, enabling conditions, and usage behavior. Furthermore, this study adopts a cross-national approach by comparing student behavior patterns in Malaysia and Indonesia to better understand AI adoption in a developing-country context. Thus, this study contributes to the growing literature by providing empirical evidence on the determinants of ChatGPT use in higher education, while emphasizing the importance of integrating AI literacy and pedagogical considerations in implementing AI technology in education.

METHODS

This study used a quantitative, survey-based approach based on the Unified Theory of Acceptance and Use of Technology (UTAUT) model developed by [Venkatesh et al. \(2003\)](#). The study was conducted from May to September 2025 at two higher education institutions: the University of Malaya (Malaysia) and the University of Muhammadiyah Jember (Indonesia), to examine and compare student use of ChatGPT to support learning in higher education. The study population consisted of university students who had used ChatGPT for academic purposes. The researchers used purposive sampling, with criteria including active students in the 2024/2025 academic year who had experience using ChatGPT in learning activities and were willing to participate voluntarily. Respondents came from various faculties and levels of study at both universities. The research team continuously monitored response distribution throughout the data collection process. Furthermore, the questionnaire was disseminated through academic channels rather than open public distribution. Approximately 100 respondents participated, with proportional representation from both universities across gender, faculty, and level of study.

The research instrument was adapted from the UTAUT questionnaire developed by [Venkatesh et al. \(2003\)](#). It consisted of 30 items measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument included seven main constructs: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Anxiety (ANX), Behavioral Intention (BI), and Use Behavior (UB). The instrument was translated into Malay and Indonesian, then back-translated to ensure meaning equivalence. A pilot test was conducted with 30 students outside the main sample to assess clarity and suitability. Reliability results showed that all constructs had Cronbach's Alpha values above 0.70 and Composite Reliability values above 0.80, indicating good internal consistency. Convergent validity was confirmed with AVE values above 0.50 for all constructs.

Data were collected online using Google Forms. The questionnaire link was distributed through academic networks at both universities, with help from academic advisors and study program coordinators. Before participating, respondents were informed about the study's purpose, data confidentiality, and their right to withdraw at any time through an informed consent statement. The data collection process took place over two months. Responses were monitored to ensure balanced participation from both institutions. The analysis excluded incomplete or invalid responses to maintain data quality. All collected data were then coded, cleaned, and prepared for statistical analysis to test the research model and the relationships between constructs.

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS. PLS-SEM was appropriate because this study aimed to predict and explain students' behavioral intentions and usage behavior toward ChatGPT using a relatively complex UTAUT-based model. Furthermore, PLS-SEM is well suited to research with moderate sample sizes, non-normal data distributions, and comparative analysis between groups. The analysis involved a measurement model evaluation stage and a structural model evaluation stage. In the measurement model evaluation, reliability and validity were assessed using factor loadings, Cronbach's Alpha, Composite Reliability, and AVE. Discriminant validity was examined using the Fornell-Larcker criteria. In the structural model evaluation, relationships between variables were analyzed using path coefficients, t-statistics, and p-values obtained through a bootstrapping procedure. In addition, a

comparative analysis was conducted to identify differences in structural relationships between the Malaysian and Indonesian samples.

RESULT AND DISCUSSION

The findings of this study are presented based on the results of the PLS-SEM analysis. The analysis included evaluation of the measurement and structural models. Overall, the measurement model demonstrated good reliability and validity. This indicates that the constructs used in this study adequately explain students' use of ChatGPT to support learning in higher education. Reliability was evaluated using Cronbach's alpha and Composite Reliability, which indicated adequate internal consistency for each construct. Convergent validity was ensured by AVE values exceeding the recommended threshold. Furthermore, discriminant validity indicated that each construct differed clearly from the others in the research model. After the measurement model was deemed adequate, the study conducted structural model analysis to examine relationships among constructs and identify factors influencing students' use of ChatGPT.

