Exploring EFL Students' Use of Generative AI for Academic Writing: An Extension of UTAUT2 Model

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Abstract
Generative artificial intelligence (GenAI) has shown potential in supporting academic writing, yet limited research addressed the intention and actual use of this technology by foreign language students. To address this gap, the study employs an extended Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model by integrating AI self-efficacy and AI trust to investigate the factors influencing EFL students' intention and actual use of GenAI in academic writing. An online survey using a cross-sectional design involving 481 purposively selected EFL students from Indonesian universities was analyzed using partial least squares structural equation modeling (PLS-SEM) with SmartPLS 4. The results revealed that performance expectancy, effort expectancy, social influence, habit, and AI self-efficacy significantly shaped EFL students' intentions to use GenAI for academic writing, while behavioral intention, habit, and AI self-efficacy significantly influence actual use. In contrast, AI trust, facilitating conditions, and hedonic motivation show no significant effect on either intention or actual use. The model demonstrated strong explanatory power, with R^2 values of 0.806 for behavioral intention and 0.617 for actual use. The study enhances the explanatory power of UTAUT2 in GenAI-supported academic writing and offers practical insights for pedagogy and policy to promote GenAI literacy, critical evaluation skills, and responsible use in academic writing.

Keywords: Academic writing, AI self-efficacy, AI trust, EFL students, GenAI, UTAUT2

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Academic writing in a foreign language is widely recognized as a linguistically complex, cognitively demanding, and emotionally taxing task. Numerous studies have reported that students often encounter various challenges during the academic writing process. For instance, EFL students commonly encounter challenges in developing grammatical accuracy, have a limited range of vocabulary, and difficulties in achieving textual cohesion and coherence (Mustafa et al., 2022). They also face obstacles such as poor reading comprehension, brainstorming and idea generation, organizing ideas logically, developing arguments and critical thinking, selecting relevant and credible sources, writing summaries and paraphrasing, maintaining originality, and avoiding plagiarism (Altikriti, 2021; Chuenchaichon, 2022; Mustafa et al., 2022; Toprak & Yücel, 2020). Beyond linguistic and cognitive barriers, many students experience affective challenges, including anxiety, lack of motivation, and low self-confidence (Bulqiyah et al., 2021), which can lead to writing apprehension and avoidance behaviors. These challenges are intensified in online and blended learning contexts, where students may have limited access to timely, personalized feedback and instructor guidance (Gupta et al., 2022). Consequently, these issues may limit students' writing growth and reduce their engagement and performance in academic tasks.

In recent years, digital technologies have become integral to reshape how students develop academic writing and digital literacy skills. Within these environments, intelligent writing tools embedded in learning management systems (LMSs), collaborative platforms, and mobile applications provide real-time and asynchronous writing support. Among these tools, generative artificial intelligence (GenAI) represents a major pedagogical advancement. Unlike earlier writing aids restricted to grammar correction, GenAI platforms such as ChatGPT, Claude, Gemini, and Bing AI act as cognitive partners in digital classrooms, facilitating brainstorming, idea development, translation, grammatical refinement, argument structuring, and feedback generation (Abdullah, 2025; Allen & Mizumoto, 2024; Cardon et al., 2023; Malik et al., 2023; Marzuki et al., 2023; Mo & Crosthwaite, 2025; Tiandem-Adamou, 2024). By supporting students in these tasks, GenAI enables iterative writing processes, personalized feedback, and the enhancement of self-regulated learning strategies. However, its integration raises concerns about overreliance on automated assistance, diminished critical thinking, and ethical issues such as plagiarism and data privacy (Picciano, 2024; Sarwanti et al., 2024). These challenges highlight the need to understand the factors that influence EFL students' intention and actual use of GenAI in academic writing, providing guidance for its ethical and pedagogically sound integration.

Theoretical models such as the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003) and its extended version, UTAUT2 (Venkatesh et al., 2012), have been widely used to study technology adoption in educational settings. While these models effectively explain technology use, their application to GenAI-supported academic writing remains limited. Previous studies (e.g., Tran, 2025; Wang, 2025; Yang, 2025) have mainly focused on technological predictors of students' adoption, paying less attention to the cognitive, psychological, and ethical factors that influence EFL students' use of GenAI in academic writing. Given that academic writing requires careful consideration of authorship, originality, and ethical issues, it is crucial to understand how students' confidence in using AI tools and their trust in AI-generated content affect their adoption decisions. To address this gap, this study extends the UTAUT2 framework by incorporating two critical psychological factors, AI self-efficacy (AIS) and AI trust (AIT), to examine EFL students' behavioral intention and actual use of GenAI in academic writing. By integrating these psychological mechanisms with technological determinants, the proposed model offers a more comprehensive understanding of GenAI adoption in higher education writing contexts. Theoretically, the study enhances the explanatory power of UTAUT2 in the context of GenAI-supported academic writing, while practically, it provides insights for instructional strategies and policy decisions that can foster GenAI literacy, critical evaluation skills, and responsible use in academic writing.

Literature Review

GenAI in Academic Writing

Advances in GenAI are profoundly transforming academic writing, largely due to the evolution of LLMs like ChatGPT, Gemini, and Claude. These models, built on massive linguistic and multimodal datasets, are capable of producing a variety of content types, from text and images to audiovisual outputs and code, by learning and replicating patterns from their data (Feuerriegel et al., 2024). As these technologies become more sophisticated and widely available, students are progressively leveraging them to facilitate academic writing and strengthen their writing competence (Kim et al., 2025; Sarwanti et al., 2024). For instance, studies by Picciano (2024) and Tiandem-Adamou (2024) highlight GenAI's role in the early stages of writing, where it helps generate ideas, stimulate brainstorming, and organize outlines, offering a clear and structured foundation for academic work. Malik et al. (2023) further emphasize that during the drafting process, these tools offer continuous and interactive feedback that helps students expand and refine their ideas while improving language accuracy and coherence. GenAI also provides real-time suggestions on content organization, appropriate word choice, and grammar correction, significantly enhancing the clarity and overall quality of writing (Malik et al., 2023; Zimmerman, 2023). Beyond correcting basic errors, GenAI fosters the enhancement of complex writing skills, including planning, monitoring, and evaluating, empowering students to manage and take responsibility for their writing more effectively (Molenaar, 2022).

Despite its advantages, GenAI's use in academic writing presents significant challenges. Sarwanti et al. (2024) found that ChatGPT can produce misinformation if not carefully reviewed, potentially compromising the credibility of academic work. Beyond issues of accuracy, scholars have questioned the moral implications of GenAI-assisted writing, particularly regarding plagiarism and authorship (Chanpradit, 2025; Mo & Crosthwaite, 2025; Picciano, 2024). Studies further suggest that GenAI may increase instances of academic dishonesty and create inequities in access, as students with greater digital skills or resources may benefit disproportionately (Bae et al., 2024; Stahl & Eke, 2024). In addition to ethical concern, the over-reliance on GenAI tools can negatively impact students' intellectual development. This concern is echoed by Kim et al. (2025), who emphasize that such dependence may prevent students from developing core academic competencies like independent problem-solving and reflective thinking, ultimately undermining the educational value of writing tasks. While prior studies have examined the potential advantages and drawbacks of employing GenAI for academic writing, there remains a lack of in-depth empirical studies exploring the factors that shape its acceptance and usage. This gap underscores the need for theory-driven investigations to better understand how and why EFL students engage with GenAI in academic writing. Accordingly, investigating the factors that shape EFL students' behavioral intention and actual use of GenAI will not only enrich our understanding of EFL students' behavior in technology-supported writing environments, but also support the development of targeted pedagogical frameworks that foster more effective and ethical use of GenAI in foreign language writing instruction.

UTAUT2

The study is grounded in the UTAUT2 model (Venkatesh et al., 2012). This model extends the original UTAUT introduced by Venkatesh et al. (2003), which identified four primary predictors of technology use: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), all of which influence behavioral intention (BI) and actual use (AU). UTAUT2 further incorporates three additional dimensions: hedonic motivation (HM), price value (PV), and habit (HT). These modifications significantly enhance the model's explanatory power, accounting for 74% of the variance in behavioral intention and 52% in actual use (Venkatesh et al., 2012). Despite its robustness, UTAUT2 was originally conceptualized for commercial environments, emphasizing the functional evaluation of technologies and not accounting for the cognitive and ethical judgments required when using GenAI in educational contexts.

Recent extensions of UTAUT2 in GenAI adoption show that performance expectancy is a strong predictor of students' intention to use GenAI tools like ChatGPT (Strzelecki, 2024; Faraon et al., 2025). In contrast, other studies reported that habit emerges as a strong determinant of GenAI adoption (Dietrich & Grassini, 2025; Moradi, 2025). These results suggest that GenAI adoption is shaped not only by students' belief that the tool enhances academic performance, but also by the extent to which GenAI use becomes a habitual learning behavior. However, the adoption is influenced not only by perceived usefulness and habitual use, but also by individual learning goals and personal engagement with the technology. Recent studies involving EFL students in China showed that motivation and personal innovativeness also significantly shape the intention to adopt GenAI (Zheng et al., 2024; Liu et al., 2025), indicating that students in language-focused environments use GenAI not merely to complete academic tasks but to enhance their language development.

