Understanding EFL Students' Adoption of Generative AI for English Learning: An Integrated UTAUT2 Model and Self-Determination Theory

Sri Surachmi W
Universitas Muria Kudus, Indonesia

Tri Agustini Solihati
Universitas Perjuangan Tasikmalaya, Indonesia

Laily Rahmatika
Universitas Muhammadiyah Surakarta, Indonesia

Musdalifah
Universitas Muhammadiyah Enrekang, Indonesia

M Monjurul Islam
Universiti Pendidikan Sultan Idris, Malaysia

Sigit Haryanto
Universitas Muhammadiyah Surakarta, Indonesia

Abstract
Despite the increasing use of generative artificial intelligence (GenAI) tools among students, limited research has examined the underlying mechanisms guiding their adoption in English as a Foreign Language (EFL) education. Drawing on the unified theory of acceptance and use of technology 2 (UTAUT2) and self-determination theory (SDT), this study examines the factors shaping Indonesian EFL students' intention and actual use of GenAI for English learning. Using a cross-sectional survey design, data were collected using an online questionnaire from 462 EFL students at three private universities in Indonesia and analyzed with the partial least squares structural equation modeling (PLS-SEM) using SmartPLS 4. The results indicated that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, autonomy, and relatedness significantly impacted EFL students' intention to adopt GenAI for English learning. While competence did not significantly influence behavioral intention, both the SDT components (autonomy, competence, and relatedness) and behavioral intention were predictors of actual usage. The integrated framework explained a high proportion of variance (R^2 = 83.1% for behavioral intention; R^2 = 77.1% for actual use). These insights advance understanding of the technological and motivational determinants of GenAI adoption in EFL education and offer evidence-based direction for designing effective, equitable, and ethically responsible AI-supported English learning practices.

Keywords: EFL students; English learning; Generative AI; SDT; UTAUT2

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Introduction

As digital advancements continue to reshape education, the ability to effectively utilize cutting-edge technologies has become vital for language students. This transformation includes the rising incorporation of generative artificial intelligence (GenAI) applications into various educational contexts. Within English as a foreign language (EFL) learning, widely used GenAI platforms like ChatGPT, Grammarly, and Quillbot offer personalized linguistic input, instant feedback, and adaptive correction, which collectively foster improved writing fluency, greater confidence, and enhanced learner autonomy (Bae & Bozkurt, 2024; Ho, 2024; Sarwanti et al., 2024). These tools are particularly valuable in resource-limited regions such as Southeast Asia, where many EFL students depend on them outside formal classrooms. In Indonesia, where mobile access is widespread but systematic GenAI use is nascent, students increasingly rely on these tools to develop writing, grammar, and speaking skills (Azwar & Jayanti, 2025; Laksana et al., 2024; Waziana et al., 2024). They effectively bridge language skill gaps by offering timely and reliable support. Despite their growing use, empirical study on what drives GenAI adoption in non-Western English as a Foreign Language (EFL) education remains limited.

Most prior investigations into educational technology adoption have been anchored in externalist models such as the technology acceptance model (TAM) (Davis, 1989) and the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al., 2003). Although these frameworks have proven effective in explaining early adoption, the application of existing technology acceptance models remains limited in comprehensively addressing specific factors that influence the use of GenAI in EFL education. UTAUT2, an expansion of the original framework, introduced additional constructs such as hedonic motivation, price value, and habit to better align with consumer technology behaviors (Venkatesh et al., 2012). However, this model remains grounded in extrinsic drivers and still lacks the motivational depth needed to capture students' self-determined engagement with autonomous technologies.

Self-determination theory (SDT), in contrast, provides a robust psychological framework to explain intrinsic motivation, emphasizing autonomy, competence, and relatedness as essential to sustained behavior (Deci & Ryan, 2000; Ryan & Deci, 2020). In educational contexts, SDT has been shown to explain students' proactive engagement with technology-enhanced environments where external control is minimal (Chai et al., 2022). This makes it highly applicable to GenAI contexts, where students independently decide how, when, and why to engage with GenAI like ChatGPT. Empirical studies have highlighted the synergy between technology acceptance models and SDT in various domains, including mobile learning (Alowayr & Al-Azawei, 2021; Şahin & Yildiz, 2024; Şahin, 2025), massive open online courses (MOOCs) (Alharbi, 2023), mobile-assisted vocabulary learning application (Han & Chen, 2024), communicational artificial intelligence (Cortez et al., 2024), e-learning environments (Osei et al., 2022), and large language models (Wang & Reynolds, 2024).

However, empirical study integrating UTAUT2 and SDT in GenAI adoption within EFL education remains limited. Existing study often emphasized on behavioral intention, overlooking the combined impact of intrinsic and extrinsic factors on both intention and actual use. Although some studies (Alowayr & Al-Azawei, 2021; Wang & Reynolds, 2024; Yakubu et al., 2025) address this intersection, they largely focus on behavioral intention without measuring actual usage. As Zheng et al. (2024) and Zhao et al. (2025) caution, behavioral intention alone may not predict actual use, particularly for emerging, self-directed technologies. Including actual use as an outcome variable is essential to understanding sustained engagement and verifying whether initial intention materializes into regular use, a dimension often overlooked in educational technology research (Strzelecki, 2024). This study addresses a documented gap in educational technology study by integrating UTAUT2 and SDT to examine the technological and psychological factors influencing Indonesian EFL students' intention and actual use of GenAI for English learning. The following research questions guide the inquiry:

(1) Which UTAUT2 factors significantly influence EFL students' intention to adopt GenAI for English learning?

(2) To what extent do SDT variables influence EFL students' intention and actual use of GenAI?

(3) To what extent does behavioral intention predict the actual use of GenAI among EFL students in higher education?

By answering these questions, the study offers a theoretically and empirically validated framework for understanding GenAI adoption and use in EFL education. Its results generate practical, pedagogical, and policy insights that can guide educators, institutions, and policymakers in designing effective, equitable, and ethically informed approaches to integrating GenAI into EFL education, particularly in under-resourced contexts.

Literature Review

UTAUT2

Developed by Venkatesh et al. (2003), UTAUT has been extensively employed as a theoretical framework to understand how individuals accept new technologies across educational, organizational, and consumer domains. This model synthesizes constructs from eight foundational theories, including the technology acceptance model, the theory of planned behavior, and the diffusion of innovations theory. The original UTAUT framework identifies four constructs (e.g., performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC)) as predictors of behavioral intention (BI), which in turn influences actual use (AU). To better reflect the consumer use of technology, Venkatesh et al. (2012) later extended the model into UTAUT2, which added three new constructs: hedonic motivation (HM), price value (PV), and habit (HT). This revised model significantly improved the explanatory power of UTAUT in informal, consumer, and educational settings. In the current study, price value is intentionally excluded, as most GenAI tools used by EFL students such as ChatGPT, Grammarly, Quillbot, and Gemini are either free or provided through institutional access. Therefore, the model focuses on six core UTAUT2 constructs to assess how these factors shape EFL students' BI and AU to adopt GenAI for English learning.

A growing number of studies affirm UTAUT2's effectiveness in explaining students' use of educational technologies. For instance, Nikolopoulou et al. (2020) integrated UTAUT2 to explore mobile phones, revealing that SI, HM, and HT significantly influenced students' BI to use the technology, with habit being the strongest influence. These results are supported by scholars (e.g., Strzelecki, 2024; Zheng et al., 2025), who identify HT as the primary factor driving students' adoption of ChatGPT and e-learning. A study by Arthur et al. (2025) reported that PE, EE, SI, and HM were significant predictors of students' BI to use ChatGPT, with HM being the strongest predictor. Additionally, studies by Grassini et al. (2024) and Zheng et al. (2024) identified PE as the most influential construct affecting BI toward GenAI tools such as ChatGPT.