Table 1. Sample Characteristics

	Malaysia		Indonesia	
	Frequency	%	Frequency	%
Gender				
Male	25	36.76	21	33.33
Female	40	58.82	42	66.37
Non-Binary/Third Gender	0	0	0	0
Prefer not to say	3	4.41	0	0
Age				
18-21	49	72.06	35	55.56
22-25	13	19.12	9	14.29
26-29	1	1.47	7	11.11
30 and above	5	7.35	12	19.05
Education				
Undergraduate	57	83.82	52	82.54
Masters/MBA	8	11.76	6	9.52
Doctoral	3	4.41	3	4.76
ChatGPT Use				
3 months	11	16.18	19	30.16
6 months	17	25.00	8	12.70
7 months	40	58.82	29	46.03
Non	0	0	7	11.11

Based on Table 1, the age distribution of respondents in both countries shows that the majority were in the 18–21 age range, namely 72.06% in Malaysia and 55.56% in Indonesia. This finding indicates that most respondents were students in the early stages of higher education. In terms of education level, most respondents were in undergraduate programs, with 83.82% in Malaysia and 82.54% in Indonesia. Furthermore, most respondents had used ChatGPT for about 7 months, namely 58.82% in Malaysia and 46.03% in Indonesia. This indicates that respondents have a relatively adequate level of experience in using ChatGPT for academic activities. These demographic characteristics and usage experience indicate that the study sample is sufficiently representative to describe the pattern of ChatGPT usage among higher education students in both countries.

Table 2. Reliability and Validity

Construct	Malaysia				Indonesia			
	Factor Loading	a*	CR	AVE	Factor Loading	a*	CR	AVE
PE1	0.935	0.922	0.951	0.866	0.927	0.909	0.943	0.846
PE2	0.939				0.952			
PE3	0.917				0.878			
EE1	0.793				0.862			
EE2	0.817				0.931			
EE3	0.878				0.848			
EE4	0.765	0.899	0.922	0.664	0.878	0.931	0.946	0.745
EE5	0.806				0.753			
EE6	0.826				0.896			
SI1	0.837				0.918			
SI2	0.923				0.954			
SI3	0.837				0.970			
FC1	0.793	0.689	0.818	0.610	0.747	0.823	0.894	0.739
FC2	0.817				0.912			
FC3	0.878				0.909			
ANX1	0.898				0.924			
ANX2	0.918				0.898			
ANX3	0.946				0.922			
BI1	0.916	0.718	0.843	0.633	0.895	0.748	0.939	0.837
BI2	0.913				0.912			
BI3	0.927				0.838			
BI4	0.051				0.284			
UB1	0.837				0.918			
UB2	0.923				0.954			
UB3	0.837	0.406	0.282	0.336	0.970	0.474	0.417	0.344

Based on Table 2, the reliability and construct validity tests show that most indicators have factor loadings above 0.70. This indicates that these indicators represent the constructs being measured well. Furthermore, the Composite Reliability (CR) values for most constructs exceed the 0.70 threshold, indicating adequate instrument reliability. The Average Variance Extracted value for most constructs also exceeds 0.50, indicating good convergent validity. Thus, the measurement model in this study has met the required reliability and validity criteria. In addition to convergent validity, discriminant validity was evaluated to ensure that each construct has clear contextual differences from the others. The results indicate that all criterion constructs meet the discriminant validity criterion, so the measurement model is deemed adequate for use in the structural model analysis stage.

Table 3. Discriminant Validity Results

Construct	ANX	BI	EE	FC	PE	SI	UB
Malaysia							
Anxiety	0.921						
Behavioural Intention	0.558	0.796					
Effort Expectancy	0.598	0.774	0.815				
Facilitating Conditions	0.691	0.520	0.564	0.781			
Performance Expectancy	0.611	0.632	0.693	0.635	0.930		
Social Influence	0.563	0.633	0.651	0.605	0.426	0.892	
Use Behaviour	0.711	0.640	0.646	0.659	0.674	0.477	0.580
Indonesia							
Anxiety	0.915						
Behavioural Intention	0.709	0.777					
Effort Expectancy	0.615	0.722	0.863				
Facilitating Conditions	0.785	0.653	0.701	0.860			
Performance Expectancy	0.615	0.634	0.840	0.726	0.920		
Social Influence	0.466	0.504	0.141	0.346	0.126	0.948	
Use Behaviour	0.710	0.773	0.741	0.729	0.700	0.247	0.586

Based on Table 3, the results of the discriminant validity test using the Fornell-Larcker criteria indicate that the square root of the AVE value for each construct is greater than its correlation with other constructs, both in the Malaysian and Indonesian samples. This finding indicates that each construct in the research model

can differentiate itself from other constructs. Thus, the measurement model in this study has met the criteria for discriminant validity. This result strengthens the quality of the measurement model used in the study. Fulfillment of discriminant validity indicates that each construct is measured specifically according to the established concept. Thus, the constructs in the model can be used to analyze structural relationships in the next stage.