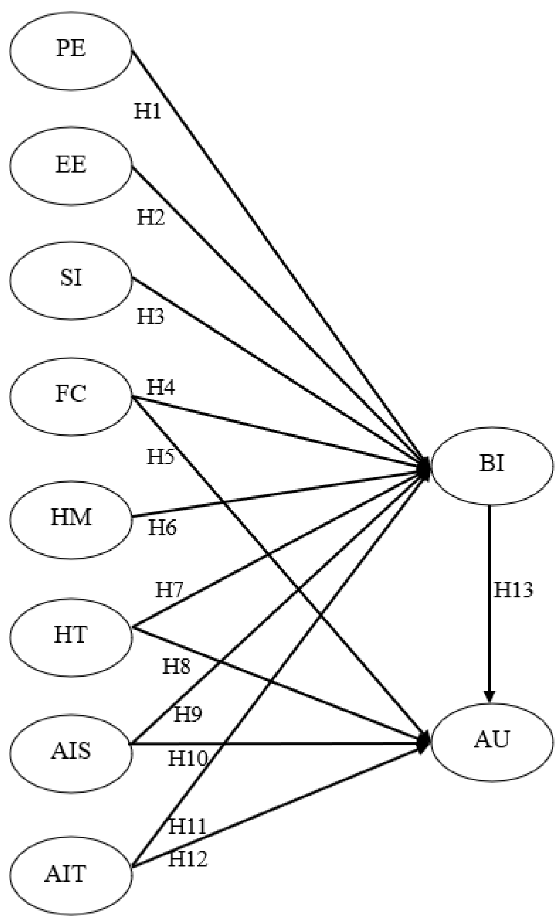
Although recent extensions of UTAUT2 have advanced understanding of technology adoption, their application to GenAI in higher education remains limited in addressing EFL students' cognitive and ethical complexities in academic writing, which requires evaluating the accuracy, credibility, originality, and citation integrity of AI-generated writing. Because of these cognitive and ethical demands, strong performance expectancy or habitual use does not necessarily translate into the actual use of GenAI in academic writing. While students may acknowledge the advantages of GenAI, many remain hesitant when they lack the necessary skills or confidence to assess its reliability or ethically apply its outputs. As a result, the intersection of cognitive competence, ethical awareness, and technology acceptance remains insufficiently examined in extended UTAUT2 research, particularly within the domain of GenAI-assisted academic writing. These overlooked dimensions have recently emerged as key determinants in AI-supported learning, where perceived competence and trust strongly influence both intention and sustained use of intelligent technologies (Amin et al., 2025; Chu et al., 2025a; Hsiao & Tang, 2024; Hsu & Silalahi, 2024; Lin et al., 2025), thereby providing the theoretical basis for incorporating AI self-efficacy and AI trust into the present model. To address this gap, the current study extends UTAUT2 by integrating these constructs to provide a more comprehensive explanation of EFL students' intention and actual use of GenAI for academic writing. Both constructs were operationalized through validated survey measures adapted from prior technology acceptance research to ensure conceptual alignment and measurement reliability. Given the study's aim to examine the interrelationships among multiple latent constructs, SEM was employed to test direct effect. The following section presents the research model and hypotheses developed from this integrated theoretical and methodological foundation.

Model Conceptualization and Hypothesis Development

The present extends the UTAUT2 model by adding two additional variables: AI self-efficacy and AI trust to provide a more comprehensive explanation of EFL students' intention and actual use of GenAI for academic writing. In this study, price value was excluded because it is a consumer-oriented construct and is not relevant in the higher education context, where most EFL students use GenAI tools at no cost. As illustrated in Figure 1, the resulting research framework informs the hypothesis development presented in the subsequent subsections.

Figure 1

The Proposed Model



Performance Expectancy

Venkatesh et al. (2003) describe performance expectancy as the belief that adopting a particular technology can improve one's ability to complete tasks more effectively. In this study, it refers to EFL students' perceptions that using GenAI tools can enhance their academic writing outcomes. Recent studies have shown that that performance expectancy is one of the strongest predictors of students' intention to adopt GenAI for learning (Grassini et al., 2024; Haryanto et al., 2026; Strzelecki, 2024; Surachmi et al., 2025; Tran, 2025; Xu et al., 2025; Yang, 2025; Zheng et al., 2024). Based on this, the study formulates the following hypothesis:

H1: Performance expectancy positively influences EFL students' behavioral intention.

Effort Expectancy

According to Venkatesh et al. (2003), effort expectancy refers to an individual's perception of how effortless and uncomplicated a technology is to operate. In this study, effort expectancy refers to students' belief that operating GenAI is simple and can be done without difficulty during the academic writing process. Effort expectancy has shown that effort expectancy plays a critical role in shaping students' behavioral intention to adopt GenAI tools (Dietrich & Grassini, 2025; Haryanto et al., 2026; Tran, 2025; Strzelecki, 2024; Surachmi et al., 2025; Xu et al., 2025; Yang, 2025; Zheng et al., 2024). Therefore, the following hypothesis is formulated:

H2: Effort expectancy positively influences EFL students' behavioral intention.

Social Influence

Venkatesh et al. (2012) define social influence as the extent to which an individual's choice to use a technology is affected by the expectations or advice of those they value. In this study, it relates to how EFL students' adoption of GenAI tools for academic writing is guided by the feedback, encouragement, or endorsement of peers, and lecturers. Numerous studies have reported that social influence is a significant predictor of behavioral intention to adopt GenAI tools such as ChatGPT (Dietrich & Grassini, 2025; Haryanto et al., 2026; Liu et al., 2025; Moradi, 2025; Strzelecki, 2024; Surachmi et al., 2025; Wang, 2025; Xu et al., 2025; Yang, 2025; Zheng et al., 2024). Based on these results, the following hypothesis is proposed:

H3: Social influence positively influences EFL students' behavioral intention.

Facilitating Conditions

Facilitating conditions encompass the belief that adequate technical resources, support systems, and infrastructure are available to enable the effective use of new technologies (Venkatesh et al., 2023). In this study, facilitating conditions denote EFL students' views on having dependable internet access, proper devices, and adequate institutional or technical support to effectively utilize GenAI tools in their academic writing. Within the UTAUT2 framework, facilitating conditions are regarded as a critical determinant that influences both users' intention to use a technology and their actual usage. Recent studies confirm that facilitating conditions are significantly associated with behavioral intention and actual use of GenAI tools such as ChatGPT (Amin et al., 2025; Dietrich & Grassini, 2025; Haryanto et al., 2026; Liu et al., 2025; Moradi, 2025; Surachmi et al., 2025; Xu et al., 2025; Yang, 2025). Accordingly, the following hypotheses are proposed:

H4: Facilitating conditions positively influence EFL students' behavioral intention.

H5: Facilitating conditions positively influence EFL students' actual use.

Hedonic Motivation

Venkatesh et al. (2012) describes hedonic motivation as the level of enjoyment or excitement that encourages individuals to adopt a new technology. In this study, it refers to the positive emotional experience EFL students gain from using GenAI tools while working on their academic writing. Previous research has demonstrated that hedonic motivation is a significant predictor of technology adoption in mobile learning (Dinh et al., 2025) and in the use of GenAI tools such as ChatGPT (Haryanto et al., 2026; Strzelecki, 2024; Surachmi et al., 2025; Zheng et al., 2024). Based on these results, this study puts forward the following hypothesis:

H6: Hedonic motivation positively influences EFL students' behavioral intention.

<u>Habit</u>

Habit denotes the degree to which an individual's use of a technology is habitual and seamlessly integrated into daily activities (Venkatesh et al., 2012). In this study, habit refers to how routinely EFL students rely on GenAI tools as part of their academic writing process. Venkatesh et al. (2012) highlight habit as a key determinant that shapes individuals' behavioral intention and actual use of technology. Recent studies further confirmed that habit significantly influences individuals' intention to use and actual use of GenAI tools such as ChatGPT (Haryanto et al., 2026; Moradi, 2025; Surachmi et al., 2025; Zheng et al., 2024). Therefore, this study hypothesizes:

H7: Habit positively influences EFL students' behavioral intention.

H8: Habit positively influences EFL students' actual use.