Building on the UTAUT2 framework, researchers have integrated various context-specific constructs to tailor the model to emerging technologies and diverse learner profiles. For instance, Zacharis and Nikolopoulou (2022) introduced learning value into UTAUT2, finding it to be a significant contributor alongside traditional UTAUT2 factors in predicting e-learning adoption. In a study on the metaverse, Al-Adwan and Al-Debei (2024) added personal innovativeness (PI) in IT to the model, demonstrating the predictive power of PE, EE, FC, HM, PV, and PI in shaping Gen Z students' intention to adopt immersive technologies in higher education. Similarly, Strzelecki (2024) included PI in his adaptation of UTAUT2, emphasizing its significant role along with SI and HM, and other core constructs in explaining ChatGPT adoption among university students. In further modifications, Amin et al. (2025) added perceived knowledge of ChatGPT and trust, illustrating how UTAUT2 remains versatile and predictive when applied to emerging digital tools. Among the most relevant studies for the current research, Zhao et al. (2025) applied the complete UTAUT2 model including PV to investigate Chinese EFL students' adoption of translation technologies. They found that all seven UTAUT2 constructs significantly predicted BI, further validating the model's utility in language-learning contexts. These studies collectively demonstrate the robustness of UTAUT2 in predicting students' technological adoption across different contexts.

SDT

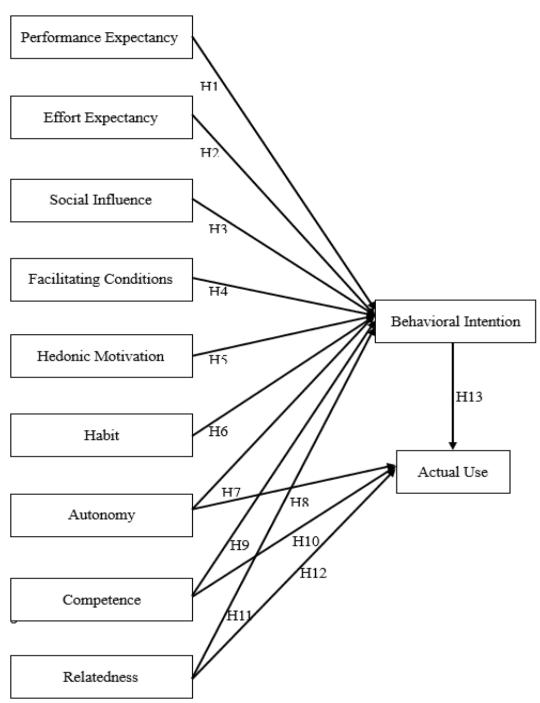
SDT (Deci and Ryan, 1985; 2000) provides a robust framework for understanding individuals' intrinsic and extrinsic motivations to engage in behaviors, including the use of educational technology. Central to SDT are three essential psychological needs: autonomy (AUTO), competence (COMP), and relatedness (REL). When these needs are satisfied, individuals are more likely to demonstrate higher motivation, engagement, and persistence in tasks. In technology-enhanced learning environments, especially those involving self-directed tools like GenAI, SDT has emerged as a critical lens to explain why students voluntarily choose to integrate such tools into their academic routines (Zogheib & Zogheib, 2024).

Several studies have highlighted SDT's relevance in explaining students' motivation and engagement in educational settings. For instance, Han and Chen (2024) explored the acceptance of mobile-assisted vocabulary learning applications among Chinese EFL students using TAM and SDT and reported that COMP strongly influenced BI. Supporting this, Raman et al. (2022) further supported this view by examining students' intention to adopt Moodle-based learning, showing that both AUTO and COMP were strong predictors of students' BI. Meanwhile, scholars (e.g., Şahin, 2025; Şahin and Yildiz, 2024; Xie et al., 2023) reported that COMP and REL significantly influenced the acceptance of autonomous vehicles and mobile learning platforms. Cortez et al. (2024) further demonstrated that AUTO and REL significantly predicted BI in AI-integrated learning environments. Expanding on this, Osei et al. (2022) examined e-learning adoption during the COVID-19 pandemic and found that all three core SDT components had significant effects on both BI and AU.

Despite its proven relevance, the empirical application of SDT in studies examining GenAI adoption remains relatively limited, particularly within the EFL educational domain. While models like UTAUT2 account for external factors, they do not fully capture students' internal motivations. Recent studies have begun to bridge this theoretical gap. For example, Alowayr and Al-Azawei (2021) integrated UTAUT, expectation confirmation, and SDT to investigate students' acceptance of mobile learning and found that AUTO significantly predicted BI. Similarly, Alharbi (2023) investigated Saudi students' intentions and AU of MOOCs by combining SDT, UTAUT, and cognitive evaluation theory, and found that all three SDT components significantly influenced BI. Wang and Reynolds (2024) took a similar approach by merging SDT with UTAUT to explore students' use of large language models for vocabulary development. Their research highlighted how psychological needs interact with technological perceptions to shape BI. However, such work is still scarce and often lacks direct focus on EFL education navigating GenAI tools in under-resourced educational settings. Therefore, this study aims to contribute to the existing literature by integrating SDT with UTAUT2 to examine how both psychological needs and technological perceptions jointly influence Indonesian EFL students' BI and AU of GenAI for English learning. By bridging these theoretical frameworks, the study enhances understanding of the key factors driving GenAI adoption in EFL education.

Research Model and Hypothesis Development

Figure 1
Proposed Framework



This study integrates six items from UTAUT2 and three items from SDT to investigate behavioral intention and actual use of GenAI for English learning among Indonesian EFL students in higher education, as shown in Figure 1. The following subsections detail the development of the study's hypotheses.

Performance Expectancy

Performance expectancy is the belief that using technology will lead to improved job performance (Venkatesh et al., 2003). In this study, it denotes how strongly EFL students believe GenAI tools can support their academic achievement in English learning, particularly for tasks such as translation, comprehension, and improving writing. Previous studies in various technology have reported that performance expectancy significantly predicts students' intentions to adopt new tools, such as mobile learning (Lutfi et al., 2022), MOOCs (Meet et al., 2022), metaverse (Al-Adwan & Al-Debel, 2024), e-learning (Zheng et al., 2025), large language models (Wang & Reynolds (2024), GenAI like ChatGPT (Amin et al., 2025; Budhathoki et al., 2024; Lai et al., 2024; Strzelecki, 2024; Xu & Thien, 2025; Yakubu et al., 2025; Zheng et al., 2024), and translation technology (Zhao et al., 2025). Hence, the following hypothesis is proposed:

H1: PE directly and positively predicts BI.

Effort Expectancy

Effort expectancy refers to the degree to which an individual perceives a new technology as being straightforward and effortless to use (Venkatesh et al., 2003). Within the context of GenAI for English learning, this pertains to how effortlessly EFL students can use the tools, including the perceived ease of navigation and the straightforward application of features to assist with their language learning activities. Research has repeatedly demonstrated that effort expectancy significantly shapes intention to adopt technologies across platforms such as Moodle (Raman et al., 2022), mobile applications (Lutfi et al., 2022), MOOCs (Alharbi, 2023), tablet-based learning (Arthur et al., 2023), and GenAI applications (Budhathoki et al., 2024; Lai et al., 2024; Strzelecki, 2024; Xu & Thien, 2025; Wang & Reynolds, 2024; Yakubu et al., 2025; Zhao et al., 2025). Accordingly, this hypothesis is proposed:

H2: EE directly and positively predicts BI.

