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Investigating EFL Students' Adoption of Generative Artificial Intelligence for English Learning through UTAUT2 and SDT: A Mixed-Methods Study

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Abstract

Generative artificial intelligence (GenAI) continues to transform English learning, but the influence of psychological needs on maintaining students' engagement remains insufficiently studied. Therefore, the study used the unified theory of acceptance and use of technology (UTAUT2) and self-determination theory (SDT) within an explanatory sequential mixed-methods design to explore the factors affecting English as a foreign language (EFL) students' intention and actual use of GenAI for English learning. Quantitative data were gathered from 462 EFL students and analyzed with PLS-SEM in SmartPLS 4, while the qualitative phase included 15 semi-structured interviews analyzed thematically. The findings showed that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit significantly influenced EFL students' intention to use GenAI for English learning. Although SDT components-perceived autonomy, perceived competence, and perceived relatedness-did not significantly impact behavioral intention, both the SDT components and behavioral intention predicted actual usage. Thematic analysis of the interview data identified five key themes: perceived performance gains, ease of use and habitual use, social influence, motivational experiences, and supportive learning environments and efficiency. These findings offer valuable insights for educators, curriculum developers, and educational institutions aiming to promote the effective integration of GenAI into English learning.

Keywords: EFL students, English learning, Generative Artificial Intelligence, SDT, UTAUT2

Generative artificial intelligence (GenAI) is increasingly recognized as a transformative innovation in English as a foreign language (EFL) education, creating new opportunities for language learning and practice. Tools such as ChatGPT and other large language model (LLM)-based platforms can generate human-like responses, translate languages, summarize information, and support writing and learning tasks (Aydın & Karaarslan, 2023; Cipta et al., 2025; Mustofa et al., 2025; Orrù et al., 2023). These tools provide instant feedback on writing, facilitate interactive conversations that enhance speaking skills, and simplify complex texts to improve reading comprehension (Assidik et al., 2025; Jegede, 2024). Empirical studies further highlight GenAI's effectiveness in EFL education, showing that it improves vocabulary, grammar, and writing performance (Lee et al., 2024; Liu et al., 2025; Sarwanti et al., 2024), develops speaking through real-time dialogue and grammar correction (Du & Daniel, 2024; Yang, 2025), fosters fluency and confidence through AI-powered chatbots (Du & Daniel, 2024), and enhances reading comprehension (Allehyani et al., 2025; Chea & Xiao, 2024; Hsiao & Chang, 2024). Moreover, GenAI contributes to the development of EFL students' critical thinking by promoting critical reading, strengthening logical reasoning, and supporting reflective learning (Liu et al., 2025). Its adaptability further strengthens these benefits by tailoring tasks and recommendations to students' proficiency, preferences, and learning needs (Carlson et al., 2023; Kasneci et al., 2023), positioning it not only as a digital resource but also as a virtual tutor that provides individualized guidance.

Despite the increasing use of GenAI in language education, concerns arise about excessive reliance, accuracy, academic dishonesty, and technical problems (Ambarita & Nurrahmatullah, 2024; Baskara et al., 2023; Bekou et al., 2024; Hidayat, 2025; Maulida & Prasetyarini, 2024; Sarwanti et al., 2024). Such challenges are also evident in Indonesia, where many EFL students rely on GenAI tools for tasks ranging from minor corrections to complex assignments (Yuliani et al., 2024). This dependence can hinder the development of essential language skills, as students bypass the critical thinking and problem-solving processes necessary for effective mastery. Zhai et al. (2024) further warn that overuse may weaken independent thinking, foster plagiarism, and constrain creativity. These issues suggest that students' adoption of GenAI is shaped by their perception of whether its benefits outweigh its drawbacks, underscoring the need to investigate factors influencing its acceptance and use in higher education. While research on GenAI in higher education is expanding, most studies have focused on structural and technological factors (Grassini et al., 2024; Moradi, 2025; Strzelecki, 2024), with limited attention to the role of psychological needs in sustaining EFL students' use of such tools. Although some recent studies (e.g., Cortez et al., 2024; Wang & Reynolds, 2024; Zheng et al., 2024) have begun to address this dimension, the emphasis remains primarily on behavioral intention. However, as Osei et al. (2022) highlight, behavioral intention alone may not be a reliable predictor of actual use, especially for self-directed technologies. Therefore, further research needs to include actual use as a central outcome variable, both to capture sustained engagement and to determine whether initial intentions are realized in regular practice. To address this gap, the present study examines the factors influencing EFL students' behavioral intention and actual use of GenAI for English learning, focusing on technological determinants and motivational needs.

This study adopts a theoretical framework grounded in the unified theory of acceptance and use of technology 2 (UTAUT2) and self-determination theory (SDT). UTAUT2 has frequently been employed to investigate students' acceptance of new technologies and to explain how behavioral intention and actual use are formed (Venkatesh et al., 2012). Since the purpose of this study is to examine EFL students' adoption of GenAI tools for English learning, UTAUT2 was selected as the theoretical foundation for analyzing the technological and behavioral factors that influence usage. However, students' engagement with GenAI is not determined solely by external technological factors, it is also shaped by their internal motivational processes. SDT provides a complementary perspective by emphasizing the psychological needs that sustain persistence, engagement, and self-directed learning (Deci & Ryan, 2000). Therefore, integrating UTAUT2 and SDT provides a comprehensive account of both extrinsic and intrinsic determinants of EFL students' behavioral intention and actual use of GenAI for English learning. This study utilizes an explanatory sequential mixed-methods design. The quantitative phase tested the integrated model to identify technological and motivational determinants of EFL students' behavioral intention and actual use of GenAI, while the qualitative phase explored their lived experiences to explain the observed patterns. This approach validates theoretical insights through empirical testing and grounds them in real learning contexts. Theoretically, the study extends technology acceptance research by combining structural models with motivational perspectives, while practically, it offers valuable insights for educators, curriculum developers, and educational institutions to support the sustained and effective use of GenAI for English learning.

Literature Review

UTAUT2

UTAUT, proposed by Venkatesh et al. (2003), has been widely applied as a theoretical framework to explain how individuals adopt new technologies in educational, organizational, and consumer contexts. This model integrates elements from eight earlier theories, including the theory of reasoned action, information diffusion theory, and the technology acceptance model. UTAUT identifies four core determinants: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) that influence behavioral intention (BI) and actual use (AU). To enhance its relevance for consumer settings, Venkatesh et al. (2012) extended the framework into UTAUT2, which introduced hedonic motivation (HM), price value (PV), and habit (HT). This extended model substantially enhanced explanatory power, accounting for up to 74% of behavioral intention and 52% in actual use (Venkatesh et al., 2012), thereby demonstrating its robustness as a model for predicting technology adoption across varied contexts.