<u>AI Self-Efficacy</u>

Self-efficacy, grounded in Social Cognitive Theory (Bandura, 1986), refers to an individual's confidence in their ability to successfully perform a task. While foundational, this construct emerged from a general psychological context and does not inherently account for situations involving digital or automated systems. To contextualize self-efficacy within technology-mediated environments, prior research introduced more domain-specific derivations such as computer self-efficacy (Compeau & Higgins, 1995), internet self-efficacy (Eastin & LaRose, 2000), and technology self-efficacy (Laver et al., 2012). These adaptations emphasize users' confidence in operating technological tools to accomplish tasks. Recent advancements in autonomous technologies further extend the construct toward AI self-efficacy, defined as an individual's confidence in their ability to interact with and effectively utilize artificial intelligence systems (Wang & Chuang, 2024). In this study, AI self-efficacy reflects EFL students' confidence in using GenAI to perform academic writing tasks. Prior studies have shown that AI self-efficacy significantly influences behavioral intention (Chu et al., 2025a, 2025b; Hsiao & Tang, 2024; Hsu & Silalahi, 2024) and also predicts actual use (Chu et al., 2025a, 2025b). Accordingly, the following hypotheses are proposed:

H9: AI self-efficacy positively influences EFL students' behavioral intention.

H10: AI self-efficacy positively influences EFL students' actual use.

<u>AI Trust (AIT)</u>

Trust was originally conceptualized in interpersonal relationships as an individual's willingness to accept vulnerability based on positive expectations of another person's actions (Deutsch, 1960; Mayer et al., 1995). In this interpersonal context, trust develops through evaluations of ability, benevolence, and integrity, which are inherently tied to human intentions.

As technology became involved in decision-making, the concept of trust expanded beyond human interactions and shifted to systems, forming the basis of technology trust, where users evaluate whether a system performs tasks reliably, securely, and consistently despite the absence of emotions or intentions (McKnight et al., 2002; Gefen et al., 2003). The emergence of autonomous and GenAI introduced yet another shift, requiring trust to encompass not only functional performance but also the system's decision-making qualities. Consequently, evaluations of AI systems extend beyond basic reliability to considerations of transparency, predictability, fairness and ethical conduct, and dependability. Hence, AI trust refers to an individual's belief that an AI system can be relied on to operate transparently, ethically, and responsibly even when its internal workings are not fully visible (Baroni et al., 2022). In this study, AI trust captures EFL students' confidence that GenAI tools behave reliably and ethically when supporting academic writing tasks. Recent studies report that AI trust significantly contributes to both students' intention (Amin et al., 2025; Lin et al., 2025) and actual usage behavior (Mustofa et al., 2025). Therefore, the following hypotheses are proposed:

H11: AI trust positively influences EFL students' behavioral intention.

H12: AI trust positively influences EFL students' actual use.

Behavioral Intention and Actual Use

Behavioral intention reflects an individual's motivational preparedness to carry out a particular action (Venkatesh et al., 2012), whereas actual use refers to the concrete execution of that action in practice. Within this study, behavioral intention is conceptualized as EFL students' willingness and drive to engage with GenAI tools for their academic writing assignments. In contrast, actual use captures the frequency and degree to which these students actively integrate GenAI tools into their writing activities. Following the UTAUT2 framework, behavioral intention is expected to directly influence actual use (Amin et al., 2025; Chu et al., 2025b; Grassini et al., 2024; Haryanto et al., 2026; Hsu & Silalahi, 2024; Liu et al., 2025; Strzelecki, 2024; Surachmi et al., 2025; Yang, 2025; Zheng et al., 2024). Accordingly, the study puts forward the following hypothesis:

H13: Behavioral intention positively influences EFL students' actual use.

Methods

Participants

This study recruited EFL students from academic writing courses offered at four universities in Indonesia, including two private and two public universities located in West Java and Central Java. These courses are compulsory subjects typically taken in the fourth or fifth semester within English Education programs and are designed to prepare students for writing their theses and developing scientific publications. The curriculum provides comprehensive training in academic writing structure and techniques, encompassing stages such as drafting research proposals and literature reviews, writing methodologies, presenting results, and applying proper citation styles. Through these courses, students acquire the knowledge and skills necessary to produce coherent, ethical, and publication-ready academic works that meet scholarly standards.

Participants were selected through purposive sampling, targeting those who had prior experience with GenAI and its use in academic writing. A total of 357 students participated in this study, consisting of 222 females (62.2%) and 135 males (37.8%). This gender distribution aligns with Wurisoedjatmiko (2017), who reported that language and literature studies tend to attract more female students. The participants were between 17 and 24 years old, with the majority (80.8%) aged between 21 and 24 years. In terms of years of study, 41.3% of the students were in their second year, while 58.7% were in their third year. The demographic details summarized in Table 1 provide important context for understanding the diversity and representativeness of the participants.

Table 1

Participants Demographic Information (N=375)

Characteristic	Number	Percentage
Sex		
Male	135	47.8
Female	222	62.2
Age		
17-20 years old	72	19.2
21-24 years old	303	80.8
Years of Study		
2	155	41.3
3	220	58.7
Type of Institutions		
Private universities	234	62.4
Public universities	141	37.6

Instrument

This study employed an online survey to gather data, structured in two sections. The first collected information on participants' demographics and backgrounds, while the second evaluated the ten constructs included in the proposed model. All measurement items were adapted from previously validated instruments. Items for performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, behavioral intention, and actual use were adapted from validated UTAUT2 scales developed by Venkatesh et al. (2012). Items for AI self-efficacy were adapted from Hsiao & Tang (2024) and Hsu & Silalahi (2024), while items for AI trust were adapted from Amin et al. (2025). All items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). No new items were developed, and only minor wording adjustments were made to fit the academic writing context. The full list of survey items is provided in the Appendix.

To enhance the content validity of the instrument, the questionnaire underwent a review process by two experts specializing in educational technology and English language teaching who have research experience in AI-assisted learning and the use of ChatGPT in academic contexts. They evaluated each item for clarity, relevance, and alignment with the theoretical constructs and research objectives. Minor revisions were made based on their feedback, particularly in terms of wording precision and clarity. Following the expert validation, a pilot test was administered to 40 undergraduate EFL students (aged 18–24) to evaluate item comprehensibility, the interpretation of statements, and the technical functionality of the Google Forms platform. The participants consisted of 28 females and 12 males from the same four Indonesian universities that later participated in the main data collection. The pilot results confirmed the reliability and validity of all variables, including discriminant validity (Hair et al., 2022). Internal consistency was satisfactory, with Cronbach's alpha values above 0.70 for every construct. To broaden accessibility, the final questionnaire was distributed online in both Indonesian and English. A back-translation procedure was adopted to ensure equivalence between the two language versions: The English version was first translated into Indonesian by a bilingual specialist, after which a second independent translator rendered it back into English. The back-translated version was compared with the original, and any inconsistencies in meaning or terminology were revised until both versions were conceptually aligned (Tyupa, 2011).

Data Collection

An online questionnaire was developed using Google Forms and distributed via WhatsApp, a widely used communication platform among Indonesian students. To expand the reach, four lecturers from two private and public universities in West Java and Central Java assisted in sharing the survey link with their EFL students and encouraging participation. The survey was administered from March to April 2025, and the questionnaire required approximately seven minutes to complete. The survey remained open for one month, yielding 375 responses.

Data Analysis

Prior to the main analysis, the study assessed potential common method bias (CMB) to ensure that the data collection process did not distort the relationships among variables. This assessment involved checking variance inflation factor (VIF) values using SmartPLS 4. All inner VIF values were found to be below the recommended cutoff of 3.3, indicating that CMB was not a major concern. After confirming this, the study employed PLS-SEM using SmartPLS 4. The analytical process was carried out in two main stages. The first stage involved assessing the measurement model to ensure that all constructs met the criteria for reliability and validity. Once the measurement model was confirmed, the second stage evaluated the structural model to test the hypothesized paths and determine the strength and significance of the relationships between constructs.

Results

Common Method Bias

Data for this study were obtained through self-reported questionnaires, which carry a potential risk of common method bias (CMB) due to the use of a single source. To check for CMB, the study followed Kock's (2015) recommendation of applying a full collinearity test with the Variance Inflation Factor (VIF), where values below 3.3 suggest that CMB is not a major issue. As shown in Table 2, all VIF values ranged between 1.046 and 2.842, remaining under the acceptable threshold. These results indicate that CMB is unlikely to be a significant issue in this study.

Table 2

Collinearity Test (VIF)

	BI	AU
PE	1.726	
EE	1.046	
SI	1.177	
FC	1.094	1.079
HM	2.842	
HT	2.514	1.596
AIS	1.267	1.322
AIT	1.040	1.035
BI		1.587
AU		

Note: PE: Performance Expectancy, EE: Effort Expectancy, SI: Social Influence, FC: Facilitating Conditions, HM: Hedonic Motivation, HT: Habit, AIS: AI Self-Efficacy, AIT: AI Trust, BI: Behavioral Intention, AU: Actual Use

Measurement Model

The reliability and validity of the constructs were confirmed through a detailed assessment of the measurement model. Initially, the PLS-SEM algorithm was used to calculate factor loadings, all of which were above 0.70, indicating that the items accurately reflected their associated latent variables. Next, reliability was evaluated using Cronbach's Alpha and Composite Reliability (CR). As shown in Table 3, every construct exceeded the 0.70 threshold for both measures, demonstrating strong internal consistency. Convergent validity was established by calculating the Average Variance Extracted (AVE), with all constructs scoring above 0.50, which implies that they captured a substantial amount of variance from their respective indicators.