Social Influence

Social influence refers to the extent to which individuals perceive that the views of important people around them affect their choice to embrace a new technology (Venkatesh et al., 2023; 2012; 2016). In this research, social influence focuses on how EFL students in higher education are influenced by the encouragement and advice of classmates, teachers, friends, and other key figures in their decision to incorporate GenAI into their English learning process. Previous studies have demonstrated the role of social influence in predicting behavior across various educational contexts, including mobile learning (Alowayr & Al-Azawei, 2021), e-learning (Zacharis & Nikolopoulou, 2022; Zheng et al., 2025), MOOCs (Alharbi, 2023), tablet-based learning (Arthur et al., 2023), GenAI like ChatGPT and large language models (Abdi et al., 2025; Amin et al., 2025; Arthur et al., 2025; Budhathoki et al., 2024; Strzelecki, 2024; Xu &

Thien, 2025; Wang & Reynolds, 2024; Yakubu et al., 2025; Zheng et al., 2024), and translation technology (Zhao et al., 2025). In light of this, the study presents the following hypotheses:

H3: SI directly and positively predicts BI.

Facilitating Conditions

Facilitating conditions are the perception that the necessary technical resources and support systems are in place to enable the effective use of new technology (Arthur et al., 2023; Venkatesh et al., 2012). In this study, facilitating conditions are described as the perceptions of EFL students in higher education of having access to the required resources, technical assistance, and infrastructure that support the effective use of GenAI tools for English learning. These factors are crucial for evaluating technology adoption, as they have a strong impact on students' intentions to use technology in higher education, including, mobile learning (Alowayr & Al-Azawei, 2021; Lutfi et al., 2022), metaverse (Al-Adwan & Al-Debei, 2024), tablet-based learning (Arthur et al., 2023), MOOCs (Alharbi, 2023; Meet et al., 2022), e-learning (Zheng et al., 2025), ChatGPT (Arthur at al., 2025), and translation technology (Zhao et al., 2025). Drawing from these insights, the study presents the following hypothesis:

H4: FC directly and positively predicts BI.

Hedonic Motivation

Venkatesh et al. (2012) define hedonic motivation as the degree to which individuals are motivated to use new technology for enjoyment or due to its novelty. In this study, hedonic motivation specifically refers to the enjoyment EFL students experience when using GenAI tools to enhance their English language learning. Hedonic motivation has been a significant predictor in studies on MOOCs (Meet et al., 2022), the metaverse (Al-Adwan & Al-Debei, 2024), tablet learning (Arthur et al., 2023), and GenAI (Abdi et al., 2025; Faroughi et al., 2023; Strzelecki, 2024; Tan et al., 2024; Zheng et al., 2024). However, its impact has shown variability in some contexts (Grassini et al., 2024; Raza et al., 2022; Tseng et al., 2022). Considering these inconsistent outcomes, the following hypotheses are put forward:

H5: HM directly and positively predicts BI.

Habit

Habit is defined as the extent to which the use of a particular technology becomes an automatic behavior, integrated into a person's daily routines (Venkatesh et al., 2012). In this study, habit is understood as the degree to which students consistently incorporate GenAI into their academic routines for English learning. Recent research suggests that habit has a significant effect on students' behavioral intention to adopt GenAI such as ChatGPT (Grassini et al., 2024; Habibi et al., 2023; Salifu et al., 2024; Strzelecki, 2024; Zheng et al., 2024), e-learning (Zacharis & Nikolopoulou, 2022; Zheng et al., 2025), and translation technology (Zhao et al., 2025). In contrast, habit was found to have no notable influence on behavioral intention in some studies (Arthur et al., 2023; Arthur et al., 2025; Meet et al., 2022). Given these mixed outcomes in prior research, this study formulates the following hypotheses:

H6: HT directly and positively predicts BI.

Autonomy

Autonomy is defined as an individual's desire to have their behavior regulated and controlled (Ryan & Deci, 2020). In this study, it relates to students' motivation to use GenAI tools as a way to independently manage their English learning. Studies have confirmed autonomy as a strong determinant in learning systems like Moodle (Raman et al., 2022), mobile learning (Alowayr & Al-Azawei, 2021; Şahin, 2025), MOOCs (Alharbi, 2023), large language models (Wang & Reynolds, 2024), and AI platforms (Chai et al., 2022; Cortez et al., 2024). Autonomy also influences actual use (Osei et al., 2022). Thus, the hypotheses are:

H7: AUTO directly and positively predicts BI.

H8: AUTO directly and positively predicts AU.

Competence

Competence is defined as the sense of confidence individuals have in their capability to successfully carry out a given task (Deci & Ryan, 1985). In this research, it involves students' belief in their ability to use GenAI tools effectively for English learning. This belief has been shown to predict technology adoption across learning platforms such as Moodle (Raman et al., 2022), e-learning systems (Osei et al., 2022), MOOCs (Alharbi, 2023), mobile tools (Şahin & Yildiz, 2024), and large language models (Wang & Reynolds, 2024). It also influences actual use behavior (Osei et al., 2022). Based on these results, the following hypotheses are presented:

H9: COMP directly and positively predicts BI.

H10: COMP directly and positively predicts AU.

Relatedness

Relatedness captures the need to feel socially connected (Ryan & Deci, 2020). For this study, it reflects EFL students' sense of belonging and connection within their learning environment, which can shape their engagement with GenAI tools. Relatedness has been shown to influence behavioral intention in MOOCs (Alharbi, 2023), e-learning (Osei et al., 2022), autonomous systems (Xie et al., 2023), AI platforms (Cortez et al., 2024), and mobile tools (Şahin & Yildiz, 2024). It has also been linked to actual technology use (Osei et al., 2022). Building on previous research, the following hypotheses are proposed:

H11: REL directly and positively predicts BI.

H12: REL directly and positively predicts AU.

Behavioral Intention and Actual Use

Behavioral intention reflects users' willingness to adopt a technology, while actual use represents the practical application of that intention (Venkatesh et al., 2003; 2012). In this study, behavioral intention captures students' willingness to engage with GenAI tools for academic purposes, and AU denotes how frequently and effectively they actually use them. Prior studies on mobile tools (Nikolopoulou et al., 2020), e-learning (Osei et al., 2022), ChatGPT (Alharbi, 2023; Amin et al., 2025; Budhathoki et al., 2024; Strzelecki, 2024; Zheng et al., 2024), and translation tools (Zhao et al., 2025) have confirmed that intention reliably predicts usage. Given that behavioral intention is widely regarded as a predictor of actual use in GenAI, the following hypotheses are proposed:

H13: BI directly and positively predicts AU.

Methods

Participants

This study recruited undergraduate students enrolled in English departments at three private universities located in Central Java, West Java, and South Sulawesi, Indonesia. Participants were selected using a convenience sampling technique. As shown in Table 1, the final sample consisted of 462 EFL students. The gender distribution revealed a notable imbalance, with 68.2% identifying as female and 31.8% as male. This pattern aligns with typical demographic trends in English departments at Indonesian universities, where female students generally outnumber males. Participants' ages ranged from 17 to above 22 years, with 62.1% falling within the 17–21 age group, and the remaining 37.9% being 22 or older. The sample also reflected a spread across academic levels, with 37.9% in their first year, 29.2% in their second year, and 32.9% in their third year.