UTAUT2 has been widely applied to investigate technology acceptance across various domains. For example, Foroughi et al. (2024) applied UTAUT2 to examine Malaysian students' intention to use ChatGPT for educational purposes and found that performance expectancy emerged as the strongest predictor on behavioral intention. Similarly, Grassini et al. (2024) employed UTAUT2 to investigated determinants of ChatGPT adoption among Norwegian university students and reported that performance expectancy was the most influential predictor of behavioral intention, followed by habit. Beyond behavioral intention, recent studies have also highlighted actual use as a critical outcome of adoption. Nikolopoulou et al. (2020) studied students' adoption of mobile phones for learning through UTAUT2 and found that social influence, hedonic motivation, and habit significantly predicted behavioral intention, with habit exerting the strongest effect, while behavioral intention, facilitating conditions, and habit significantly influenced actual use. Arthur et al. (2024) also used UTAUT2 to examine students' intention and actual usage of ChatGPT, showing that Hedonic motivation, performance expectancy, effort expectancy, and social influence significantly predicted behavioral intention, whereas behavioral intention and facilitating conditions determined actual use. In the EFL context, Zheng et al. (2024) integrated UTAUT2 to analyze EFL students' adoption of GenAI for English learning and found that performance expectancy, effort expectancy, social influence, hedonic motivation, and habit predicted behavioral intention, while behavioral intention and habit significantly influenced actual use. Likewise, Moradi (2025) investigated Chinese university students' acceptance of ChatGPT using UTAUT2 and demonstrated that performance expectancy, social influence, and habit were significant predictors of behavioral intention, while facilitating conditions and habit determined actual use. Collectively, these studies demonstrate the robust explanatory power of UTAUT2 in predicting both behavioral intention and actual use of technology across diverse educational contexts.

SDT

SDT, developed by Deci and Ryan (2004), provides a framework for understanding human motivation by distinguishing among its different forms (Vallerand, 1997). The theory has been widely applied in educational and organizational contexts, emphasizing three fundamental psychological needs: perceived autonomy (PA), perceived competence (PC), and perceived relatedness (PR) (Ryan & Deci, 2017). When these needs are fulfilled, individuals tend to develop stronger intrinsic motivation, which has been identified as the most effective and enduring source of sustained effort, improved performance, and long-term achievement (Deci & Ryan, 2013).

To strengthen its explanatory power, SDT has frequently been integrated with technology acceptance models, particularly in educational settings. For example, it has been applied to examine students' acceptance of mobile learning in Saudi Arabia (Alowayr & Al-Azawei, 2021), e-learning adoption among tertiary students in Ghana (Osei et al., 2022), the acceptance and use of massive open online courses by EFL learners (Hsu, 2023), engagement with large language models among Chinese university students (Wang & Reynolds, 2024), the acceptance of mobile-assisted vocabulary learning applications among EFL students (Han & Chen, 2024), and the adoption of digital literacy among students (Peng & Qiu, 2025).

Zheng et al. (2024) further explored motivational factors affecting Chinese EFL students' acceptance of GenAI. Their model conceptualized the three psychological needs of SDT as a single higher-order construct of motivation mediating users' behavioral intention and actual use. The present study differs from earlier work in both its conceptualization and analytical design. In this study, SDT is operationalized through three distinct constructs: perceived autonomy, perceived competence, and perceived relatedness. These constructs are modeled as direct predictors of both behavioral intention and actual use. This design provides a more nuanced understanding of how basic psychological needs contribute not only to EFL students' intention but also to their actual use of GenAI in English learning.

Although prior studies have integrated technology acceptance models such as UTAUT and UTAUT2 with motivational theories like SDT, most have focused primarily on behavioral intention while giving limited attention to actual use. The present study therefore combines UTAUT2 and SDT to provide a more comprehensive framework for examining both behavioral intention and actual use of GenAI among EFL students. By integrating structural, contextual, and motivational dimensions, this theoretical model not only advances the understanding of technology acceptance but also offers practical insights for promoting the effective and sustainable use of GenAI in EFL education.

Research Model and Hypothesis Development

This study adopts UTAUT2 and SDT as the theoretical frameworks to examine the factors affecting EFL students' behavioral intention and actual use of GenAI for English learning. One standard variable in such models "Price value" has been excluded from our UTAUT2 framework. Although price value has been shown to play a critical role in consumer adoption contexts by capturing the cost–benefit trade-off of technology use (Venkatesh et al., 2012), its relevance diminishes in educational settings where technologies are often freely available. Most GenAI tools adopted by EFL students, including ChatGPT, Grammarly, Quillbot, and Gemini, can be accessed without cost. Consequently, price value does not provide meaningful differentiation among users and is unlikely to exert any significant effect on behavioral intention. Accordingly, six UTAUT2 constructs were employed to examine the factors influencing EFL students' behavioral intention to adopt GenAI in English learning. The initial research model, depicted in Figure 1, serves as the foundation for this investigation. Subsequent sections will provide a more detailed analysis of the hypothesized relationship within the model.

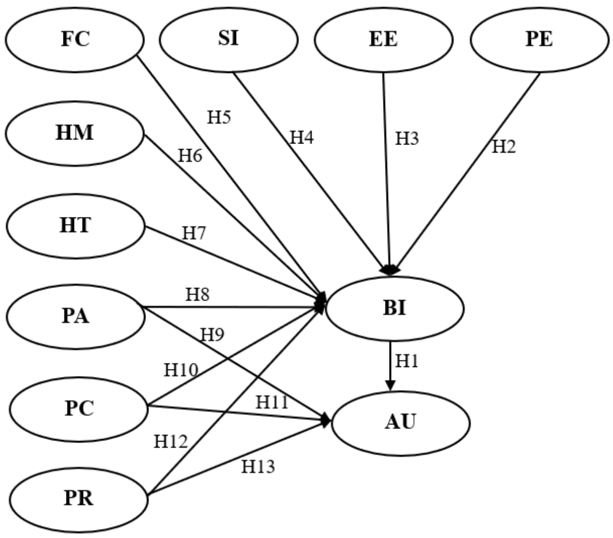

Figure 1. Proposed Framework

Behavioral Intention and Actual Use

Behavioral intention (BI) refers to an individual's intention to adopt and use a particular technology, whereas actual use (AU) refers to the real-world implementation of that intention (Venkatesh et al., 2012). In this study, behavioral intention reflects the extent to which students plan to use GenAI for English learning tasks, while actual use refers to the degree to which students actually employ GenAI tools in their learning process. Following UTAUT2, behavioral intention is expected to have a direct effect on actual use (Alharbi, 2023; Amin et al., 2024; Budhathoki et al., 2024; Strzelecki, 2024; Surachmi et al., 2025; Zheng et al., 2024). Accordingly, this study puts forward the following hypothesis:

H1: Behavioral intention directly and positively predicts EFL students' actual use to use GenAI for English learning.