Table 3

Measurement Model

Variables	Item	Factor Loading	Cronbach's Alpha	CR	AVE
PE	PE1	0.904	0.913	0.939	0.793
	PE2	0.886			
	PE3	0.895			
	PE4	0.878			
EE	EE1	0.881	0.912	0.938	0.790
	EE2	0.897			
	EE3	0.873			
	EE4	0.904			
SI	SI1	0.868	0.895	0.927	0.760
	SI2	0.874			
	SI3	0.868			
	SI4	0.877			
FC	FC1	0.893	0.893	0.933	0.823
	FC2	0.905			

	FC3	0.923			
HM	HM1	0.918	0.894	0.934	0.825
	HM2	0.920			
	HM3	0.886			
HT	HT1	0.845	0.881	0.918	0.737
	HT2	0.862			
	HT3	0.861			
	HT4	0.867			
AIS	AIS1	0.823	0.842	0.894	0.678
	AIS2	0.802			
	AIS3	0.841			
	AIS4	0.827			
AIT	AIT1	0.793	0.904	0.916	0.731
	AIT2	0.804			
	AIT3	0.894			
	AIT4	0.923			
BI	BI1	0.876	0.910	0.937	0.788
	BI2	0.895			
	BI3	0.876			
	BI4	0.903			
AU	AU1	0.872	0.901	0.931	0.771
	AU2	0.890			
	AU3	0.875			
	AU4	0.876			

To ensure the robustness of the measurement model, discriminant validity was evaluated through both the Heterotrait-Monotrait (HTMT) ratio and the Fornell–Larcker criterion. Based on the guidelines of Henseler et al. (2015), HTMT values below 0.90 suggest that constructs are sufficiently distinct. As indicated in Table 4, the HTMT values in this study ranged from 0.057 to 0.846, all well below the recommended threshold, signifying clear differentiation among the constructs. Furthermore, the Fornell–Larcker approach stipulates that the square root of each construct's AVE must surpass its correlations with any other construct. Table 5 shows that this requirement was met, with AVE square roots between 0.824 and 0.954, all exceeding the respective inter-construct correlations. These results confirm that the model achieves acceptable reliability, convergent validity, and discriminant validity, thereby providing a strong basis for proceeding with the structural model analysis.

Table 4

Discriminant Validity Based on HTMT

	PE	EE	SI	FC	HM	HT	AIS	AIT	BI	AU
PE										
EE	0.107									
SI	0.307	0.159								
FC	0.083	0.055	0.162							

HM	0.694	0.098	0.247	0.148						
HT	0.512	0.178	0.296	0.217	0.827					
AIS	0.317	0.075	0.292	0.067	0.347	0.459				
AIT	0.062	0.060	0.053	0.075	0.094	0.152	0.121			
BI	0.744	0.326	0.528	0.124	0.625	0.622	0.500	0.072		
AU	0.490	0.198	0.481	0.097	0.535	0.583	0.529	0.037	0.741	

Table 5

Discriminant Validity Based on Fornell-Lacker Criterion

	PE	EE	SI	FC	HM	HT	AIS	AIT	BI	AU
PE	**0.891**									
EE	0.101	**0.889**								
SI	0.280	0.147	**0.872**							
FC	0.076	0.050	0.146	**0.907**						
HM	0.627	0.091	0.222	0.131	**0.909**					
HT	0.461	0.163	0.264	0.195	0.734	**0.859**				
AIS	0.279	0.063	0.255	-0.054	0.302	0.395	**0.824**			
AIT	0.069	0.058	-0.012	-0.092	0.076	0.135	0.087	**0.855**		
BI	0.679	0.304	0.478	0.111	0.564	0.558	0.439	0.069	**0.887**	
AU	0.444	0.180	0.435	0.088	0.481	0.521	0.464	0.042	0.672	**0.878**

Note: The bold values represent the square root of AVE

Structural Model

Following the validation of the robust measurement model, the structural model was evaluated using bootstrapping with 5,000 resamples. To evaluate the explanatory power of the structural model, the coefficient of determination (R2) was assessed for each endogenous construct. According to Hair (2022), R^2 values may be classified as strong (0.75), moderate (0.50), or weak (0.25), depending on the degree of variance explained. As presented in Figure 2, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit collectively produced an R^2 value of 0.659 for behavioral intention, indicating moderate to strong explanatory power. Furthermore, actual use achieved an R^2 value of 0.508, explained by behavioral intention, AI self-efficacy, habit, facilitating conditions, and AI trust, reflecting a moderate level of predictive accuracy. The results indicate that the extended UTAUT2 model provides a solid explanation of students' intentions to use GenAI and their subsequent actual use, with stronger predictive power for behavioral intention.

According to the PLS-SEM analysis shown in Table 6, eight of the thirteen hypotheses were statistically supported, while the remaining five were not. Performance expectancy (β = 0.445, $p < 0.001$), effort expectancy (β = 0.184, $p < 0.001$), social influence (β = 0.229, $p <$ 0.001), habit (β = 0.160, p = 0.006), and AI self-efficacy (β = 0.167, $p < 0.001$) exerted significant positive effects on behavioral intention, confirming H1, H2, H3, H7, and H9. Among these predictors, performance expectancy demonstrated the strongest influence, indicating that students' decisions to adopt GenAI are shaped primarily by perceived academic benefits rather than usability factors or social pressure.

For actual use, habit ($\beta = 0.176$, $p < 0.001$), AI self-efficacy ($\beta = 0.179$, $p < 0.001$), and behavioral intention ($\beta = 0.497$, $p < 0.001$) significantly influenced students' use of GenAI, supporting H8, H10, and H13. Behavioral intention emerged as the strongest predictor of actual use, implying that once students form the intention to use the technology, that intention becomes the main driver of their actual engagement with GenAI.

In contrast, facilitating conditions did not significantly influence either behavioral intention ($\beta = 0.006$, $p = 0.867$) or actual use ($\beta = 0.005$, $p = 0.888$). Hedonic motivation also had no significant effect on behavioral intention ($\beta = 0.050$, $p = 0.390$). Likewise, AI trust did not significantly predict behavioral intention ($\beta = -0.009$, $p = 0.813$) or actual use ($\beta = -0.031$, $p = 0.472$). Thus, H4, H5, H6, H11, and H12 were rejected. These non-significant findings suggest that students' adoption of GenAI is driven more by its functional academic value than by enjoyment, institutional support, or trust in the technology.

The effect size (f^2) for each independent variable in the structural model offers valuable insight into the magnitude of its influence. According to Hair et al. (2022), f^2 values of 0.02, 0.15, and 0.35 correspond to small, medium, and large effects, respectively. Sarstedt et al. (2022) further explain that f^2 values below 0.02 are considered negligible. As shown in Table 6, the analysis found that performance expectancy had a large effect on behavioral intention, followed by behavioral intention on actual use. Smaller effects were observed for social influence on behavioral intention, effort expectancy on behavioral intention, habit on behavioral intention and actual use, and AI self-efficacy on both behavioral intention and actual use. In contrast, facilitating conditions, hedonic motivation, and AI trust had negligible effect sizes, indicating minimal influence on behavioral intention and actual use.