Table 1

Participants' Information

	Number	%
Gender		
Male	147	31.8
Female	315	68.2
Age		
17-21 years	287	62.1
22 years and over	175	37.9
Study year		
First	175	37.9
Second	135	29.2
Third	152	32.9

Instrument

The questionnaire was structured into three main sections. The first section gathered demographic details from participants, such as their gender, age, and study year. The second section focused on constructs related to students' technology acceptance measured six factors from the UTAUT2 model developed by Venkatesh et al. (2012). These constructs included PE, EE, SI, FC, HM, and HT. The items were adapted to the context of GenAI in English learning (see appendix), with reference to updated findings from Zheng et al. (2024), ensuring the scale remained contextually relevant and theoretically grounded. These constructs helped in identifying the technological factors that influence students' behavioral intention to adopt GAI tools. The third section focused on motivational factors based on SDT including 4 items autonomy, 3 items competence, and 4 items relatedness was adapted from Hew and Kadir (2016). The questionnaire employed a five-point Likert scale, ranging from strongly disagree = 1, disagree = 2, neutral = 3, agree = 4, to strongly agree = 5. Since the research took place in Indonesia, a back-translation method was used to validate the instrument. One researcher translated the items from English into Indonesian, while a second researcher independently translated them back into English to ensure accuracy in language and cultural relevance.

To enhance the content validity of the instrument, the questionnaire was reviewed by two specialists in technology-assisted language learning. Their feedback focused on the relevance, clarity, and alignment of the items with the study's objectives and theoretical framework. Suggestions from these experts were carefully incorporated into the final version of the instrument. Prior to launching the formal survey, a pilot test was conducted with 15 undergraduate students who matched the profile of the target respondents. This stage was essential for identifying any ambiguous language, confusing instructions, or technical issues related to the online survey platform. Following the feedback, a few subtle edits were applied to make the questionnaire more understandable and well-structured. After incorporating expert and student feedback, the final version of the questionnaire was distributed through Google Forms, allowing easy access for participants and ensuring efficient data collection.

Data Collection

This study adopted a single cross-sectional design, collecting data through Google Forms (an online survey platform) between October and November 2024. The survey link was distributed to students via WhatsApp group class from three lecturers in different private universities. Before participating, students were provided with an informed consent form that outlined the study's objectives, procedures, and their right to withdraw at any time. The survey took approximately seven to ten minutes to complete, and participation was entirely voluntary. To ensure confidentiality, all responses remained anonymous, and pseudonyms were assigned throughout the study. Survey questionnaires were distributed to 600 students across three universities, resulting in 470 returned responses. After excluding 8 participants who reported no prior experience with ChatGPT, a total of 462 valid questionnaires were included in the analysis. This corresponds to a response rate of approximately 78.3%.

Data Analysis

In this study, SmartPLS 4 was utilized alongside the partial least squares structural equation modeling (PLS-SEM) technique for data analysis. The evaluation process followed the two-step approach proposed by Hair et al. (2022), beginning with an assessment of the measurement model, followed by an evaluation of the structural model. To ensure the reliability of the data, common method bias (CMB) was first checked using the Variance Inflation Factor (VIF). The measurement model was then evaluated in the first step to verify its internal consistency and validity. Once these criteria were met, the second step focused on evaluating the structural model. Finally, the predictive power of the model was assessed using PLS Predict (Shmueli et al., 2019), providing a thorough evaluation of the model's performance.

Results

Common Method Bias

This study relied on an online self-reported survey using a cross-sectional design to collect data at a single point in time, which may introduce common method variance and potentially inflate the observed relationships between variables. To assess CMB, VIF was examined in this study. According to Kock (2015), VIF values below 3.3 are considered acceptable, indicating no significant CMB and multicollinearity issues. As shown in Table 2, all VIF values fell below the 3.3 threshold ranging from 1.334 to 2.836, confirming that CMB and multicollinearity were not a concern in this study.

Table 2

Collinearity Statistics (VIF)

	PE	EE	SI	FC	HM	HT	AUTO	COMP	REL	BI	AU
PE										2.548	
EE										2.100	
SI										2.836	
FC										2.554	
HM										1.383	
HT										2.112	
AUTO										2.754	2.501
COMP										2.481	2.142
REL										1.379	1.334
BI											1.891
AU											

Measurement Model Evaluation

The measurement model was assessed to ensure that each indicator reliably and validly measured its intended construct by evaluating reliability, convergent validity, and discriminant validity. Reliability was confirmed by examining Cronbach's alpha and composite reliability (CR). As shown in Table 3, Cronbach's alpha values ranged from 0.806 to 0.955, and CR values ranged from 0.881 to 0.947, both surpassing the acceptable threshold of 0.70. Convergent validity was established by evaluating factor loadings and average variance extracted (AVE). All factor loadings ranged from 0.774 to 0.951, surpassing the recommended value of 0.70, while AVE values ranged from 0.648 to 0.857, all above the 0.50 benchmark (Hair et al., 2022). These results indicate that the measurement items possess adequate reliability and convergent validity.

To assess discriminant validity, both the Fornell-Larcker criterion and cross-loadings were employed. The Fornell-Larcker criterion, presented in Table 4, demonstrated that the square root values of the AVE for each construct (0.887, 0.878, 0.870, 0.849, 0.926, 0.883, 0.845, 0.865, 0.862, 0.821, and 0.805) consistently exceeded the correlations between constructs, confirming adequate discriminant validity across all constructs. Additionally, the cross-loading analysis in Table 5 demonstrated that each indicator loaded higher on its respective construct than on any other construct, providing further evidence for discriminant validity (Hair et al., 2022). These results demonstrate that the measurement model meets the standards for reliability, convergent validity, and discriminant validity, supporting its use in further analysis.

Table 3

Measurement Model Assessment

Construct	Item	Mean	SD	Factor Loading	Cronbach's Alpha	CR	AVE
PE	PE1	0.891	0.011	0.891	0.910	0.937	0.787
	PE2	0.894	0.011	0.894			
	PE3	0.890	0.011	0.890			
	PE4	0.874	0.014	0.874			
EE	EE1	0.878	0.013	0.879	0.901	0.931	0.770
	EE2	0.877	0.011	0.876			
	EE3	0.867	0.014	0.867			
	EE4	0.888	0.010	0.888			
SI	SI1	0.863	0.022	0.863	0.893	0.926	0.758
	SI2	0.886	0.011	0.886			
	SI3	0.892	0.011	0.892			
	SI4	0.839	0.019	0.839			
FC	FC1	0.867	0.018	0.866	0.806	0.886	0.721
	FC2	0.889	0.013	0.889			
	FC3	0.788	0.033	0.790			
HM	HM1	0.875	0.011	0.875	0.916	0.947	0.857
	HM2	0.950	0.006	0.951			
	HM3	0.950	0.006	0.950			
HT	HT1	0.884	0.014	0.883	0.906	0.934	0.780
	HT2	0.878	0.019	0.879			
	HT3	0.861	0.017	0.861			
	HT4	0.908	0.011	0.909			
AUTO	AUTO1	0.830	0.025	0.830	0.867	0.909	0.715
	AUTO2	0.870	0.019	0.870			
	AUTO3	0.863	0.017	0.864			
	AUTO4	0.817	0.020	0.817			
COMP	COMP1	0.818	0.025	0.819	0.832	0.899	0.748
	COMP2	0.879	0.011	0.879			
	COMP3	0.895	0.011	0.895			

REL	REL1	0.774	0.036	0.774	0.884	0.920	0.743
	REL2	0.903	0.014	0.904			
	REL3	0.903	0.012	0.903			
	REL4	0.860	0.020	0.860			
BI	BI1	0.818	0.016	0.819	0.838	0.892	0.673
	BI2	0.807	0.018	0.808			
	BI3	0.831	0.016	0.831			
	BI4	0.825	0.016	0.825			
AU	AU1	0.808	0.018	0.808	0.819	0.881	0.648
	AU2	0.799	0.020	0.799			
	AU3	0.814	0.019	0.814			
	AU4	0.798	0.020	0.799			