Performance Expectancy

Performance expectancy (PE) refers to an individual's perception of how well a technological tool can improve their academic performance (Venkatesh et al., 2012). In this study, performance expectancy represents EFL students' perception that using GenAI tools will facilitate their English learning and contribute to better academic performance. Recent studies have consistently shown that performance expectancy is a significant predictor of behavioral intention to adopt GenAI like ChatGPT in educational settings (Amin et al., 2024; Budhathoki et al., 2024; Lai et al., 2024; Moradi, 2025; Strzelecki, 2024; Surachmi et al., 2025; Xu & Thien, 2025; Yakubu et al., 2025) Accordingly, the following hypothesis is proposed:

H2: Performance expectancy directly and positively predicts EFL students' behavioral intention to use GenAI for English learning.

Effort Expectancy

Effort expectancy (EE) describes the level of ease users associate with learning and using a technology, particularly the degree to which it requires minimal mental or physical effort (Venkatesh et al., 2003). In this study, effort expectancy represents the degree to which EFL students believe that engaging with GenAI tools for English learning is simple, intuitive, and requires minimal effort. Effort expectancy has been widely recognized as a significant predictor of individual' behavioral intention to adopt technological innovations (Lai et al., 2024; Strzelecki, 2024; Surachmi et al., 2025; Wang & Reynolds, 2024; Xu & Thien, 2025; Yakubu et al., 2025). In line with prior research, this study proposes the following hypothesis:

H3: Effort expectancy directly and positively predicts EFL students' behavioral intention to use GenAI for English learning.

Social Influence

Social influence (SI) refers to how much individuals feel that important people around them affect their decision to adopt new technology (Venkatesh et al., 2012). In this study, it focuses on how EFL students are influenced by peers, teachers, and others when deciding to use GenAI for English learning. Empirical studies have shown that social influence is a significant determinant of behavioral intention to adopt technology (Amin et al., 2024; Arthur et al., 2024; Budhathoki et al., 2024; Strzelecki, 2024; Surachmi et al., 2025; Wang & Reynolds, 2024; Xu & Thien, 2025; Yakubu et al., 2025; Zheng et al., 2024). Accordingly, this study puts forward the following hypothesis:

H4: Social influence directly and positively predicts EFL students' behavioral intention to use GenAI for English learning.

Facilitating Conditions

Facilitating conditions (FC) encompass the perception that the necessary technical resources, infrastructure, and support are available for successful technology use (Arthur et al., 2024; Venkatesh et al., 2003). In this study, facilitating conditions pertain to EFL students' views on whether they have sufficient access to what is needed to utilize GenAI for English learning. Prior research has shown that facilitating conditions positively influence behavioral intention (Alharbi, 2023; Alowayr & Al-Azawei, 2021; Arthur et al., 2024; Surachmi et al., 2025; Zheng et al., 2024). Therefore, the following hypothesis is put forward:

H5: Facilitating conditions directly and positively predict EFL students' behavioral intention to use GenAI for English learning.

Hedonic Motivation

Hedonic motivation (HM), as defined by Venkatesh et al. (2012), refers to the extent to which individuals are driven to use new technology for the pleasure or excitement it provides. In this study, hedonic motivation describes the enjoyment EFL students feel when using GenAI for English learning. Previous research has found hedonic motivation to be a significant predictor of technology adoption (Foroughi et al., 2024; Strzelecki, 2024; Surachmi et al., 2025; Zheng et al., 2024). Therefore, the following hypothesis is proposed:

H6: Hedonic motivation directly and positively predicts EFL students' behavioral intention to use GenAI for English learning.

Habit

Habit (HT) is defined as the extent to which technology use becomes automatic and embedded in an individual's daily life (Venkatesh et al., 2012). In this study, habit is defined as the extent to which EFL university students have consistently used GenAI tools such as ChatGPT or similar platforms as part of their English learning routines, including activities like vocabulary building, writing practice, or grammar correction. As noted by Venkatesh et al. (2012), habit serves as a powerful predictor of both behavioral intention and actual use. However, recent studies have further confirmed that habit significantly shapes students' behavioral intention to use GenAI (Grassini et al., 2024; Salifu et al., 2024; Strzelecki, 2024; Surachmi et al., 2025; Zheng et al., 2024). Accordingly, the following hypothesis is proposed:

H7: Habit directly and positively predicts EFL students' behavioral intention to use GenAI for English learning.

Perceived Autonomy

Perceived autonomy (PA), as described by Ryan and Deci (2020), refers to the desire and ability to self-direct one's own actions. In this study, perceived autonomy relates to EFL students' sense of having control and personal choice in using GenAI tools for English learning. Prior research highlights perceived autonomy as a key determinant of behavioral intention toward technology adoption (Alharbi, 2023; Alowayr & Al-Azawei, 2021; Cortez et al., 2024; Raman et al., 2022; Şahin, 2025; Surachmi et al., 2025; Wang & Reynolds, 2024). Moreover, perceived autonomy has also been shown to influence actual use of technology (Osei et al., 2022; Surachmi et al., 2025). Thus, the following hypotheses are presented:

H8: Perceived autonomy directly and positively predicts EFL students' behavioral intention to use GenAI for English learning.

H9: Perceived autonomy directly and positively predicts EFL students' actual use to use GenAI for English learning.

Perceived Competence

Performance competence (PC) refers to the assurance individuals have in their ability to successfully perform a given task (Deci & Ryan, 1985). In this study, performance competence reflects students' self-assurance in effectively using GenAI tools for English learning. Research has identified performance competence as a key factor influencing both behavioral intention (Alharbi, 2023; Osei et al., 2022; Raman et al., 2022; Şahin & Yıldız, 2024; Wang & Reynolds, 2024) and actual use (Osei et al., 2022; Surachmi et al., 2025) Thus, the study formulates the following hypotheses:

H10: Perceived competence directly and positively predicts EFL students' behavioral intention to use GenAI for English learning.

H11: Perceived competence directly and positively predicts EFL students' actual use to use GenAI for English learning.

Perceived Relatedness

Perceived relatedness (PR) is defined as the innate need to feel connected to others and to experience a sense of belonging (Ryan & Deci, 2020). In the present study, perceived relatedness pertains to how much EFL students feel socially integrated within their learning context, which may affect their inclination to use GenAI tools. Studies indicated that perceived relatedness significantly affects behavioral intention to adopt educational technologies (Alharbi, 2023; Cortez et al., 2024; Şahin & Yıldız, 2024; Surachmi et al., 2025), while another study has found that perceived relatedness also affects actual use (Osei et al., 2022; Surachmi et al., 2025). Drawing from these results, the study proposes the following hypotheses:

H12: Perceived relatedness directly and positively predicts EFL students' behavioral intention to use GenAI for English learning.

H13: Perceived relatedness directly and positively predicts EFL students' actual use to use GenAI for English learning.

Methods

This study employed an explanatory sequential mixed-methods design (Creswell, 2011), starting with quantitative data collection and followed by qualitative data collection. This design allows for a deeper understanding of the quantitative findings by examining them further through qualitative methods. It also makes it possible to capture insights and viewpoints that might be overlooked by quantitative analysis. Specifically, quantitative data were initially gathered via an online questionnaire, and these results were then further explored and enriched through follow-up interviews.