Figure 2

Results of the Proposed Extended UTAUT2 Model

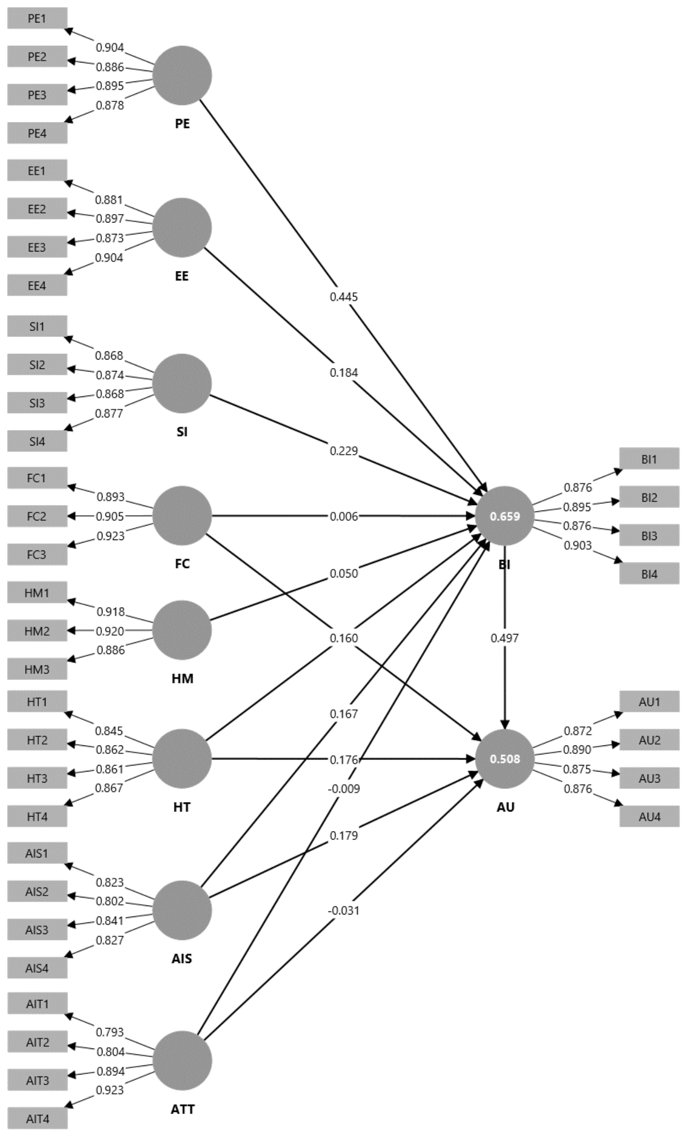


Table 6

Structural Model Results

Hypothesis	Relationship	Path	*t*-values	*p*-values	f^2	Decision
H1	PE → BI	0.445	10.203	0.000	0.335	Yes
H2	EE → BI	0.184	5.516	0.000	0.095	Yes
H3	SI → BI	0.229	6.792	0.000	0.131	Yes

H4	FC → BI	0.006	0.168	0.867	0.000	No
H5	FC → AU	0.005	0.140	0.888	0.000	No
H6	HM → BI	0.050	0.860	0.390	0.003	No
H7	HT → BI	0.160	2.733	0.006	0.030	Yes
H8	HT → AU	0.176	3.657	0.000	0.039	Yes
H9	AIS → BI	0.167	4.562	0.000	0.065	Yes
H10	AIS → AU	0.179	4.263	0.000	0.049	Yes
H11	AIT → BI	-0.009	0.236	0.813	0.000	No
H12	AIT → AU	-0.031	0.719	0.472	0.002	No
H13	BI → AU	0.497	10.234	0.000	0.316	Yes

Discussion

This study extends the UTAUT2 framework by integrating AI self-efficacy and AI trust to explain EFL students' behavioral intention and actual use of GenAI for academic writing. The extended model demonstrates strong explanatory power, accounting for 80.6% of the variance in behavioral intention and 61.7% in actual use. This study extends UTAUT2 by demonstrating that in academic writing contexts, AI self-efficacy predicts both intention and actual use, whereas AI trust loses predictive power when usage is task-oriented and low-risk. The extended UTAUT2 model proves theoretically robust in the GenAI–academic writing context. This indicates that students' decisions to adopt GenAI are driven more by perceived capability and performance benefits than by trust in the system. Thus, this study not only validates UTAUT2 but also refines it for academic writing contexts in which users can control and revise GenAI output.

Performance expectancy emerged as the strongest predictor of behavioral intention. This result is in line with Grassini et al. (2024), Tran (2025), Xu et al. (2025), and Zheng et al. (2024), who reported that performance expectancy is the most influential factor in students' adoption of GenAI, as students are more willing to adopt GenAI tools when they believe that the technology can enhance their learning outcomes. The strong effect of performance in this study indicates that EFL students choose to use GenAI tools such as ChatGPT because they believe it can improve their academic writing performance. Consistent with this, Wang (2025) found that Chinese EFL learners are more likely to use large language models (LLMs) such as ChatGPT when they perceive that these tools can improve the quality, clarity, and efficiency of their academic writing. Yang (2025) further confirms that performance expectancy is the primary factor driving students to adopt GenAI because they believe the technology helps them complete writing tasks more efficiently. Similarly, Strzelecki (2024) reported that performance expectancy is the strongest determinant of students' intention to use ChatGPT, as they prioritize its functional benefits such as increased efficiency, improved output quality, and academic support when deciding to adopt the technology.

Behavioral intention also emerged as a strong predictor of actual use for GenAI tools among EFL students, consistent with previous studies (Grassini et al., 2024; Hsu & Silalahi, 2024; Liu et al., 2025; Zheng et al., 2024). Supporting this, Wang (2025) reported that Chinese EFL learners with strong intentions and favorable attitudes toward large language models (LLMs) such as ChatGPT consistently apply the technology in their academic writing activities. Yang (2025) further explained that the translation of intention into actual use is primarily driven by internal motivation, which develops when students perceive the technology as useful, easy to use, and reinforced by social encouragement. In line with this, Amin et al. (2025) confirmed that positive perceptions of ChatGPT strengthen behavioral intention, which subsequently increases the actual use of the technology in learning tasks. However, Moradi (2025) noted that the influence of behavioral intention may decrease once ChatGPT use becomes habitual and supported by sufficient facilities, as students begin using the tool automatically without needing to form a conscious intention.

The effect of social influence on behavioral intention was also statistically significant to adopt GenAI for academic writing. This result indicates that recommendations from peers, social media, and lecturers play a role in shaping EFL students' willingness to adopt GenAI in their academic writing tasks. This is consistent with Amin et al. (2025), who reported that in collectivist cultures such as Bangladesh, encouragement from peers, family members, lecturers, or classmates increases students' intention to adopt ChatGPT in higher education. However, the effect was small because social recommendations only encouraged students to try GenAI initially, while their intention to continue using it was driven more by personal academic needs, the benefits they experienced, and their individual writing preferences rather than by ongoing external influence. Yang (2025) supports this by explaining that social support typically functions only as an initial trigger through internalization, whereas continued usage is shaped by personal needs and beliefs. Strzelecki (2024) further shows that early GenAI adopters, particularly those with higher digital literacy, depend more on personal initiative than on external expectations. Thus, while social influence may encourage initial experimentation, sustained adoption of GenAI for academic writing is largely guided by self-directed academic goals rather than external encouragement.

Effort expectancy was also a significant positive predictor of behavioral intention, though with a relatively smaller effect size. This may be because EFL students involved in academia writing are already accustomed to working with digital tools and are highly adaptable to new technologies. Consequently, using GenAI requires little effort or learning time, which reduces the importance of perceived ease of use in shaping their decision to adopt the technology. This is supported by Yang (2025), who highlights that students tend to adopt GenAI when they believe that the technology does not require extensive learning effort and can streamline academic tasks efficiently. Likewise, Strzelecki (2024) found that GenAI like ChatGPT is generally viewed as easy and practical to use, which further lowers technical barriers and encourages adoption. However, this result contrasts with Amin et al. (2025), who reported that effort expectancy does not significantly influence students' behavioral intention because students who are not familiar with advanced AI tools such as ChatGPT tend to prioritize academic credibility and perceived performance benefits over ease of use. Likewise, Moradi (2025) found that university EFL learners no longer consider ease of use in their decision to adopt GenAI because these digital tools have already become part of their daily routines, rendering effort expectancy irrelevant in their decision-making process. These inconsistencies suggest that GenAI adoption in academic writing is more utilitarian than hedonic, and trust becomes secondary when students retain full control over revision and editing.

AI self-efficacy showed a statistically significant effect on both behavioral intention and actual use, but with a small impact on EFL students' intention to use GenAI for academic writing. This result aligns with Chu et al. (2025a, 2025b), who explain that students who believe they are capable of operating a learning technology tend to form the intention to use it, which subsequently translates into actual use. Consistent with this, Hsiao and Tang (2024) observed that higher levels of self-efficacy encourage students to engage with GenAI without fear of making mistakes, thereby strengthening their intention to continue using it. Chen et al. (2024) further reported that AI self-efficacy significantly influences actual use, as confidence in interacting with AI creates a sense of control and motivates sustained engagement in learning tasks. However, although students generally feel capable of using GenAI, their decisions to apply it in academic writing are constrained by lecturer expectations and institutional policies. In the Indonesian context, GenAI use is often permitted but subject to strict conditions, such as maintaining AI-generated text below a specified detection threshold (e.g., 20%), which leads students to limit GenAI to supplementary functions, such as idea generation or language refinement, rather than relying on it for full task completion. This cautious adoption pattern reflects students' efforts to benefit from GenAI while simultaneously complying with academic integrity requirements.

Habit was found to have a significant but weak effect on both behavioral intention and actual use of GenAI for academic writing. This result is consistent with Zhao et al. (2025), who reported that habit influences both intention and usage because repeated engagement with a technology increases users' familiarity and comfort, which in turn encourages continued use. Moradi (2025) further adds that when a behavior becomes habitual, students tend to use GenAI automatically without requiring deliberate intention or conscious decision-making. The weak effect observed in this study suggests that although some EFL students have begun using GenAI tools such as ChatGPT, these tools have not yet become a regular or automatic component of their academic writing routine. Instead, students tend to rely on GenAI only when facing specific academic demands, such as meeting deadlines, overcoming writer's block, or resolving language-related difficulties. This differs from earlier studies that identified habit as a strong predictor of ChatGPT use (Grassini et al., 2024; Dietrich & Grassini, 2025), indicating that habitual use becomes dominant only when the technology is fully integrated into users' daily workflow.