Table 4. Hypotheses Testing

Hypothesis	Path	Malaysia		Decision	Indonesia		Decision
		T Value	P Value		T Value	P Value	
H1	PE -> BI	1.316	0.189	Rejected	0.175	0.862	Rejected
H2	EE -> BI	2.835	0.005	Accepted	3.143	0.002	Accepted
H3	SI -> BI	1.741	0.082	Accepted	2.553	0.011	Accepted
H4	FC -> UB	1.741	0.082	Rejected	1.368	0.172	Rejected
H5	ANX -> BI	0.429	0.668	Rejected	1.419	0.157	Rejected
H6	ANX -> UB	2.992	0.003	Accepted	0.350	0.727	Rejected
H7	BI -> UB	2.150	0.032	Accepted	1.632	0.103	Rejected

Based on Table 4, the hypothesis-testing results indicate differences in the patterns of relationships between variables in the Malaysian and Indonesian samples. Hypothesis H1 was not supported in either country, indicating that performance expectancy does not significantly influence behavioral intention. Conversely, H2 and H3 were supported in both countries, indicating that effort expectancy and social influence significantly influence behavioral intention. H4 was not supported in either country, indicating that enabling conditions did not significantly influence actual usage behavior. H5 was also not supported in either country, indicating that anxiety did not significantly influence behavioral intention. However, H6 showed different results between countries, where anxiety significantly influenced usage behavior in Malaysia, but not in Indonesia. Similarly, H7 was supported in Malaysia but not in Indonesia, indicating that behavioral intention influenced actual usage behavior only in the Malaysian sample.