Participants

Participants in this study were selected through convenience sampling from undergraduate students enrolled in English departments at four private universities in Central Java and South Sulawesi, Indonesia. As shown in Table 1, the final sample included 462 EFL students. The gender distribution was highly uneven, with 68.2% female and 31.8% male, a trend commonly observed in English departments across Indonesian universities. All participants aged between 17 to 24 years. A total of 61.3% were between 17-20 years old, while 38.7% were between 21 and 24 years old. In terms of study year, most students were in their third year (45.4%), followed by the second year (37.9%), while a smaller proportion were in their fourth year (16.7%).

Table 1. Participants' Information

Category	Number	%
Gender		
Male	147	31.8
Female	315	68.2
Age		
17-20 years	283	61.3
21-24 years	179	38.7
Study year		
Year 2	175	37.9
Year 3	210	45.4
Year 4	77	16.7

Participants for the semi-structured interviews were selected using convenience sampling, which entails choosing participants based on their accessibility and willingness to participate (Etikan et al., 2016). A total of fifteen EFL students agreed to take part in the follow-up interviews. Table 2 presents an overview of participant's characteristics. The sample comprised seven males and eight females, aged between 21 and 25 years, most of whom were in their third or fourth year of study. All participants had prior experience using GenAI tools for

English learning. Among these, ChatGPT emerged as the primary platform, while other applications such as Gemini, Grammarly, QuillBot, Perplexity, Cici AI, DeepSeek, and Blackbox AI were used to complement different learning needs. In terms of intensity, participants reported medium to high levels of GenAI engagement, reflecting varied patterns of adoption across the group. To uphold ethical standards, each participant was fully informed of the study's aims and procedures, provided written consent, and was assigned a pseudonym to protect confidentiality in all research materials.

Table 2. Participants in the Semi-structured Interviews

Pseudo-nym	Gender	Age	Year of Study	GenAI Tool Used	Usage Level
S1	Male	22	3	ChatGPT, Gemini, Blackbox AI, Grammarly	High
S2	Female	22	3	ChatGPT, Gemini, QuillBot	Medium
S3	Female	22	3	ChatGPT, Perplexity, Blackbox AI	High
S4	Female	25	4	ChatGPT, Gemini, Cici AI	High
S5	Female	22	3	ChatGPT, Gemini, Grammarly	High
S6	Male	23	4	ChatGPT, Cici AI	High
S7	Male	22	3	ChatGPT, DeepSeek, Perplexity	High
S8	Female	22	3	ChatGPT, Gemini, Perplexity, Cici AI	High
S9	Male	21	3	ChatGPT, Gemini, Cici AI	High
S10	Male	22	3	ChatGPT, Perplexity	High
S11	Male	21	3	ChatGPT, Gemini	High
S12	Female	22	3	ChatGPT, Perplexity, Cici AI	High
S13	Female	23	4	ChatGPT, Gemini, Perplexity	High
S14	Female	21	3	ChatGPT, Grammarly, QuillBot, Gemini	High
S15	Female	22	4	ChatGPT, Perplexity, Cici AI	Medium

Instrument

The questionnaire was divided into three main sections. The first section gathered demographic information, such as their gender, age, and study year. The second section evaluated students' technology acceptance by drawing on six constructs from the UTAUT2 (Venkatesh et al., 2012): performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit. This section comprised 30 items adapted to the GenAI context in English learning, following Zheng et al. (2024), to examine influences on EFL students' adoption of GenAI. The third section measured motivational factors based on SDT, including perceived autonomy, perceived competence, and perceived relatedness, using 11 items adapted from Hew and Kadir (2016). All items used a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). To ensure linguistic and cultural suitability for Indonesia, the questionnaire was validated through back-translation: one researcher translated the items into Indonesian, and another independently back-translated them into English to verify accuracy.

To ensure the questionnaire's content validity, the instrument was first reviewed by two experts in technology-assisted language learning, who evaluated each item for clarity, relevance, and alignment with the study's objectives and theoretical framework. Their feedback was used to revise and improve the questionnaire. A pilot test was then conducted with 15 undergraduate students whose profiles matched the target population. This stage helped identify unclear wording, confusing instructions, or technical issues in the online survey. Insights from the pilot led to additional refinements, further enhancing the clarity and usability of the instrument. The finalized questionnaire was then distributed via Google Forms, ensuring easy participant access and efficient data collection.

For the qualitative phase, semi-structured interviews were employed to collect qualitative data that enriched and clarified the statistical findings from the survey phase (Creswell & Clark, 2018). This follow-up stage enabled the researcher to capture students' detailed perspectives and experiences that could not be fully represented through quantitative measures. This method was considered the most suitable because it offered both structure through predetermined core questions, and flexibility, through the use of sub-questions and probes to encourage elaboration. The interview guide was developed based on the constructs of UTAUT2 and SDT, allowing participants to elaborate on their experiences while ensuring alignment with the study's theoretical framework. To enhance validity, the protocol was reviewed by two experts in educational technology and piloted with a small group of EFL students. Feedback from this process informed minor refinements in wording and sequencing to improve clarity and contextual relevance. Some of the questions were:

- How does using GenAI help you in learning English?
- Was it easy or difficult to start using GenAI for your learning tasks?
- Do your peers or lecturers influence your use of GenAI?
- What factors motivate or discourage you for continuing GenAI?

These guiding questions, supported by follow-up probes, enabled the researcher to capture both external influences and internal motivational factors such as autonomy, competence, and relatedness. Thus, this study provides a deeper understanding of EFL students' BI and AU of GenAI for English learning.

Data Collection

A cross-sectional online survey was administered through Google Forms during the data collection period of July–August 2025.The survey link was shared with students through WhatsApp class groups managed by five lecturers from different private universities. Before starting the survey, participants received an informed consent form explaining the study's purpose, procedures, and their right to withdraw at any time. Completing the questionnaire took approximately seven to ten minutes, and participation was entirely voluntary. Anonymity and confidentiality were strictly maintained, with pseudonyms assigned to all participant data.

In the qualitative phase, participants were contacted through WhatsApp invitation after quantitative data analysis. Online semi-structured interviews were conducted via Zoom with 15 EFL students to investigate the factors influencing their adoption of GenAI for English learning. The online interviews were arranged at a time convenient for the voluntary participants. Each individual interview lasted approximately 30-45 minutes and was conducted in a private setting after obtaining informed consent. With participants' permission, all sessions were audio-recorded and transcribed verbatim to ensure a comprehensive and accurate analysis of the factors involved. The purpose and voluntariness of the study were first stated, and the anonymity of personal information was guaranteed. Informed consent was obtained from participants. Then, the in-depth interviews were conducted in Indonesian, as preferred by the participants, and were audio-recorded with their consent before being fully transcribed. To ensure trustworthiness, two independent coders cross-checked the transcripts, and any discrepancies were resolved through discussion. This process enhanced the study's credibility and established a rigorous foundation for the subsequent thematic analysis.