Interestingly, hedonic motivation showed a negligible, non-significant effect on behavioral intention. Moradi (2025) similarly observed that hedonic motivation does not influence behavioral intention because students do not use GenAI for enjoyment; instead, they rely on it to accomplish academic writing tasks that require precision, productivity, and compliance with lecturers' expectations and institutional regulations. This result contradicts several prior studies on technology adoption (Dinh et al., 2025; Strzelecki, 2024), which reported significant positive relationships between hedonic motivation and behavioral intention. The non-significant effect of hedonic motivation on behavioral intention in this study is likely due to the utilitarian nature of GenAI use. Indonesian EFL students interact with the technology primarily to accomplish academic writing tasks within limited time frames. Under such goal-driven conditions, emotional enjoyment is less relevant, and students focus more on the performance advantages the tool provides rather than on its entertainment value.

Unlike earlier studies that emphasized AI trust as a key predictor of technology adoption (Lin et al, 2025; Mustofa et al., 20255), this study found that AI trust did not have a direct and significant effect on EFL students' behavioral intention and actual use of GenAI in academic writing. This result differs from Amin et al. (2025), who reported that trust significantly influences intention, where students who strongly believe in ChatGPT's reliability are more inclined to adopt it, and such trust acts as a mediating factor linking perceived usefulness, ease of use, and social influence to their intention. A plausible explanation for the insignificant effect of AI trust in this study is that EFL students prioritize task efficiency and the quality of their academic output rather than considerations of system reliability or ethical transparency. The use of GenAI tools for academic writing is self-directed and low risk, allowing students to freely revise or discard the generated text at any time. Because most students rely on free and accessible versions like ChatGPT, they focus more on the immediate benefits such as speed, reduced writing effort, and improved clarity than on developing a deep sense of trust toward the system. In this context, perceived performance benefits outweigh the role of trust in shaping intention or actual use.

Facilitating conditions also showed negligible, non-significant effect on behavioral intention and actual use, consistent with prior studies reporting similarly non-significant relationships with behavioral intention (Dinh et al., 2025; Grassini et al., 2024; Liu et al., 2025; Moradi, 2025; Strzelecki, 2024; Zheng et al., 2024) and actual use (Dietrich & Grassini, 2025; Zheng et al., 2024; Wang, 2025). This inconsistency may be explained by the digital autonomy of Indonesian EFL students, who already possess the necessary devices and are capable of independently accessing GenAI tools like ChatGPT. Given the wide availability, user-friendly design, and minimal learning curve of such tools, EFL students rarely depend on institutional support. As a result, external support structures become less relevant, diminishing the role of facilitating conditions in shaping their behavioral intention and actual use. In contrast, Yang (2025) demonstrated that facilitating conditions have a significant effect on actual use in GenAI-assisted second language writing, indicating that sufficient access to resources and technical support directly increases students' frequency of using GenAI. Likewise, Amin et al. (2025) reported that in developing countries, students with sufficient technological infrastructure, including reliable internet, smartphones, and personal computers, and who feel supported in using ChatGPT, are more willing to adopt and incorporate the technology into their academic routines.

Limitations

Although this study contributes valuable insights into the use of GenAI in EFL education, certain limitations should be acknowledged. First, the study adopted a cross-sectional design, collecting data at a single point in time, which limits the ability to infer causality or examine how students' engagement with GenAI tools may evolve over time. Future studies should consider longitudinal or experimental designs to capture changes in GenAI use. Second, the data were obtained through self-reported questionnaires, which may introduce response bias due to subjective perceptions and social desirability. To enhance data validity, future studies are encouraged to incorporate mixed-methods approaches to capture richer and more nuanced student experiences. Third, although this extended UTAUT2 model explains GenAI adoption effectively, the study did not examine moderating variables such as age, gender, or digital literacy. Previous research suggests that these factors may influence technology acceptance (Venkatesh et al., 2012). Including these moderators in future models may provide a deeper understanding of differences across user groups and inform more targeted pedagogical strategies. Finally, the sample was taken from only two provinces in Indonesia (Central Java and West

Java), which may limit the representativeness of the findings, as factors influencing GenAI use can vary across regions with different cultural, technological, and educational conditions. Nonetheless, the results are expected to offer meaningful insights for regions or institutions with similar characteristics in promoting the responsible and ethical use of GenAI in academic writing. Future studies should involve larger and more diverse samples, including cross-regional or cross-cultural comparisons, to better understand how contextual factors influence GenAI adoption in education.

Theoretical and Practical Implications

Building on these theoretical insights, the findings also offer important implications for education, professional practice, and institutional policy regarding the integration of GenAI tools into academic writing. In educational settings, because AI self-efficacy significantly influences both intention and actual use, lecturers should not only introduce the tool but also integrate guided, hands-on activities into online or blended formats that allow students to practice using GenAI to support academic writing. These activities can include developing outlines, refining drafts, paraphrasing text, and improving coherence, allowing students to practice applying GenAI to support academic writing. Incorporating formative feedback cycles, such as comparing AI-assisted drafts with student-written versions, encourages critical evaluation, prevents overreliance, and helps students understand when and how GenAI can effectively support learning. This approach enables students to view GenAI as a cognitive partner rather than a replacement for independent thinking, building confidence, critical thinking skills, and AI self-efficacy. By embedding these strategies, the study not only extends UTAUT2 but also provides contextual refinements for the pedagogical use of GenAI in academic writing.

The results also suggest implications for professional practice. The non-significant effect of AI trust indicates that increasing confidence and competence matters more than persuading students to trust the technology. Lecturers should therefore focus on teaching practical skills such as crafting effective prompts, evaluating the accuracy and credibility of AI-generated suggestions, and applying academic writing conventions when integrating GenAI output. Demonstrating responsible use in teaching, such as acknowledging when GenAI was used or showing how to verify sources, helps students internalize ethical and critical use of AI. These strategies ensure that students develop disciplined engagement with GenAI, using it to strengthen their academic reasoning rather than substitute for it.

Finally, at the institutional policy level, the results suggest that confidence and perceived usefulness drive adoption more strongly than trust. Thus, universities should provide clear and actionable guidelines for ethical GenAI use rather than focus solely on promoting the technology. Policies should clearly define permissible uses of GenAI, expectations for acknowledging AI contributions, and any AI-detection limits set by the institution. To support these policies, institutions can offer capacity-building programs such as AI literacy workshops or writing center support to ensure that students and lecturers are adequately prepared to use GenAI responsibly. By aligning governance with skill development, institutions can encourage responsible, ethical, and effective adoption of GenAI in academic writing.

Conclusion

This study enhances understanding of GenAI adoption in academic writing by extending the UTAUT2 model with AI self-efficacy and AI trust. The results demonstrate that AI self-efficacy significantly predicts both behavioral intention and actual use, whereas AI trust becomes less influential when students retain control over revising GenAI output. This provides a theoretical contribution by showing that, in EFL academic writing contexts, technology acceptance is driven more by capability and performance benefits than by trust in the system. Pedagogically, the results provide practical guidance for teachers and institutions: rather than encouraging students to trust GenAI, instructional efforts should focus on building AI literacy, strengthening students' ability to evaluate AI output, and supporting responsible and ethical use. Future research may apply the model in different cultural or educational settings, use qualitative approaches to explore students' reasoning and ethical concerns, and conduct longitudinal studies to understand how GenAI use evolves over time. As GenAI becomes increasingly embedded in academic writing, maintaining a balance between leveraging its benefits and ensuring responsible use will be essential to support learning without undermining students' critical thinking and writing skills.

Declarations

Disclosure Statement

The authors declare that there are no potential conflicts of interest related to this study.

Ethics Approval

Ethical approval for this study was obtained from the Research Ethics Committee of Universitas Negeri Yogyakarta. The committee reviewed and approved all research procedures, including participant recruitment, informed consent, data handling, and confidentiality protection, ensuring compliance with institutional and international ethical standards for research involving human participants. Participation was entirely voluntary. Before completing the survey, participants were informed about the study's purpose, their right to withdraw at any time without penalty, and how their data would be used. Informed consent was obtained electronically at the beginning of the questionnaire. No personal identifiable information (e.g., name, email address, student ID) was collected, and all responses were anonymized and stored securely.