Table 4

Discriminant Validity (Fornell-Lacker criterion)

	PE	EE	SI	FC	HM	HT	AUTO	COMP	REL	BI	AU
PE	**0.887**										
EE	0.645	**0.878**									
SI	0.675	0.686	**0.870**								
FC	0.639	0.593	0.695	**0.849**							
HM	0.441	0.457	0.363	0.378	**0.926**						
HT	0.508	0.492	0.576	0.538	0.403	**0.883**					
AUTO	0.490	0.501	0.639	0.630	0.336	0.631	**0.845**				
COMP	0.441	0.505	0.597	0.550	0.362	0.637	0.719	**0.865**			
REL	0.424	0.303	0.309	0.431	0.270	0.383	0.405	0.319	**0.862**		
BI	0.845	0.686	0.727	0.712	0.561	0.615	0.625	0.549	0.483	**0.821**	
AU	0.805	0.572	0.648	0.642	0.462	0.616	0.735	0.678	0.603	0.774	**0.805**

Table 5

Discriminant Validity (Cross Loadings)

	PE	EE	SI	FC	HM	HT	AUTO	COMP	REL	BI	AU
PE1	**0.891**	0.527	0.564	0.547	0.372	0.443	0.438	0.372	0.383	0.763	0.587
PE2	**0.894**	0.578	0.640	0.598	0.386	0.466	0.479	0.386	0.370	0.754	0.605
PE3	**0.890**	0.612	0.603	0.539	0.392	0.409	0.400	0.392	0.356	0.734	0.542
PE4	**0.874**	0.572	0.589	0.584	0.415	0.483	0.421	0.415	0.394	0.747	0.562
EE1	0.561	**0.879**	0.499	0.509	0.383	0.398	0.432	0.383	0.269	0.580	0.484
EE2	0.590	**0.876**	0.534	0.520	0.392	0.441	0.425	0.392	0.261	0.603	0.504
EE3	0.565	**0.867**	0.532	0.522	0.451	0.475	0.450	0.451	0.264	0.629	0.524

EE4	0.546	**0.888**	0.509	0.529	0.375	0.409	0.450	0.375	0.268	0.593	0.493
SI1	0.544	0.521	**0.863**	0.604	0.285	0.510	0.587	0.285	0.183	0.605	0.556
SI2	0.681	0.554	**0.886**	0.614	0.358	0.486	0.556	0.358	0.353	0.690	0.609
SI3	0.578	0.505	**0.892**	0.591	0.334	0.537	0.574	0.334	0.276	0.644	0.588
SI4	0.534	0.474	**0.839**	0.611	0.280	0.473	0.508	0.280	0.253	0.584	0.497
FC1	0.581	0.563	0.659	**0.866**	0.330	0.473	0.619	0.330	0.332	0.651	0.610
FC2	0.558	0.515	0.612	**0.889**	0.335	0.449	0.579	0.335	0.371	0.629	0.566
FC3	0.482	0.420	0.484	**0.790**	0.295	0.451	0.385	0.295	0.407	0.524	0.446
HM1	0.432	0.441	0.361	0.360	**0.875**	0.361	0.276	0.875	0.225	0.542	0.431
HM2	0.394	0.416	0.322	0.350	**0.951**	0.368	0.342	0.951	0.262	0.502	0.425
HM3	0.394	0.409	0.321	0.337	**0.950**	0.388	0.317	0.950	0.264	0.509	0.425
HT1	0.516	0.526	0.575	0.524	0.404	**0.883**	0.636	0.404	0.358	0.627	0.611
HT2	0.407	0.390	0.441	0.430	0.377	**0.879**	0.512	0.377	0.355	0.526	0.523
HT3	0.410	0.392	0.504	0.449	0.339	**0.861**	0.508	0.339	0.273	0.483	0.497
HT4	0.446	0.409	0.502	0.485	0.291	**0.909**	0.553	0.291	0.359	0.514	0.529
AUTO1	0.397	0.401	0.575	0.522	0.239	0.465	**0.830**	0.239	0.310	0.501	0.600
AUTO2	0.449	0.499	0.531	0.551	0.316	0.554	**0.870**	0.316	0.357	0.558	0.646
AUTO3	0.372	0.401	0.529	0.551	0.279	0.522	**0.864**	0.279	0.357	0.501	0.604
AUTO4	0.435	0.387	0.528	0.508	0.299	0.586	**0.817**	0.299	0.344	0.548	0.632
COMP1	0.296	0.350	0.462	0.383	0.267	0.590	0.553	**0.819**	0.259	0.401	0.542
COMP2	0.447	0.486	0.548	0.556	0.355	0.485	0.654	**0.879**	0.340	0.538	0.645
COMP3	0.388	0.463	0.533	0.472	0.309	0.593	0.651	**0.895**	0.219	0.472	0.562
REL1	0.278	0.145	0.228	0.294	0.163	0.313	0.248	0.163	**0.774**	0.329	0.450
REL2	0.346	0.225	0.246	0.389	0.202	0.279	0.365	0.202	**0.904**	0.428	0.532
REL3	0.413	0.283	0.268	0.409	0.291	0.340	0.359	0.291	**0.903**	0.451	0.537
REL4	0.409	0.368	0.318	0.384	0.264	0.388	0.408	0.264	**0.860**	0.443	0.552
BI1	0.695	0.534	0.573	0.562	0.460	0.504	0.521	0.460	0.352	**0.819**	0.642
BI2	0.697	0.553	0.619	0.585	0.430	0.485	0.480	0.430	0.378	**0.808**	0.610
BI3	0.707	0.584	0.597	0.561	0.505	0.521	0.500	0.505	0.432	**0.831**	0.647
BI4	0.674	0.582	0.598	0.630	0.444	0.507	0.550	0.444	0.421	**0.825**	0.640
AU1	0.557	0.449	0.510	0.502	0.405	0.494	0.580	0.405	0.463	0.639	**0.808**
AU2	0.534	0.451	0.533	0.508	0.353	0.517	0.577	0.353	0.470	0.628	**0.799**
AU3	0.506	0.472	0.533	0.517	0.368	0.491	0.610	0.368	0.487	0.628	**0.814**
AU4	0.488	0.469	0.512	0.542	0.363	0.482	0.600	0.363	0.521	0.597	**0.799**

Structural Model Evaluation

To proceed with the analysis, the structural model was evaluated by computing the coefficient of determination (R^2), SRMR, path coefficients, and effect sizes (Hair et al., 2022), following the validation of the measurement model. The analysis was conducted using Smart-PLS 4.0 software, applying the PLS algorithm with a subsample of 5,000 to compute and present the path coefficients, t-values, and p-values for the structural model, as shown in Table 6.

According to Hair et al. (2022), the coefficient of determination (R^2) values of 0.75, 0.50, and 0.25 are interpreted as indicating substantial, moderate, and weak explanatory power, respectively. In this study, the R^2 values for behavioral intention and actual use were 0.831 and 0.771, respectively (refer to Figure 2), showing a substantial level of explanatory power for both constructs. To evaluate the model fit, the Standardized Root Mean Square Residual (SRMR) was calculated. The SRMR value of 0.050 in this study indicates that the proposed model fits the data well and is considered acceptable.