Data Analysis

Data were analyzed using the partial least squares structural equation modeling (PLS-SEM) technique with SmartPLS 4.0. The analysis followed the two-step procedure recommended by Hair et al. (2022). First, the measurement model was assessed for internal consistency reliability, convergent validity, and discriminant validity. Once the measurement model met the required criteria, the structural model was evaluated to test the hypothesized relationships among constructs. Finally, the predictive accuracy of the model was assessed using partial least squares predict (PLS Predict), as suggested by Shmueli et al. (2019).

Thematic analysis was conducted following Braun and Clarke's (2006) framework to analyze data from semi-structured interviews. An inductive approach was applied, allowing themes to emerge directly from the raw data through the identification of patterns and meanings without predetermined categories. NVivo 12 was used to facilitate the analysis. In the initial phase, the researchers familiarized themselves with the data by repeatedly reading the transcripts imported into NVivo 12. The second phase involved generating initial codes to capture salient features of the data. In the third phase, the initial codes were collated into broader categories and clustered into potential themes. The themes were subsequently reviewed and refined through iterative discussions with collaborators, during which some codes were modified, merged, or removed. At this stage, a thematic map was created to visualize interconnections among the themes. In the fifth phase, themes were carefully defined and named to capture their scope and essence, ensuring alignment with participants' voices. Finally, vivid extracts were selected to illustrate each theme.

In a qualitative study, trustworthiness plays a central role in ensuring rigor. According to Ary et al. (2014), three key criteria are used to establish trustworthiness: credibility, transferability, and dependability. To enhance credibility, peer debriefing and member checking were employed. Two experts in technology-enhanced teaching and learning reviewed sections of the data to verify the consistency of the identified themes, and all EFL student participants were involved in validating the themes through member checking. Transferability was ensured through cross-case comparison, with participants drawn from four private universities to strengthen the applicability of the findings. Dependability was ensured through an inter-coder agreement process, in which a second coder reviewed a subset of the data and confirmed a high level of coding consistency, thereby strengthening the stability of the findings.

Ethical Considerations

This study was conducted in accordance with institutional ethical standards, with approval obtained from the Research Ethics Committee of Universitas Muhammadiyah Surakarta. Participants were fully informed of the study's aims, procedures, and their rights before providing voluntary consent. For the survey, anonymity was maintained by avoiding the collection of identifiable data, and responses were stored securely. For the interview, participants gave additional consent for audio recording, and confidentiality was safeguarded through pseudonyms and removal of identifying details in transcripts. Participation involved no academic risk, and students were informed that they could withdraw from the study at any time without penalty. These measures ensured that autonomy, confidentiality, and ethical integrity were maintained across both the quantitative and qualitative strands of the research.

Quantitative Results

Measurement Model Evaluation

The measurement model was assessed through an evaluation of internal consistency reliability, convergent validity, and discriminant validity to confirm the suitability of the latent constructs. Internal consistency reliability was first examined using Cronbach's Alpha and composite reliability (CR). As presented in Appendix 1, all Cronbach's Alpha values ranged from 0.801 to 0.911, and CR values ranged from 0.883 to 0.937, which are well above the recommended minimum threshold of 0.70 (Hair et al., 2022). Convergent validity was then assessed through standardized factor loadings and average variance extracted (AVE). Standardized factor loadings ranged from 0.781 to 0.925, all above the 0.70 benchmark, while AVE values between 0.703 and 0.824 exceeded the 0.50 criterion (Hair et al., 2022), thus confirming convergent validity. These results collectively demonstrate that the measurement model exhibits strong reliability and convergent validity, confirming that the latent constructs are measured consistently and that the indicators effectively represent their respective constructs.

Discriminant validity was assessed using the Heterotrait-Monotrait Ratio (HTMT). As shown in Appendix 2, all HTMT values were below the conservative threshold of 0.85 (Henseler et al., 2015), with the highest values observed between behavioral intention-habit (0.841), behavioral intention-performance expectancy (0.835), and social influence-hedonic motivation (0.824), and the lowest between perceived competence and facilitating conditions (0.027), indicating clear distinctions between constructs. Therefore, the measurement model demonstrates robust reliability, convergent validity, and discriminant validity, confirming its adequacy for testing the proposed structural relationships.

Structural Model Evaluation

Following the confirmation and the establishment of the measurement model's validity and reliability, the structural model was subsequently evaluated to examine the hypothesized relationships among the constructs. This evaluation involved several key criteria, including the coefficient of determination (R^2), path coefficients, t-statistics, and p-values, and effect sizes, all estimated using a bootstrapping method with 5,000 resamples, as recommended by Hair et al. (2022). Prior to conducting further analyses, the model was evaluated for potential collinearity, following the guidelines of Hair et al. (2022). As shown in Appendix 3, the variance inflation factor (VIF) values for all constructs were below the recommended cutoff of 3, suggesting that multicollinearity was not present.

The structural model's explanatory power was then assessed using the coefficient of determination (R^2). According to Hair et al. (2022), R^2 values of 0.75, 0.50, and 0.25 are considered substantial, moderate, and weak, respectively. In this study, the R^2 value for behavioral intention is 0.817, indicating that the model explains a substantial proportion of the variance in behavioral intention. Meanwhile, the R^2 value for actual use is 0.538, suggesting a moderate level of explanatory power. These results suggest that the proposed model offers a robust explanation of the factors influencing both behavioral intention and actual use, with notably stronger predictive power for behavioral intention. Overall, these results demonstrate that the model has a strong ability to explain the key endogenous constructs.

Table 3 presents the findings from the PLS-SEM analysis, indicating that 10 out of the 13 hypotheses were statistically supported. The results show that behavioral intention had a significant effect on actual use. In addition, performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit had significant effects. Also, perceived autonomy, perceived competence, and perceived relatedness had significant effects on actual use. Hypotheses H1, H2, H3, H4, H5, H6, H7, H9, H11, and H13 were thus confirmed. Of all the significant relationships, performance expectancy exerted the strongest influence on behavioral intention, while behavioral intention had the most substantial effect on actual use. In contrast, H8 (perceived autonomy on behavioral intention), H10 (perceived competence on behavioral intention), and H12 (perceived relatedness on behavioral intention) were not supported as their effects were not statistically significant ($p > 0.05$).