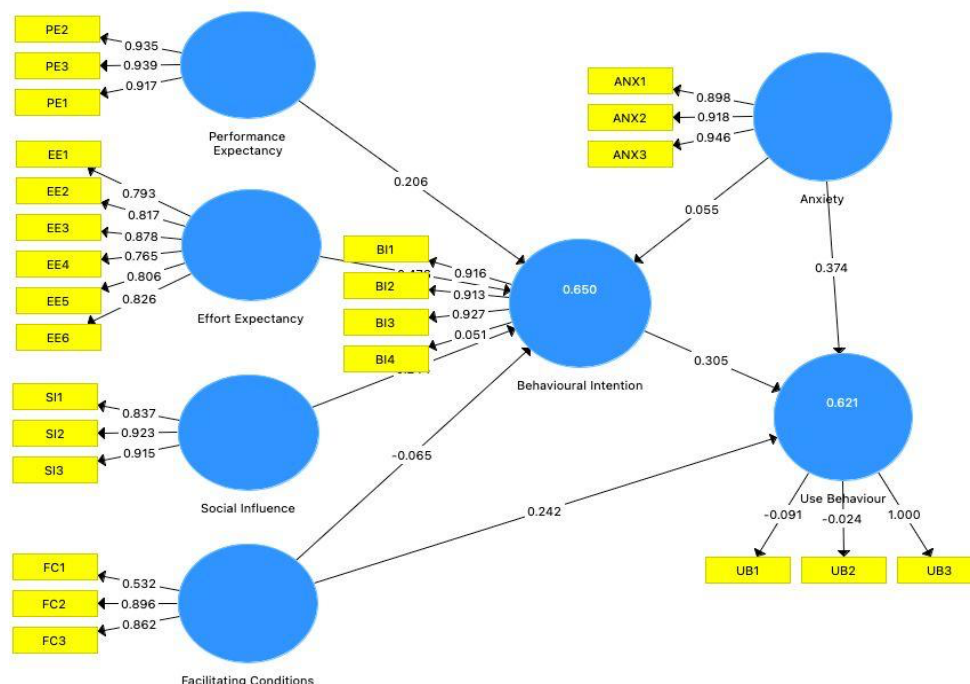


Figure 1. Malaysia Model Chart

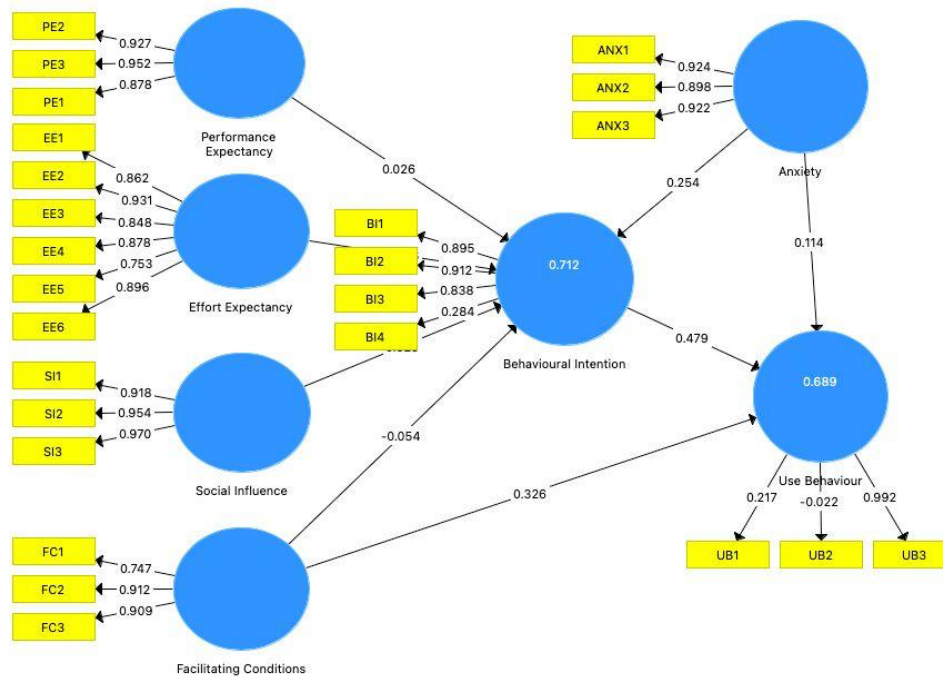


Figure 2. Indonesia Model Chart

Figure 1 presents the structural model from the PLS-SEM analysis for the Malaysian sample, showing the relationships among constructs in the UTAUT model, while Figure 2 shows the structural model for the Indonesian sample. Based on Figure 1, the structural model for the Malaysian sample shows that several constructs influence behavioral intention and usage behavior. The path coefficient values indicate that effort expectancy and social influence positively influence behavioral intention. Conversely, performance expectancy shows a relatively weak influence on behavioral intention. Furthermore, behavioral intention positively influences usage behavior, indicating that usage intention contributes to actual usage. Meanwhile, supportive conditions and anxiety show a relatively limited influence in the model, especially on behavioral intention and usage behavior.

Based on Figure 2, the structural model for the Indonesian sample indicates that several constructs contribute to behavioral intention and usage behavior. The path coefficient shows that effort expectancy positively affects behavioral intention. This suggests that perceived ease of use is an important factor driving students' intention to use ChatGPT. However, behavioral intention did not significantly affect usage behavior in the Indonesian sample. Furthermore, supporting conditions also did not significantly affect usage behavior. Anxiety and performance expectancy showed relatively weak influences on usage intention. Overall, these findings suggest that Indonesian students' decision to use ChatGPT is more influenced by perceived ease of use than by utility factors, environmental support, or psychological barriers. The results indicate that performance expectancy did not significantly influence students' behavioral intentions to use ChatGPT in either country. This finding aligns with [Sudan et al. \(2024\)](#) and [Bahadur et al. \(2024\)](#). [Sudan et al. \(2024\)](#) stated that intention to use ChatGPT is more influenced by habit and perceived usefulness, and [Bahadur et al. \(2024\)](#) also emphasized that habit, learning values, and social influence are more dominant than performance expectancy. However, this finding differs from [Singh et al. \(2025\)](#), which showed that performance expectancy predicts intention to use AI technology. These differences suggest that the influence of performance expectancy on intention to use AI is contextual and can be shaped by user characteristics, usage goals, and learning environments.

Performance expectations did not significantly affect students' behavioral intentions to use ChatGPT, suggesting that ChatGPT performance expectations are not yet a primary consideration for students when deciding to use it. This condition indicates that students do not believe that using ChatGPT can improve their ability to complete specific tasks. In the learning context, students must search for, evaluate, and organize information independently ([Abdelouarit et al., 2016](#); [Díaz, 2015](#); [Pavlovski & Dunder, 2015](#)). In this regard, ChatGPT is viewed more as a supporting tool for exploring ideas, clarifying concepts, and developing assignment frameworks ([McGrew & Chinoy, 2022](#)). Furthermore, academic policies that emphasize originality in assignments may limit students' perceived direct benefits of using ChatGPT to complete assignments. [Crompton and Burke \(2024\)](#) support this finding, noting that concerns regarding accuracy, plagiarism, and ethics influence students' perceptions of AI. Thus, ChatGPT in higher education is positioned more as a learning support tool than as a primary tool for improving student academic performance.