The structural model assessment results, presented in Table 6, indicate that 12 out of the 13 proposed hypotheses were supported. Specifically, PE ($\beta = 0.469$, $t = 14.770$, $p = 0.000$), EE ($\beta = 0.087$, $t = 3.165$, $p = 0.002$), SI ($\beta = 0.120$, $t = 3.488$, $p = 0.000$), FC ($\beta = 0.095$, $t = 3.017$, $p = 0.003$), HM ($\beta = 0.160$, $t = 6.950$, $p = 0.000$), and HT ($\beta = 0.072$, $t = 2.714$, $p = 0.007$) all had significant positive effects on BI, supporting hypotheses H1 through H6. Similarly, AUTO ($\beta = 0.108$, $t = 3.230$, $p = 0.000$) and REL ($\beta = 0.075$, $t = 3.332$, $p = 0.001$) were found to positively impact BI, thereby confirming hypothesis H7 and H11.

In contrast, COMP ($\beta = -0.032$, $t = 1.004$, $p = 0.315$) had no significant effect on BI, resulting in the rejection of hypothesis H8. However, AUTO ($\beta = 0.237$, $t = 6.172$, $p = 0.000$), COMP ($\beta = 0.215$, $t = 5.757$, $p = 0.000$), and REL ($\beta = 0.386$, $t = 8.558$, $p = 0.000$) all showed strong positive effects on AU, confirming hypotheses H9, H10, and H12. Additionally, the relationship between BI and AU was found to be statistically significant ($\beta = 0.386$, $t = 0.789$, $p = 0.000$), thereby supporting hypothesis H13. These results emphasize that PE, motivational factors, and BI play a crucial role in determining AU among EFL students. Both extrinsic (UTAUT2) and intrinsic (SDT) factors jointly shape adoption behavior, indicating that EFL students' intentions effectively translate into actual use of GenAI for English learning.

The effect size (f^2) is used to determine the unique predictive power of each exogenous construct. PE emerges as the strongest predictor of BI, with an effect size of $f^2 = 0.512$. Constructs such as SI ($f^2 = 0.030$), FC ($f^2 = 0.021$), HM ($f^2 = 0.110$), HT ($f^2 = 0.015$), AUTO ($f^2 = 0.025$), EE ($f^2 = 0.021$) and REL ($f^2 = 0.024$) exhibited small effects on BI, indicating their complementary but less substantial roles in shaping behavioral intention. In terms of predicting AU, BI had a large effect ($f^2 = 0.343$), while motivational and related constructs such as REL ($f^2 = 0.208$), AUTO ($f^2 = 0.097$), and COMP ($f^2 = 0.094$) showed small to medium effects. Notably, COMP had a negligible effect on BI ($f^2 = 0.002$), suggesting minimal influence on behavioral intention.

Figure 2

Structural Model Results

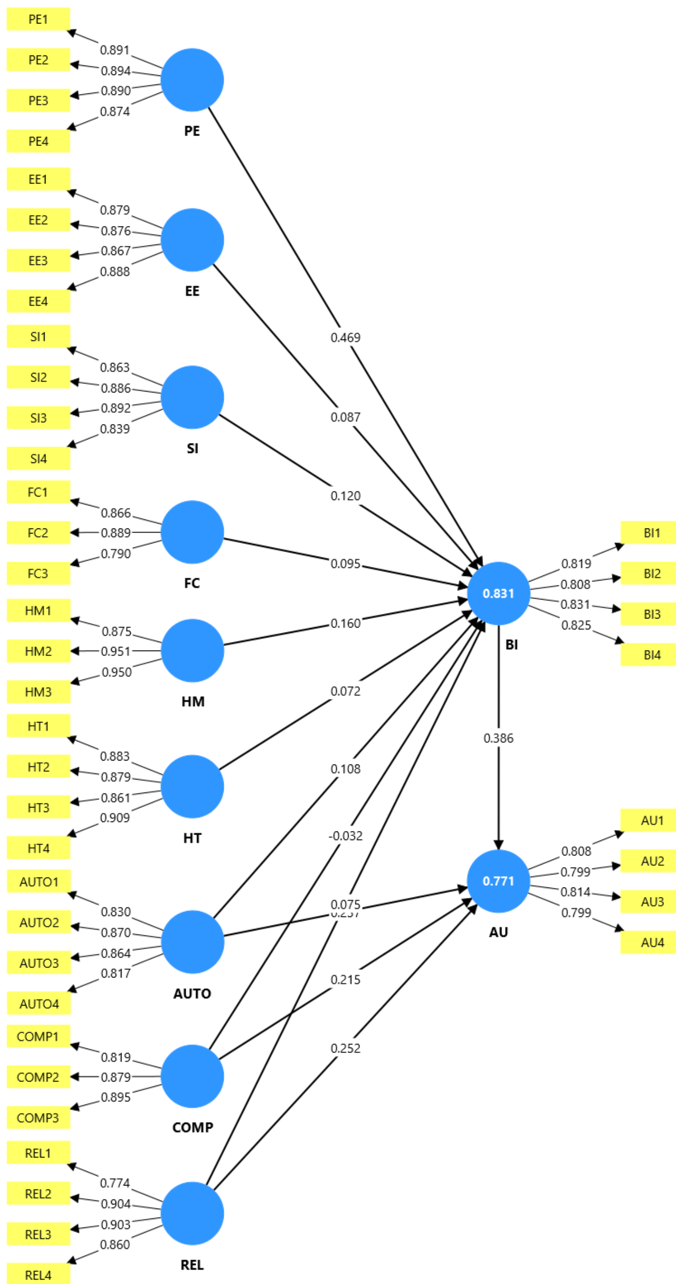


Table 6

Structural Model Assessment

Hypotheses	Path Coefficients	T statistics	p values	f^2	Results
H1: PE → BI	0.469	14.770	0.000	0.512	Yes
H2: EE → BI	0.087	3.165	0.002	0.021	Yes
H3: SI → BI	0.120	3.488	0.000	0.030	Yes
H4: FC → BI	0.095	3.017	0.003	0.021	Yes
H5: HM → BI	0.160	6.950	0.000	0.110	Yes
H6: HT → BI	0.072	2.714	0.007	0.015	Yes
H7: AUTO → BI	0.108	3.230	0.001	0.025	Yes
H8: AUTO → AU	0.237	6.172	0.000	0.097	Yes
H9: COMP → BI	-0.032	1.004	0.315	0.002	No
H10: COMP → AU	0.215	5.757	0.000	0.094	Yes
H11: REL → BI	0.075	3.332	0.001	0.024	Yes
H12: REL → AU	0.252	8.558	0.000	0.208	Yes
H13: BI → AU	0.386	9.789	0.000	0.343	Yes

This study also implemented an out-of-sample prediction analysis (see Table 7) to evaluate the model's predictive performance, focusing on Q^2predict, RMSE, and MAE values for the endogenous constructs (AU, BI). To assess predictive accuracy, we applied the PLSpredict method, as recommended by Shmueli et al. (2019), which utilizes a 10-fold cross-validation procedure to generate predictions at both the item and construct levels. According to Shmueli et al. (2019), strong predictive power is indicated when the prediction errors (RMSE and MAE) from the PLS-SEM model are consistently lower than those produced by the linear model (LM) and the naïve benchmark (IA). The results indicated that all indicators (AU1 to AU4 and BI1 to BI4) had positive Q^2predict values (ranging from 0.469 to 0.579), signifying predictive relevance. Furthermore, the PLS-SEM model yielded lower RMSE and MAE values than the LM and IA benchmarks for every indicator, confirming superior predictive accuracy. Based on these results, all indicators were categorized as having strong predictive power.