The effect size (f^2) for each independent variable in the structural model provides valuable insights into the strength of their influence on the dependent variables. Following Hair et al. (2022), f^2 values of 0.02, 0.15, and 0.35 are interpreted as small, medium, and large effects, while Sarstedt et al. (2021) classify f^2 below 0.02 as negligible. As shown in Table 3, the analysis found that performance expectancy had a large effect on behavioral intention. Medium effects were identified for behavioral intention on actual use, habit on behavioral intention, and effort expectancy on behavioral intention. Small effects were found for perceived autonomy on actual use, perceived competence on actual use, social influence on behavioral intention, facilitating conditions on behavioral intention, hedonic motivation on behavioral intention, and perceived relatedness on actual use. Meanwhile, the effects of perceived autonomy, perceived competence, and perceived relatedness on behavioral intention were negligible, indicating that these variables had little to no impact on behavioral intention in this model

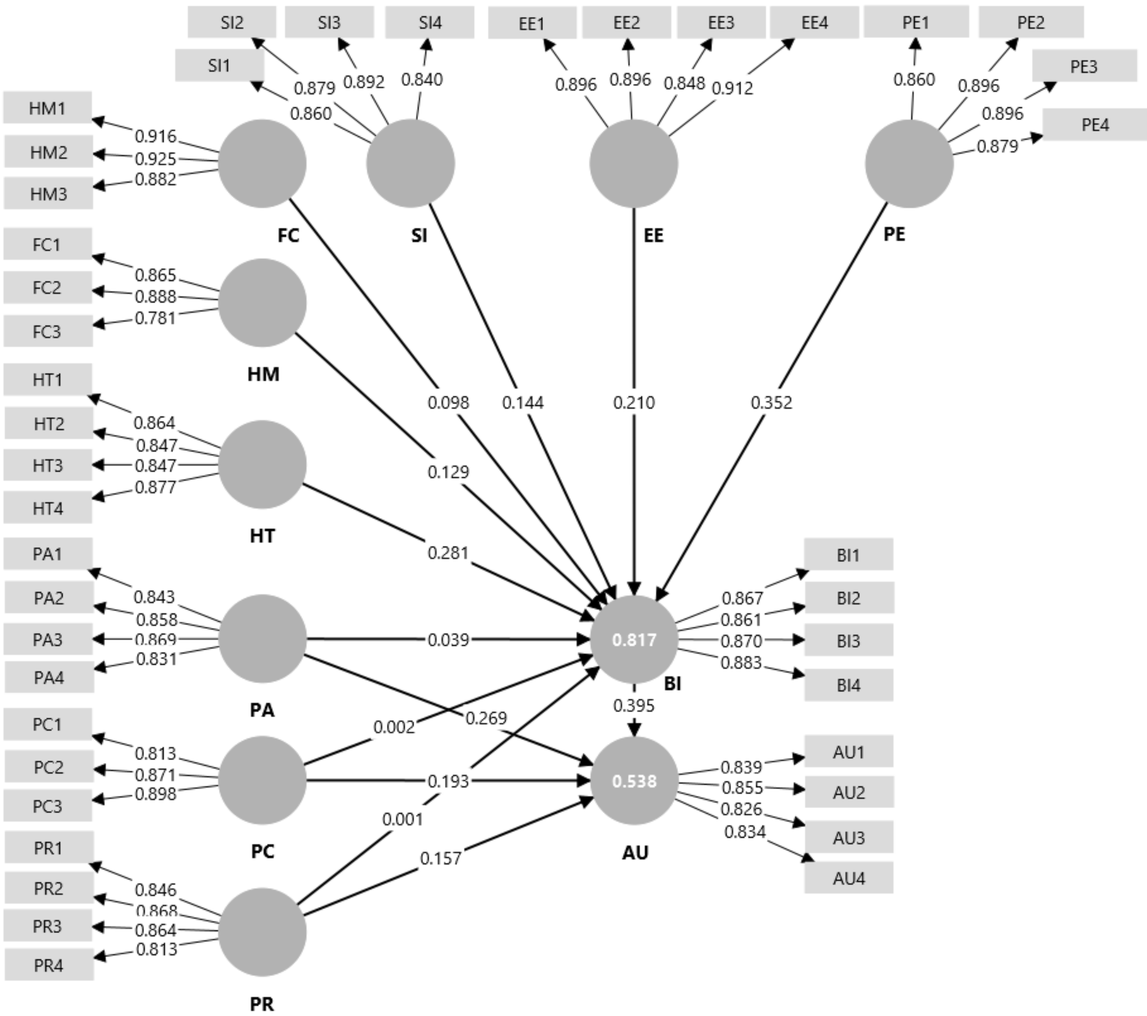

Figure 2. Structural Model Results

Table 3. Structural Model Assessment

Hypotheses	Path Coefficients	T statistics	p values	f^2	Results
H1: BI → AU	0.395	8.864	0.000	0.241	Supported
H2: PE → BI	0.352	9.548	0.000	0.377	Supported
H3: EE → BI	0.210	9.384	0.000	0.206	Supported
H4: SI → BI	0.144	4.030	0.000	0.044	Supported
H5: FC → BI	0.098	4.186	0.000	0.041	Supported
H6: HM → BI	0.129	4.076	0.000	0.040	Supported
H7: HT → BI	0.281	8.596	0.000	0.223	Supported
H8: PA→ BI	0.039	1.405	0.160	0.005	Not Supported
H9: PA → AU	0.269	5.065	0.000	0.094	Supported
H10: PC → BI	0.002	0.110	0.912	0.000	Not Supported
H11: PC → AU	0.193	5.010	0.000	0.075	Supported
H12: PR → BI	0.001	0.052	0.958	0.000	Not Supported
H13: PR → AU	0.157	3.553	0.000	0.038	Supported

To further assess the model's predictive capabilities, an out-of-sample prediction analysis was conducted using the PLSpredict method, which applies k-fold cross-validation to compare the prediction accuracy of the PLS-SEM model with two benchmarks: a linear model (LM) and an indicator average (IA) using Q^2predict, root mean squared error (RMSE), and mean absolute error (MAE) values. According to Hair et al. (2022), Q^2predict values greater than 0.25 indicate moderate predictive relevance, while values above 0.50 reflect strong predictive power. As shown in Table 4, all indicators demonstrated positive Q^2predict values, ranging from 0.332 to 0.629. This result indicates that the model exhibits satisfactory predictive relevance for all endogenous constructs, as the Q^2predict values for every indicator are substantially above zero. Additionally, the predictive accuracy was further examined by comparing RMSE and MAE of the PLS-SEM model with those of LM and IA across all indicators. According to the guideline proposed by Shmueli et al. (2019), a model demonstrates strong predictive power when the prediction errors (RMSE and MAE) generated by the PLS-SEM model are consistently lower than those from both LM and IA across most or all indicators. The present results meet this criterion for every indicator, confirming that the model achieves strong out-of-sample predictive power.

Table 4. Model's Predictive Power

Indicators	Q^2predict	PLS SEM_		LM		IA	
		RMSE	MAE	RMSE	MAE	RMSE	MAE
BI1	0.581	0.320	0.249	0.328	0.254	0.495	0.413
BI2	0.618	0.312	0.243	0.327	0.254	0.506	0.421
BI3	0.614	0.318	0.248	0.331	0.256	0.512	0.423
BI4	0.629	0.314	0.243	0.327	0.254	0.515	0.429
AU1	0.335	0.620	0.475	0.645	0.501	0.760	0.633
AU2	0.398	0.611	0.466	0.632	0.480	0.787	0.670
AU3	0.332	0.669	0.515	0.680	0.530	0.818	0.669
AU4	0.362	0.650	0.491	0.662	0.506	0.814	0.678

Qualitative Results

The qualitative interviews were conducted to complement and extend the results of the structural model assessment. Through thematic analysis, five main themes were identified that either supported or clarified the significant and non-significant hypotheses. These themes are:

perceived performance gains, ease of use and habitual use, social influence, motivational experiences, and supportive learning environments and efficiency.