References

Abdullah, M. Y. (2025). Probing into EFL students' perceptions about the impact of utilizing AI-powered tools on their academic writing practices. *Education and Information Technologies*, 1–32. https://doi.org/10.1007/s10639-025-13601-w

Allen, T. J., & Mizumoto, A. (2024). ChatGPT over my friends: Japanese English-as-a-Foreign-Language learners' preferences for editing and proofreading strategies. *RELC Journal*, 00336882241262533. https://doi.org/10.1177/00336882241262533

Altikriti, S. (2021). Challenges facing Jordanian undergraduates in writing graduation research paper. *Journal of Language and Linguistic Studies*, *18*(1), 58–67. https://doi.org/10.52462/jlls.166

Amin, M. A., Kim, Y. S., & Noh, M. (2025). Unveiling the drivers of ChatGPT utilization in higher education sectors: The direct role of perceived knowledge and the mediating role of trust in ChatGPT. *Education and Information Technologies*, *30*(6), 7265–7291. https://doi.org/10.1007/s10639-024-13095-y

Bae, H., Hur, J., Park, J., Choi, G. W., & Moon, J. (2024). Pre-service teachers' dual perspectives on generative AI: Benefits, challenges, and integration into their teaching and learning. *Online Learning*, *28*(3), 131–156.https://doi.org/10.24059/olj.v28i3.4543

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory.* Prentice-Hall.

Baroni, I., Calegari, G. R., Scandolari, D., & Celino, I. (2022). AI-TAM: a model to investigate user acceptance and collaborative intention in human-in-the-loop AI applications. *Human Computation*, *9*(1), 1–21. https://doi.org/10.15346/hc.v9i1.134

Bulqiyah, S., Mahbub, M., & Nugraheni, D. A. (2021). Investigating writing difficulties in essay writing: Tertiary students' perspectives. *English Language Teaching Educational Journal*, *4*(1), 61–73. https://doi.org/10.12928/eltej.v4i1.2371

Cardon, P., Fleischmann, C., Aritz, J., Logemann, M., & Heidewald, J. (2023). The challenges and opportunities of AI-assisted writing: Developing AI literacy for the AI age. *Business and Professional Communication Quarterly*, *86*(3), 257–295. https://doi.org/10.1177/23294906231176517

Chanpradit, T. (2025). Generative artificial intelligence in academic writing in higher education: A systematic review. *Edelweiss Applied Science and Technology*, *9*(4), 889–906. https://doi.org/10.55214/25768484.v9i4.6128

Chu, P. Q., Chowdhury, R., & Thu, L. T. T. (2025a). Factors affecting EFL students' acceptance of blended learning for writing: Examining the mediating effect of self-efficacy and writing performance. *Cogent Education*, *12*(1), 2538325. https://doi.org/10.1080/2331186X.2025.2538325

Chu, P. Q., Chowdhury, R., & Thu, L. T. T. (2025b). Using the UTAUT2 model to determine the factors affecting students' acceptance of blended learning for English writing. *CALL-EJ*, *26*(3), 24–42. https://doi.org/10.54855/callej.252632

Chuenchaichon, Y. (2022). The problems of summary writing encountered by Thai EFL students: A case study of the fourth year English major students at Naresuan University. *English Language Teaching*, *15*(6), 15–31. https://doi.org/10.5539/elt.v15n6p15

Compeau, D. R., & Higgins, C. A. (1995). Computer self-efficacy: Development of a measure and initial test. *MIS quarterly*, 189–211. https://doi.org/10.2307/249688

Deutsch, M. (1960). The effect of motivational orientation upon trust and suspicion. *Human Relations*, *13*(2), 123–139. https://doi.org/10.1177/001872676001300202

Dietrich, L. K., & Grassini, S. (2025). Assessing ChatGPT acceptance and use in education: A comparative study among German-speaking students and teachers. *Education and Information Technologies*, 1-26. https://doi.org/10.1007/s10639-025-13658-7

Dinh, K. P., Thang, P. C., & My, N. T. T. (2025). Unpacking the adoption and use of mobile education apps: A UTAUT2 perspective from a developing country. *Social Sciences & Humanities Open*, *12*, 101665. https://doi.org/10.1016/j.ssaho.2025.101665

Eastin, M. S., & LaRose, R. (2000). Internet self-efficacy and the psychology of the digital divide. *Journal of Computer-Mediated Communication*, *6*(1), JCMC611. https://doi.org/10.1111/j.1083-6101.2000.tb00110.x

Faraon, M., Rönkkö, K., Milrad, M., & Tsui, E. (2025). International perspectives on artificial intelligence in higher education: An explorative study of students' intention to use ChatGPT across the Nordic countries and the USA. *Education and Information Technologies*, 1–46. https://doi.org/10.1007/s10639-025-13492-x

Feuerriegel, S., Hartmann, J., Janiesch, C., & Zschech, P. (2024). Generative AI. *Business & Information Systems Engineering, 66*(1), 111–126. https://doi.org/10.1007/s12599-023-00834-

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly, 27*(1), 51–90. https://doi.org/10.2307/30036519

Grassini, S., Aasen, M. L., & Møgelvang, A. (2024). Understanding university students' acceptance of ChatGPT: Insights from the UTAUT2 model. *Applied Artificial Intelligence*, *38*(1), 2371168. https://doi.org/10.1080/08839514.2024.2371168

Gupta, S., Jaiswal, A., Paramasivam, A., & Kotecha, J. (2022). Academic writing challenges and supports: Perspectives of international doctoral students and their supervisors. In *Frontiers in Education, 7,* 891534. https://doi.org/10.3389/feduc.2022.891534

Hair, J. F., Thomas, G., Hult, M., Ringle, C. M., & Sarstedt, M. (2022). *A primer on partial least squares structural equation modeling* (3rd ed.). Thousand Oakes, CA: Sage.

Haryanto, S., Rahmatika, L., Islam, M. M., Setiyoningsih, T., Anandha, & Surachmi W., S (2026). Investigating EFL students' adoption of generative artificial intelligence for English learning through UTAUT2 and SDT: a mixed-methods study. *Teaching English as a Second Language Electronic Journal (TESL-EJ)*, *29*(4), 1–34. https://doi.org/10.55593/ej.29116a3

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science, 43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hsiao, C. H., & Tang, K. Y. (2024). Beyond acceptance: an empirical investigation of technological, ethical, social, and individual determinants of GenAI-supported learning in higher education. *Education and Information Technologies*, 1-26. https://doi.org/10.1007/s10639-024-13263-0

Hsu, W. L., & Silalahi, A. D. K. (2024). Exploring the paradoxical use of ChatGPT in education: Analyzing benefits, risks, and coping strategies through integrated UTAUT and PMT theories using a hybrid approach of SEM and fsQCA. *Computers and Education: Artificial Intelligence*, *7*, 100329. https://doi.org/10.1016/j.caeai.2024.100329

Kim, J., Yu, S., Detrick, R., & Li, N. (2025). Exploring students' perspectives on generative AI-assisted academic writing. *Education and Information Technologies*, *30*(1), 1265–1300. https://doi.org/10.1007/s10639-024-12878-7

Kock, N. (2015). Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration, 11*(4), 1–10. https://doi.org/10.4018/ijec.2015100101

Laver, K., George, S., Ratcliffe, J., & Crotty, M. (2012). Measuring technology self-efficacy: Reliability and construct validity of a modified computer self-efficacy scale in a clinical rehabilitation setting. *Disability and rehabilitation*, *34*(3), 220–227. https://doi.org/10.3109/09638288.2011.593682

Lin, C. S., Kuo, Y. F., & Wang, T. Y. (2025). Trust and acceptance of AI caregiving robots: The role of ethics and self-efficacy. *Computers in Human Behavior: Artificial Humans*, *3*, 100115. https://doi.org/10.1016/j.chbah.2024.100115

Liu, N., Deng, W., & Ayub, A. F. M. (2025). Exploring the adoption of AI-enabled English learning applications among university students using extended UTAUT2 model. *Education and Information Technologies*, 1–33. https://doi.org/10.1007/s10639-025-13349-3

Malik, Pratiwi, Y., Andajani, K., Numertayasa, I. W., Suharti, S., Darwis, A., & Marzuki (2023). Exploring artificial intelligence in academic essay: Higher education student's perspective. *International Journal of Educational Research Open, 5*, 100296. https://doi.org/10.1016/j.ijedro.2023.100296.