Table 7

Model's Predictive Power

Indicators	Q^2predict	PLS-SEM_		LM		IA	
		RMSE	MAE	RMSE	MAE	RMSE	MAE
AU_1	0.469	0.620	0.475	0.646	0.487	0.851	0.738
AU_2	0.473	0.622	0.472	0.644	0.492	0.856	0.749
AU_3	0.494	0.606	0.461	0.635	0.494	0.853	0.742
AU_4	0.488	0.609	0.464	0.632	0.489	0.851	0.738
BI_1	0.541	0.636	0.483	0.657	0.499	0.938	0.791
BI_2	0.543	0.605	0.469	0.635	0.481	0.896	0.763

BI_3	0.579	0.609	0.462	0.631	0.489	0.939	0.793
BI_4	0.553	0.606	0.463	0.627	0.485	0.906	0.767

Discussion

This study contributes to educational technology study by integrating UTAUT2 and SDT to investigate the factors influencing Indonesian EFL students' BI and AU of GenAI for English learning. Unlike prior studies that examine external or internal factors in isolation, this study presents a comprehensive framework that unifies both technological perceptions and psychological motivations, thereby offering a more holistic and theoretically grounded understanding of GenAI adoption in EFL education. The results show that integrating UTAUT2 and SDT significantly improves the prediction of both BI and AU of GenAI among Indonesian EFL students, thereby advancing theoretical development of technology adoption in educational contexts.

The result reveals that PE emerged as the strongest predictor of BI, consistent with earlier results that highlight PE as a key driver in students' willingness to utilize tools such as ChatGPT and large language models for vocabulary acquisition (Budhathoki et al., 2024; Grassini et al., 2024; Zheng et al., 2024; Wang & Reynolds, 2024). This strong link suggests that EFL students are more inclined to adopt GenAI tools when they perceive them as beneficial to academic performance, particularly for language-related tasks such as writing, translating, and comprehending complex texts. GenAI's ability to deliver real-time support and feedback appears to boost students' motivation by making learning more efficient and effective.

EE also significantly influenced EFL students' BI to use GenAI for English language learning, although with a small effect size. The significance of EE in shaping students' intention to adopt technology has been acknowledged in prior studies (Meet et al., 2022; Strzelecki, 2024; Wang & Reynolds, 2024). The weak relationship may be explained by the fact that EFL students, especially those learning English, tend to adapt quickly to new technologies and require minimal effort to learn how to use tools like GenAI (Strzelecki, 2024). This suggests that EFL students likely have enough prior experience with technology, so the perceived ease of use is less influential in shaping their intention to adopt GenAI.

SI was found to positively and significantly affect BI, supporting prior study (Arthur et al., 2023; Strzelecki, 2024; Zacharis & Nikolopoulou, 2022; Yakubu et al., 2025; Zhao et al., 2025; Zheng et al., 2024; 2025). This s suggests that peer, teacher, and academic influencer engagement with GenAI positively shapes students' own intention to adopt the technology. When students observe those around them actively using GenAI tools, their likelihood of adoption increases, underscoring the social nature of learning and technology diffusion. This highlights the importance of SI in encouraging the use of GenAI for language learning, as EFL students are more likely to embrace the technology when they see its adoption by others.

FC was identified as a significant factor influencing EFL students' BI to use GenAI for English learning, consistent with previous studies (Alowayr & Al-Azawei, 2021; Al-Adwan & Al-Debei, 2024; Arthur et al., 2023, 2025; Zheng et al., 2025). However, the relationship was weak, with a small effect size, indicating that while access to resources and technical support remains relevant, it is not a major determinant of students' intention to adopt the tool. This limited influence may reflect students' high level of digital readiness, as many EFL learners are already accustomed to using technology for academic purposes. As digital natives, they tend to engage in self-directed learning and can navigate GenAI tools independently, reducing dependence on institutional support. Consequently, their intention to adopt GenAI appears to be shaped more by the perceived usefulness and ease of use of the tool than by external resources.

HM had a significant but moderate effect on BI. This indicates while enjoyment is a factor, it is not the primary driver behind students' intention to use GenAI for English learning. This result is supported by previous research (Abdi et al., 2025; Tan et al., 2024; Zheng et al., 2025; Zhao et al., 2025), which highlights the importance of HM in technology acceptance across various fields, such as ChatGPT, e-learning, and translation technology. Moreover, HT was found to have a significant but minimal effect on the BI to use GenAI for English learning. This result is consistent with previous studies that have highlighted the role of HT in technology adoption across various fields, including ChatGPT (Grassini et al., 2024; Habibi et al., 2023; Salifu et al., 2024; Strzelecki, 2024; Zheng et al., 2024) e-learning (Zacharis & Nikolopoulou, 2022; Zheng et al., 2025), and translation technology (Zhao et al., 2025). The minimal effect suggests that EFL students may still be in the early stages of exploring GenAI tools and have yet to form regular usage patterns. Consequently, their intention to adopt GenAI appears to be driven more by perceived usefulness and ease of use than by established habits.

Within the SDT framework, AUTO and REL emerged as significant predictors of BI. These results are in line with previous studies that emphasize the role of self-direction and social connection in motivation (Alharbi, 2023; Osei et al., 2022; Wang & Reynolds, 2024). When EFL students feel in control of their learning and experience supportive peer interactions, their intention to engage with new tools increases. Interestingly, COMP did not significantly influence BI, possibly because students already possess a foundational level of technological skill, reducing its influence on their decision to adopt new tools. However, earlier studies (e.g., Han & Chen, 2024; Şahin & Yildiz, 2024) emphasized COMP as a crucial element in forecasting the intention to embrace technology. This discrepancy could reflect the rapid evolution of technology, where newer tools like GenAI emphasize simplicity and user-centered design such as adaptive interfaces, personalized feedback, and automated corrections, thus minimizing perceived complexity. Although COMP did not affect BI, all three components of SDT significantly predicted AU of GenAI for English learning among EFL students, consistent with Osei et al. (2022). REL, in particular, had a strong impact on AU, suggesting that social connectedness and supportive interactions play a pivotal role in sustaining students' engagement with GenAI tools.

BI strongly predicted AU, showing that EFL students who plan to use GenAI are highly likely to apply it actively in English learning. The strong linkage may result from GenAI's immediate feedback, accessibility, and relevance to EFL students' learning goals, which make it easier for students to translate their motivation into consistent use. This result is consistent with prior studies examining various educational technologies, including mobile phones (Nikolopoulou et al., 2020), e-learning (Osei et al., 2022), ChatGPT (Alharbi, 2023; Amin et al., 2025; Budhathoki et al., 2024; Strzelecki, 2024; Zheng et al., 2024), and translation tools (Zhao et al., 2025), where BI consistently predicted AU. The results underscore the importance of strengthening EFL students' BI to support the effective and sustained integration of GenAI in English learning.

Implications

This study offers practical, pedagogical, and policy implications for integrating GenAI for English learning, particularly in under-resourced contexts. From a practical perspective, since PE was identified as the strongest factor influencing EFL students' BI to use GenAI for English learning, educators should prioritize activities that clearly demonstrate how GenAI can enhance English learning outcomes. For example, educators can use a single shared device to model AI-assisted improvements in vocabulary choice, grammatical accuracy, and paragraph organization. Short demonstrations comparing students' initial drafts with revised versions produced with GenAI can help learners immediately recognize the added value of the technology, even when individual device access is limited. Moreover, the strong effect of BI on AU highlights the importance of embedding GenAI into routine English learning activities such as weekly writing, reading, or speaking tasks rather than using it only occasionally. Collaborative tasks involving one shared smartphone, including generating ideas, evaluating AI feedback, or identifying linguistic errors, allow students to build consistent habits of GenAI use while ensuring equitable participation in resource-constrained classrooms.