Theme 1: Perceived Performance Gains

A central theme that emerged from the interviews was the strong perception that GenAI as a powerful support tool that enhanced academic performance in English learning. This aligns with the quantitative result, which showed that performance expectancy was the most significant determinant for GenAI adoption. Interview participants emphasized four main areas of perceived performance gains: overcoming writer's block and generating ideas, improving writing quality, enhancing efficiency and workload management, and developing vocabulary.

Many EFL students highlighted the role of GenAI in helping them overcome difficulties at the initial stages of writing. They explained that brainstorming and starting a draft often created significant blocks, but GenAI tools such as ChatGPT helped them overcome these challenges and maintain the flow of their work. As S1 noted:

> I usually use GenAI when I encounter a block in generating ideas, for instance, when I have an assignment from a lecturer to write an opinion piece or a mini research project. Whenever I feel stuck, I turn to GenAI, such as ChatGPT, to assist with brainstorming and help generate new ideas.

This highlights that GenAI lowers the cognitive barriers associated with the initial stages of writing, enabling students to maintain productivity and confidence when facing creative challenges. Similarly, S5 described how GenAI sustained writing flow by supporting idea development and preventing disruptions from temporary blocks.

> When I get stuck, ChatGPT can help me continue my writing, especially in academic tasks. For example, when I cannot find the right words or do not know how to develop a sentence further, ChatGPT suggests alternative phrases and sentence structures. This makes my writing flow more smoothly, and I don't waste too much time trying to figure out how to continue

EFL students also emphasized that GenAI raised the quality of their writing. They reported that GenAI not only corrected grammatical errors but also extended to enhancing coherence, cohesion, and academic style. S3 stated: *"My writing has improved with ChatGPT. For example, my grammar is more precise, and the content I write is of higher quality."* This suggests that students perceived GenAI as a tool for elevating the standard of their work, moving beyond surface corrections. S11 expressed a similar view, particularly regarding cohesion and coherence:

> I use ChatGPT to improve my grammar, especially with cohesion and coherence, because I often struggle with writing in English. Sometimes I am not sure whether my writing flows smoothly, so ChatGPT is very helpful in ensuring clarity and coherence in my work.

This shows that the benefits of GenAI go beyond correcting grammar at the sentence level and extend to improving the overall organization of texts, helping EFL students produce writing that is clearer, more logical, and easier to follow. S7 reinforced this point by drawing attention to style, explaining: *"ChatGPT makes my writing more academic, for example, by adding formal expressions that I rarely used before."* This indicates that GenAI not only corrected errors but also modeled the conventions of academic writing. By exposing EFL students to formal language and structured expressions, it encouraged them to adopt scholarly styles of communication, thereby enhancing both the quality and credibility of their work.

Moreover, EFL students emphasized that GenAI significantly improved efficiency and time management. S10 explained: *"For me, ChatGPT is very fast ... so tasks can be completed more efficiently. I no longer need to spend a lot of time manually searching for references."* This highlights how GenAI streamlined academic work by offering clear time-saving advantages. By reducing the effort required for drafting and revising, it enabled EFL students to meet deadlines more easily while lowering stress levels. A similar point was made by S15, who noted: "With ChatGPT, completing assignments becomes faster and more efficient. This also has an impact on the final results, as the grades obtained can improve, for example achieving an A or AB." This illustrates that EFL students not only valued GenAI for its efficiency but also associated these gains with tangible academic outcomes such as higher grades, which further motivated them to use the tool. S13 added another perspective by pointing to the way GenAI lightened their workload: *"ChatGPT makes my workload feel lighter, especially when I have several deadlines at the same time."* This illustrates that students perceived GenAI as an effective tool for enhancing efficiency. By easing the process of drafting and revising, GenAI allowed them to handle overlapping assignments more effectively.

Furthermore, EFL students emphasized that GenAI contributes to vocabulary development, which they perceived as directly enhancing their writing quality. S8 noted:

> Through ChatGPT, I have improved my writing skills and expanded my vocabulary. It guides me to write in a more systematic way, while the new vocabulary I learn makes my work more refined and of higher quality.

This illustrates how GenAI not only expanded EFL students' vocabulary but also encouraged them to express ideas in a more structured and sophisticated manner. EFL students' reflections also suggested that expanding their lexical repertoire increased their confidence, allowing them to express complex ideas more effectively.

Theme 2: Ease of Use and Habitual Use

Another prominent theme concerned EFL students' perceptions of the ease of using GenAI tools and how these gradually became habitual in their learning routines. This theme resonates with the quantitative results, where effort expectancy significantly influenced behavioral intention and habit emerged as a strong predictor of behavioral intention. The qualitative data further illustrated how GenAI's simplicity, accessibility, and familiar design collectively facilitated effortless adoption and routinization in English learning.

EFL students repeatedly described GenAI as straightforward to operate and not requiring any special training. Its uncomplicated interface and conversation-based interaction helped remove the technical challenges that usually come with adopting new tools. This simplicity enhanced their confidence and encouraged sustained use. As S4 pointed out: "I don't need any tutorial; I just type my question and get the answer." This illustrates that EFL students regarded GenAI as immediately accessible, with its practicality motivating them to continue using it. S9 shared a similar perspective

> The first time I used ChatGPT, it felt easy. With ChatGPT, you just type what you want to know, and the answer comes up right away. If I'm not satisfied with the response, I can simply ask again for a clearer and more logical answer.

This illustrates how GenAI's conversational format reduced cognitive effort. EFL students felt empowered to manage their learning by requesting clarification, which reinforced their intention to incorporate it into their study practices. Ease of use was also linked to the simplicity of the interface design and its resemblance to everyday applications. S2 explained: *"It's easy because the design is simple and easy to understand, and the features are user-friendly."* Similarly, S12 remarked: *"The design is like WhatsApp, which makes it easy to use."* These quotes highlight how a clear layout, user-friendly features, and similarity to popular applications made students feel more comfortable. Such familiarity reduced the fear of engaging with new technologies, thereby encouraging quicker adoption and strengthening their intention to reuse the tool.

Several EFL students also explicitly stated that their main reason for using ChatGPT was its simplicity. S6 stressed this point: *"The main reason I use ChatGPT is because of its ease of use. The process is simple, the results are fast, and it can be adjusted to my needs. This makes me feel more effective in completing tasks."* Similarly, EFL students emphasized that its ease of use directly motivated repeated engagement. As S14 explained*: "Because I know it's easy, I want to keep using ChatGPT."* S7 echoed this view: *"Its ease of use actually motivates me to use it again."* These statements reveal that perceived simplicity fosters both confidence and consistency, transforming occasional use into continuous engagement.