In contrast, the results indicate that students' decisions to use ChatGPT are influenced by other factors more relevant to everyday use, namely effort expectancy and social influence. From an effort expectancy perspective, students tend to use ChatGPT because this technology is easy to learn, easy to operate, and capable of providing fast responses. Therefore, the ease of use aspect becomes a more tangible consideration than the resulting performance benefits. These findings indicate that students still adopt ChatGPT primarily because it is easy to use, rather than because they expect it to improve their academic performance. The dominance of effort expectancy over performance expectancy may indicate that adoption of generative AI in higher education is still in the early stages of acceptance, where ease of interaction and accessibility matter more than increased productivity. In this context, students appear to view ChatGPT more as a practical learning companion than as a formal academic performance tool. This aligns with [Le and Tran \(2024\)](#), [Nguyen \(2025\)](#), and [Turmuzi \(2024\)](#), who state that ease of use is an important factor in the initial stages of technology acceptance. Similarly, [Amin et al. \(2026\)](#) and [Cheong and Chen \(2025\)](#) explain that perceived ease of use strongly influences technology adoption intentions because users tend to choose practical, efficient systems. Beyond convenience, social influence also plays a significant role in shaping ChatGPT usage intentions, especially when students perceive that peers, lecturers, and the broader digital learning culture support its use. This aligns with [Arthur et al. \(2024\)](#), [Duong \(2024\)](#), and [Rizun et al. \(2026\)](#), who state that social influence is a significant factor when students perceive that their environment supports technology use. Similarly, [Chen et al. \(2025\)](#) and [Jesus et al. \(2024\)](#) explain that social observation influences student behavior, as students tend to imitate behaviors deemed valuable and acceptable in their environment. Beyond interpersonal influences, these findings may also indicate the emergence of social normalization in the use of AI in education. As ChatGPT becomes more visible in academic interactions and peer learning environments, students may perceive AI-assisted learning as socially acceptable and academically legitimate. This suggests that the adoption of generative AI is shaped not only by individual perceptions but also by the collective digital learning culture. However, the influence of effort expectations and social influence on ChatGPT usage still needs to be balanced with digital literacy and academic ethics so students not only follow technology trends but can also evaluate information quality and understand their academic responsibilities. Thus, these findings confirm that effort expectancy and social influence have a strategic role in shaping students' decisions to use ChatGPT as part of the academic learning process.

The results indicate that enabling conditions do not significantly influence university students' actual use of ChatGPT in Malaysia and Indonesia. This finding suggests that students' actual use of ChatGPT does not depend heavily on the availability of technical facilities, institutional support, or formal learning resources provided by universities. This finding aligns with [Husain \(2024\)](#), [Kaur and Singh \(2025\)](#), and [Khasawneh et al. \(2025\)](#), which state that AI-based technologies like ChatGPT tend not to require complex infrastructure or strong institutional support for optimal use. This suggests that enabling conditions are no longer a primary factor in ChatGPT use because the technology is designed to be widely accessible and user-independent. The insignificant role of supporting conditions may indicate that traditional UTAUT assumptions regarding infrastructure dependability become less relevant in the context of consumer-oriented generative AI technologies such as ChatGPT. Unlike conventional institutional technologies that require organizational support, training, or specialized infrastructure, ChatGPT can be accessed independently through personal devices and internet connectivity. These findings suggest that generative AI adoption may increasingly occur outside formal institutional ecosystems, challenging the relevance of enabling-conditions explanations within the classic UTAUT framework. This is because ChatGPT is easily accessible through personal devices, such as smartphones and laptops, with a simple internet connection ([Moradi, 2025](#); [Striegl et al., 2025](#)). This gives students flexibility to use it according to their academic needs. This ease of access allows students to use ChatGPT to search for information, explore ideas, clarify concepts, and help organize assignments more efficiently. In this context, actual ChatGPT usage behavior is more influenced by internal factors, such as academic needs, technology habits, and pre-existing perceptions of ease of use, than by the presence of formal supporting conditions.