Marzuki, Widiati, U., Rusdin, D., Darwin, & Indrawati, I. (2023). The impact of AI writing tools on the content and organization of students' writing: EFL teachers' perspective. *Cogent Education, 10*(2), 2236469. https://doi.org/10.1080/2331186x.2023.2236469.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, *20*(3), 709–734. https://doi.org/10.5465/amr.1995.9508080335

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, *13*(3), 334–359. https://doi.org/10.1287/isre.13.3.334.81

Mizumoto, A., Yasuda, S., & Tamura, Y. (2024). Identifying ChatGPT-generated texts in EFL students' writing: Through comparative analysis of linguistic fingerprints. *Applied Corpus Linguistics*, *4*(3), 100106. https://doi.org/10.1016/j.acorp.2024.100106

Mo, Z., & Crosthwaite, P. (2025). Exploring the affordances of generative AI large language models for stance and engagement in academic writing. *Journal of English for Academic Purposes*, *75*, 101499. https://doi.org/10.1016/j.jeap.2025.101499

Moradi, H. (2025). Integrating AI in higher education: Factors influencing ChatGPT acceptance among Chinese university EFL students. *International Journal of Educational Technology in Higher Education*, *22*(1), 30. https://doi.org/10.1186/s41239-025-00530-4

Mustafa, A., Arbab, A. N., & El Sayed, A. A. (2022). Difficulties in academic writing in English as a second/foreign language from the perspective of undergraduate students in higher education institutions in Oman. *Arab World English Journal*, *13*(3), 41–53. https://doi.org/10.24093/awej/vol13no3.3

Mustofa, R. H., Kuncoro, T. G., Atmono, D., & Hermawan, H. D. (2025). Extending the Technology Acceptance Model: The role of subjective norms, ethics, and trust in AI tool adoption among students. *Computers and Education: Artificial Intelligence*, 100379. https://doi.org/10.1016/j.caeai.2025.100379

Picciano, A. G. (2024). Graduate teacher education students use and evaluate ChatGPT as an essay-writing tool. *Online Learning*, *28*(2), 1–20. https://doi.org/10.24059/olj.v28i2.4373

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2022). Partial least squares structural equation modeling. In C. Homburg, M. Klarmann, & A. Vomberg (Eds.), *Handbook of market research* (pp. 587–632). Springer International Publishing. https://doi.org/10.1007/978-3-319-57413-4_15

Sarwanti, S., Sariasih, Y., Rahmatika, L., Islam, M. M., & Riantina, E. M. (2024). Are they literate on ChatGPT? University language students' perceptions, benefits and challenges in higher education learning. *Online Learning*, *28*(3), 105–130. https://doi.org/10.24059/olj.v28i3.4599

Stahl, B. C., & Eke, D. (2024). The ethics of ChatGPT–exploring the ethical issues of an emerging technology. *International Journal of Information Management*, *74*, 102700. https://doi.org/10.1016/j.ijinfomgt.2023.102700

Surachmi, S. W., Solihati, T. A., Rahmatika, L., Musdalifah, Islam, M. M., & Haryanto, S. (2025). Understanding EFL students' adoption of generative AI for English learning: An integrated UTAUT2 model and self-determination theory. *Online Learning*, *29*(4), 311-340. https://doi.org/10.24059/olj.v29i4.5129

Strzelecki, A. (2024). ChatGPT in higher education: Investigating bachelor and master students' expectations towards AI tool. *Education and Information Technologies*, 1–25. https://doi.org/10.1007/s10639-024-13222-9

Tiandem-Adamou, Y. (2024). Using generative artificial intelligence to support EFL students' writing proficiency in university in China. *Journal of Educational Technology and Innovation*, *6*(4), 59–81. https://doi.org/10.61414/jeti.v6i4.213

Toprak, Z., & Yücel, V. (2020). A peculiar practice of academic writing: Epidemic writing in the Turkish graduate education. *Cogent Education*, *7*(1), 1774098. https://doi.org/10.1080/2331186X.2020.1774098

Tran, T. N. M. (2025). Factors affecting the use of ChatGPT in academic writing perceived by English-majored students. *VNU Journal of Foreign Studies*, *41*(3), 110–125. https://doi.org/10.63023/2525-2445/jfs.ulis.5519

Tyupa, S. (2011). A theoretical framework for back-translation as a quality assessment tool. *New Voices in Translation Studies*, *7*(1), 35–46. https://doi.org/10.14456/nvts.2011.4

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly*, 425–478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157–178. https://doi.org/10.2307/41410412

Wang, Q. (2025). EFL learners' motivation and acceptance of using large language models in English academic writing: an extension of the UTAUT model. *Frontiers in Psychology*, *15*, 1514545. https://doi.org/10.3389/fpsyg.2024.1514545

Wang, Y. Y., & Chuang, Y. W. (2024). Artificial intelligence self-efficacy: Scale development and validation. *Education and Information Technologies, 29(*4), 4785–4808. https://doi.org/10.1007/s10639-023-12015-w

Wurisoedjatmiko, S. (2017). *Guru wanita lebih banyak dari pria: Mengapa dirisaukan? Wurisoedjatmiko* [More female teachers than male: Why is it a concern?].https://wurisoedjatmiko.blogspot.com/2017/10/guru-wanita-lebih-banyak-dari-pria.html

Xu, J., Li, Y., Shadiev, R., & Li, C. (2025). College students' use behavior of generative AI and its influencing factors under the unified theory of acceptance and use of technology model. *Education and Information Technologies*, 1–24. https://doi.org/10.1007/s10639-025-13508-6

Yang, Y. (2025). Exploring factors influencing L2 learners' use of GAI-assisted writing technology: Based on the UTAUT model. *Asia Pacific Journal of Education*, 1–20. https://doi.org/10.1080/02188791.2025.2505664

Zhao, J., Li, X., & Liao, H. (2025). A context-specific analysis of translation technology usage behavior among college EFL students: Insights from the UTAUT2 model. *Education and Information Technologies*, 1–35. https://doi.org/10.1007/s10639-025-13454-3

Zheng, Y., Wang, Y., Liu, K. S. X., & Jiang, M. Y. C. (2024). Examining the moderating effect of motivation on technology acceptance of generative AI for English as a foreign language learning. *Education and Information Technologies*, 1–29. https://doi.org/10.1007/s10639-024-12763-3

Zimmerman, A. (2023). A ghostwriter for the masses: ChatGPT and the future of writing. *Annals of Surgical Oncology*, *30*(6), 3170–73. https://doi.org/10.1245/s10434-023-13436-0

Appendix

Final set of questionnaire items based on the extended UTAUT2 Model

Construct	Item	
Performance Expectancy (PE)	PE1	GenAI tools are beneficial for improving my academic writing quality.
	PE2	Using GenAI enables me to complete academic writing tasks more quickly.
	PE3	GenAI increases my productivity when working on academic writing activities.
	PE4	Using GenAI improves my chances of achieving higher grades on academic writing assignments.
Effort Expectancy (EE)	EE1	Interacting with GenAI tools is clear and easy to understand.
	EE2	I am confident in operating GenAI tools for academic writing.
	EE3	Learning to use GenAI tools is easy for me.
	EE4	I find it easy to get GenAI tools to produce the outputs I need for academic writing.
Social Influence (SI)	SI1	My lecturers and peers encourage me to use GenAI for academic writing.
	SI2	People I interact with regularly believe I should use GenAI tools for academic writing tasks.
	SI3	Students who are more experienced than me are supportive and offer guidance on using GenAI tools for academic writing.
	SI4	My university provides support or promotes the use of GenAI in academic work
Facilitating Conditions (FC)	FC1	I have access to the necessary resources (internet, device, etc.) to use GenAI.
	FC2	I possess the knowledge and skills required to use GenAI effectively.
	FC3	Help is available when I encounter difficulties while using GenAI tools.
Hedonic Motivation (HM)	HM1	I find using GenAI tools for my academic writing is fun.
	HM2	Using GenAI tools gives me a pleasant and satisfying experience during academic writing activities.
	HM3	I find GenAI tools for my academic writing is entertaining.
Habit (HT)	HT1	Using Gen AI tools for academic writing has become part of my routine.

	HT2	I frequently rely on GenAI tools when working on academic writing tasks.
	HT3	I must use GenAI tools for my academic writing.
	HT4	Using GenAI tools has become natural for my academic writing tasks.
AI Self-Efficacy (AIS)	AIS1	I am confident that I have the necessary skills to use GenAI tools for academic writing.
	AIS2	I can use GenAI tools for academic writing even if no one is available to guide me.
	AIS3	I can use GenAI tools for academic writing as long as I can contact someone for help when needed.
	AIS4	I am confident that I can effectively apply GenAI tools' output to improve my academic writing.
AI Trust (AIT)	AIT1	I trust GenAI tools to provide accurate and consistent information that supports my academic
	AIT2	I believe GenAI tools are capable of giving useful guidance for academic writing tasks.
	AIT3	GenAI tools provide information in a clear and transparent manner, allowing me to understand how the output is generated.
	AIT4	I trust that GenAI tools provide information honestly and acts with integrity when supporting my academic writing.
Behavioral Intention (BI)	BI1	I plan to continue using GenAI tools for my academic writing in the future.
	BI2	I expect that I will continue using GenAI tools in my academic writing activities.
	BI3	I intend to use GenAI in the future.
	BI4	I would encourage my friends to use GenAI tools for academic writing.
Actual Use (AU)	AU1	I consider myself a regular user of GenAI tools.
	AU2	When available, I prefer to use GenAI.
	AU3	I complete most of my academic writing activities with the support of GenAI tools.
	AU4	Whenever possible, I choose to use GenAI when working on academic writing tasks.