Pedagogically, educators should emphasize the observable language-learning benefits of GenAI for EFL students, as these perceptions strongly shape their intention to use the technology for English learning. Learning activities therefore need to be structured in ways that foster autonomy and peer support, reflecting the significant roles these motivational and social factors play in sustaining GenAI-mediated engagement. Encouraging students to work independently with GenAI, for example to generate ideas, analyze linguistic patterns, or revise sentences, while complementing these tasks with guided group discussions and collaborative evaluations of AI-generated outputs, can deepen critical thinking, metalinguistic awareness, and interpersonal interaction. Since enjoyment also contributes meaningfully to students' behavioral intention, activities that incorporate GenAI should be designed to be engaging and anxiety-reducing, helping students develop positive emotional experiences that support continued use. Although technical competence does not influence intention, its strong effect on actual use highlights the value of scaffolded training, gradual practice, and timely feedback to strengthen students' confidence in applying GenAI tools for writing, reading, and language analysis. These pedagogical strategies can promote meaningful, sustained, and ethically responsible integration of GenAI into English learning, particularly in educational environments with limited digital resources.

At the policy level, universities should develop institutional guidelines that reflect these behavioral determinants by promoting ethical, transparent, and pedagogically meaningful uses of GenAI in coursework and assessment. The significant role of social and environmental conditions in shaping intention indicates the need for improved digital infrastructure, AI-enabled learning spaces, and device-loan programmed to ensure equitable access. Policies should also incorporate responsible AI literacy programmed that help students understand the limitations, potential biases, and ethical considerations of GenAI, ensuring that increased autonomy and peer-supported learning are accompanied by informed decision-making. Professional development for educators and ongoing monitoring of GenAI integration are essential to ensure that institutional strategies evolve in alignment with students' needs and emerging technological developments.

Conclusion

This study investigated the key factors influencing EFL students' behavioral intention and actual use of GenAI tools for English learning in Indonesian universities, using an integrated model of UTAUT2 and SDT. By surveying 462 undergraduate students and applying PLS-SEM, the research revealed that both external technological perceptions (PE, EE, SI, FC, HM, and HT) and internal motivational drivers (AUTO and REL) significantly impacted EFL students' BI to adopt GenAI, with PE exerting the strongest effect. Importantly, BI was found to be the most significant predictor of AU, while motivational constructs such as AUTO, COMP, and REL also demonstrated significant direct effects on AU. This dual-theoretical approach provides a holistic understanding that encompasses both the functional and motivational dynamics of GenAI adoption in EFL education. As artificial intelligence becomes more integrated into digital learning, these results highlight the necessity of aligning technological design and pedagogical strategies with students' psychological needs. By integrating UTAUT2 and SDT, this study provides a more holistic model for understanding BI and AU of GenAI tools in online language learning, thereby advancing both technology-adoption and motivational frameworks.

Limitation and Future Research

Despite its contributions, this study has several limitations that suggest directions for future research. First, the use of convenience sampling, where participants were selected based on availability rather than through random selection, may limit the generalizability of the findings. Future studies should consider using probability-based sampling methods to enhance representativeness and reduce selection bias. Second, reliance on self-reported measures introduces the possibility of bias due to participants' subjective perceptions. To strengthen the validity of results, future research could incorporate mixed-method approaches, such as interviews or classroom observations, to cross-validate self-reported data. Third, the cross-sectional design restricts the ability to infer causality, as it captures responses at a single point in time. Employing longitudinal or experimental designs in future studies could help track changes over time and better establish causal relationships between variables. Fourth, although the overall participation rate was high, the possibility of non-response bias remains, as individuals who did not participate might differ in important ways from those who did. Future research should address this by implementing follow-up strategies or conducting non-response analyses to improve sample representativeness. Fifth, the study focused exclusively on university students in Indonesia, capturing only a narrow segment of the education system. Expanding future research to include secondary and higher secondary students could provide more comprehensive insights. Sixth, the sample was drawn from only three private universities in Central Java, West Java, and South Sulawesi. Including public universities and institutions from other regions would offer a more complete understanding of GenAI adoption across Indonesia's diverse educational contexts. Lastly, the majority of participants were from English education departments, with minimal representation from other academic disciplines. Future research should aim for a broader disciplinary scope to explore potential differences in GenAI usage and perceptions across various academic fields.

Declarations

Disclosure Statement

The authors declare no conflicts of interest related to this study.

Ethics Considerations

This study was reviewed and approved by the Research Ethics Committee of Universitas Muria Kudus. All participants provided informed consent prior to participation, and their responses were anonymized to protect confidentiality.

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Appendix

Questionnaire Measures for Students

Construct	Item	Measures
Performance Expectancy	PE1	I find GenAI tools helpful for enhancing my English learning.
	PE2	Using GenAI increases my ability to achieve important goals in learning English.
	PE3	GenAI tools help me learn English more effectively and efficiently.
	PE4	GenAI tools make it easier for me to complete English learning tasks quickly.
Effort Expectancy	EE1	I find it easy to learn how to use GenAI tools for my English studies.
	EE2	My interaction with GenAI tools during English learning is clear and easy to understand.
	EE3	I find it easy to use GenAI tools to support my English learning needs.
	EE4	It is easy for me to become skilled at using GenAI tools to improve my English.
Social Influence	SI1	My lecturers and classmates believe that I should use GenAI tools for my English studies.
	SI2	My instructors and peers think that it is beneficial for me to use GenAI to enhance my English learning.
	SI3	My mentors and friends recommend that I use GenAI tools to improve my English skills.
	SI4	My university encourages and supports the use of GenAI tools to enhance my English learning.
Facilitating Conditions	FC1	I have the necessary tools and resources to use GenAI for learning English.
	FC2	I possess the knowledge and skills needed to use GenAI tools effectively in my English studies.
	FC3	I can easily get support from others if I encounter difficulties using GenAI tools for English learning.
Hedonic Motivation	HM1	Using GenAI tools makes learning English enjoyable for me.
	HM2	I feel satisfied and engaged when I use GenAI tools for learning English.
	HM3	GenAI tools make my English learning experience fun and interesting.
Habit	HT1	Using GenAI tools has become a regular part of how I learn English.

	HT2	I rely heavily on GenAI tools in my English learning process.
	HT3	I feel the need to use GenAI tools whenever I study English.
	HT4	Using GenAI tools feels instinctive when it comes to learning English.
Autonomy	AUTO1	I feel that I have significant control over how I use GenAI tools in my English learning.
	AUTO2	I am free to share my thoughts and preferences regarding the use of GenAI tools in my English studies.
	AUTO3	My perspectives and feelings about using GenAI tools are acknowledged in the learning process.
	AUTO4	I feel I can use GenAI tools in ways that suit my personal learning style and needs.
Competence	COMP1	My classmates think I'm good at using GenAI tools for learning English.
	COMP2	I often get compliments from classmates on how well I use GenAI tools in my English studies.
	COMP3	Most days, I feel a sense of achievement when I use GenAI tools to support my English learning.
Relatedness	REL1	I feel supported by my classmates when I use GenAI for English learning.
	REL2	My classmates encourage me to use GenAI tools in English class.
	REL3	I feel connected to my classmates through using GenAI.
	REL4	I enjoy collaborating with classmates when we use GenAI for language tasks.
Behavioral Intention	BI1	I intend to continue using GenAI tools for English learning in the future.
	BI2	I will always try to use GenAI tools in my English studies.
	BI3	I plan to continue to use GenAI tools frequently for my English learning.
	BI4	I intent to use GenAI tools to help complete my English learning task.
Actual Use	AU1	I consider myself a regular user of GenAI tools.
	AU2	I prefer to use GenAI tools when available.
	AU3	I complete most of my English learning tasks using GenAI tools.
	AU4	I tend to use GenAI tools whenever possible.