The results indicate that anxiety does not significantly influence students' behavioral intentions to use ChatGPT in Malaysia or Indonesia. This finding is inconsistent with previous research that identified anxiety as a factor inhibiting digital technology adoption ([Han & Ko, 2025](#); [Tailor & Tailor, 2025](#)). Previous research explains that technology anxiety can lead to discomfort, hesitation, and perceived risks associated with technology use, such as uncertainty about information accuracy, dependency, plagiarism, and academic consequences, which can ultimately reduce usage intentions. This difference may be explained by students' growing familiarity with generative AI, which may reduce perceived risks relative to perceived benefits ([Chan & Hu, 2023](#); [Gasaymeh et al., 2024](#); [Kwakye et al., 2025](#)). This situation tends to cause students to view ChatGPT as a practical, fast, and accessible academic tool, so their decision to use it is more influenced by utility orientation than emotional factors such as anxiety. These findings may indicate a shift in student attitudes toward generative AI, where perceived usefulness and familiarity outweigh emotional resistance or technological concerns. In this context, anxiety may no longer be a major barrier to AI adoption, particularly among students exposed to digital technologies and increasingly viewing generative AI as part of everyday academic practice. Although anxiety did not significantly influence behavioral intentions, the results of this study indicate that anxiety has a significant

influence on usage behavior through behavioral intentions in Malaysia, but does not show a significant influence in Indonesia. These findings suggest that anxiety may not be strong enough to inhibit students' initial intentions to use ChatGPT. However, it may still influence how students use the technology in practice. The differences in results between Malaysia and Indonesia suggest that anxiety's influence on actual usage is contextual and may be shaped by academic culture, levels of trust in technology, and norms around AI use in each educational setting. Thus, these findings confirm that anxiety in ChatGPT usage plays a greater role in the implementation stage of actual use than in the formation of usage intentions. The differences between Malaysia and Indonesia suggest that generative AI adoption is shaped not only by perceptions of the technology but also by the contextual educational environment. The significant influence of behavioral intentions on actual use in Malaysia may reflect a more institutionalized digital learning ecosystem, where AI use is more formally integrated into academic practice. In contrast, Indonesian students may use ChatGPT more flexibly and independently, with actual use driven more by situational academic needs than by stable behavioral intentions.

CONCLUSION

This study demonstrates that students' adoption of ChatGPT in higher education is driven more strongly by perceived ease of use and social influence than by performance-related expectations. These findings suggest that the conventional UTAUT assumption that technology adoption is primarily performance-oriented may not fully explain the adoption of generative AI tools in educational contexts. Instead, generative AI adoption appears to be shaped by practical accessibility, peer normalization, and the growing social acceptance of AI-assisted learning practices. Furthermore, the limited influence of facilitating conditions indicates that consumer-based AI platforms such as ChatGPT may reduce the importance of institutional technological support traditionally emphasized in UTAUT research. This finding implies that generative AI technologies differ conceptually from earlier educational technologies because they are highly accessible, cloud-based, and independently adopted by students. Consequently, the study contributes to the growing literature by extending UTAUT's interpretation to generative AI adoption in higher education, particularly in developing-country settings. The cross-country differences identified between Malaysia and Indonesia further highlight the importance of contextual, cultural, and educational environments in shaping the relationship between behavioral intention and actual use behavior. These findings emphasize that AI adoption in higher education should be understood not only from a functional or technological perspective, but also through broader social and psychological dimensions. Practically, the findings suggest that universities should move beyond focusing exclusively on technological infrastructure and instead prioritize AI literacy development, ethical AI guidelines, responsible prompting skills, and lecturer professional development to support critical and effective AI-assisted learning. Such strategies are essential to ensure that students use generative AI tools not merely for convenience, but also in academically responsible and reflective ways. This study has several limitations. First, the study focused only on students from two universities in Malaysia and Indonesia, which may limit the generalizability of the findings to other educational and cultural contexts. Second, the cross-sectional design restricts the ability to capture changes in AI adoption behavior over time. Third, this study primarily examined behavioral factors within the UTAUT framework and did not extensively explore other psychological variables such as trust, AI anxiety, self-regulation, or ethical concerns. Future research may therefore expand this study by using longitudinal approaches, including broader international samples, and integrating additional psychological and pedagogical variables better to explain generative AI adoption behavior in higher education. Further studies could also investigate how AI literacy, institutional policy, and academic culture influence students' responsible and sustainable use of AI.

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