As this ease of use repeatedly encouraged continued engagement, it gradually evolved into habitual reliance. EFL students reported that their use of GenAI, which started as an occasional aid for difficult assignments, eventually evolved into regular daily dependence In interviews, they emphasized that GenAI had become a natural part of their study routines, used not only for major assignments but also for everyday academic tasks. For example, EFL students consistently expressed how this shift occurred over time:

> At first, I only used it when I had difficult assignments, but because I am now used to it, I really intend to keep using it even for small tasks. S1)
>
> I have developed a routine of using AI for my assignments, and this habit makes me more determined to keep using it whenever I study. (S5)
>
> Now it feels like a habit. Because of this, I don't just use it automatically, but I also really intend to keep relying on it for my English learning. S10)
>
> Using GenAI every day has built my intention to keep using it whenever I have assignments. (S11)

Theme 3: Social Influence

A third theme that emerged from the interviews was the role of social influence in shaping EFL students' adoption of GenAI. This theme aligns with the quantitative findings, where social influence significantly predicted behavioral intention to use GenAI tools. EFL students consistently emphasized that encouragement from peers, lecturers, and broader social environments such as social media platforms influenced both their initial exposure to GenAI and their motivation to continue using it.

Many EFL students emphasized that their initial decision to adopt GenAI was strongly influenced by encouragement or examples from their peers. Friends frequently served as the first source of information, demonstrated how to use the tools, and even created a classroom norm around adoption. In individual interviews, many EFL students emphasized that peer influence not only introduced them to GenAI but also motivated them to continue using it. For example:

> I first learned about GenAI such as ChatGPT and Gemini from my friends. They suggested I try it, and once I did, I realized it really made almost everything easier. (S2)
>
> At first, I didn't know about it, but my friends told me to try. Now, almost everyone in my class uses ChatGPT for writing practice. (S5)
>
> I knew about GenAI from my friends … they were using ChatGPT … so I decided to try it. (S7)

> There was pressure from my campus environment because most of my friends also used ChatGPT. Sometimes I even felt that when I didn't use it, my confidence decreased … (S9)

> I know about AI from my friend. At that time, we were in a group discussion and they suggested using Cici AI. From there, I got curious and started using AI. (S15)

Beyond peer influence, lecturer also played an important role in encouraging EFL students to adopt GenAI. This encouragement came through explicit recommendations, classroom integration, and practical training that familiarized students with AI tools. Students explained that such guidance not only legitimized GenAI use but also provided the technical know-how needed for effective application. For example:

> Besides from friends, I also received encouragement from lecturers. Some lecturers directly suggested that students use GenAI as a learning tool. In fact, from my lecturers, I learned about other applications like Scite Space … (S3)

> Several lecturers also suggested using GenAI, but not to rely too much on ChatGPT. (S6)

> The lecturer gave advice and showed us how to create prompts in class, though the lecturer used the premium version. (S10)

> There was a lecturer who gave a tutorial on how to design a research project with the help of ChatGPT … (S12)

Some students also revealed that they became familiar with GenAI through social media, particularly popular platforms such as TikTok and Instagram. As expressed by S4: "I learned about ChatGPT from TikTok". Similarly, S13 noted: *"Actually, I first knew about ChatGPT from Instagram"*. These quotes show that social media provided a rapid and effective channel of exposure, particularly for students who were already active on these platforms.

Theme 4: Motivational Experiences

A fourth theme highlighted the motivational dimensions of GenAI adoption, reflecting both the UTAUT2 construct of hedonic motivation as a determinant of behavioral intention and the SDT constructs of perceived autonomy, perceived competence, and perceived relatedness as predictors of actual use. These results demonstrate that GenAI adoption was shaped by enjoyment and the fulfillment of psychological needs.

EFL students described GenAI as enjoyable and less intimidating compared to traditional learning methods. Several EFL students reported that it reduced the stress of English learning and made practice more engaging. For instance, S7 reflected: *"It feels fun to practice with AI because I don't feel judged when I make mistakes."* This sense of enjoyment and psychological safety not only reduced anxiety but also encouraged repeated engagement, motivating students to return to ChatGPT regularly. Enjoyment was also closely tied to feelings of satisfaction and pleasure during interaction. S5 emphasized: *"It's very interesting because every question I ask is always answered. That makes me feel satisfied and eager to keep using ChatGPT."* The reliability of receiving accurate and immediate responses fostered both interest and enjoyment, which in turn reinforced students' intention to continue using the tool. Similarly, S13 highlighted how the human-like quality of ChatGPT increased motivation: *"ChatGPT provides instant feedback and feels more human-like, as if I'm talking to a friend… Because this experience is enjoyable, I'm motivated to keep using it."* These positive emotional experiences created a reinforcing cycle of satisfaction, enjoyment, and confidence that sustained students' behavioral intention to adopt GenAI in their learning practices.

EFL Students' motivation to continue using GenAI was shaped by experiences of perceived autonomy, perceived competence, and perceived relatedness. EFL students emphasized that GenAI allowed them to manage their learning independently, offering support without replacing their own efforts. The ability to maintain control over their study routines reinforced a sense of ownership that sustained ongoing use. S12 highlighted that: *"I feel more independent because I can check my work anytime without waiting for my teacher."* In a similar way, S3 pointed out that: *"Sometimes I don't want to use it ... I write first on my own, then use ChatGPT for feedback."* Such reflections demonstrate that autonomy empowered learners to integrate GenAI flexibly into their practices, strengthening their motivation to use it regularly. EFL students also described how GenAI enhanced their competence by providing immediate and constructive feedback. The tool not only helped them address language-related challenges but also encouraged them to refine their critical thinking. S4 explained that: *"AI shows me how to improve my vocabulary and grammar, so I feel more capable."* Similarly, S6 noted that: *"I cross-check every response with journals or other sources. This process trains me to think critically and ensures my writing remains credible."* These reveal that competence was developed through repeated interaction with GenAI, which boosted confidence and reinforced continued engagement. Beyond autonomy and competence, EFL students valued the sense of relatedness that GenAI fostered. They described how collaboration with peers through exchanging prompts and comparing responses created a collective learning experience. S10, for instance, mentioned that: *"My friends and I often exchange prompts and compare answers, and it feels like we are learning together."* This sense of belonging highlights how relatedness complemented the other motivational factors, embedding GenAI use in social interaction and maintaining learners' motivation over time.

Theme 5: Supportive Learning Environments and Efficiency

A final theme that emerged from the interviews was supportive learning environments and efficiency-oriented GenAI adoption. This theme aligns with the quantitative findings, which showed that while facilitating conditions significantly influenced behavioral intention, and behavioral intention strongly predicted actual use, the SDT variables (perceived autonomy, perceived competence, and perceived relatedness) did not have a significant effect on behavioral intention. EFL students emphasized that training, institutional support, and access enabled adoption, while barriers such as unstable internet, premium limits, and detection checks prompted adaptive strategies rather than discouragement. They also stressed that their intention to use GenAI, primarily driven by utility and efficiency, consistently translated into actual, routine use.

EFL students emphasized that structured training sessions and direct guidance from lecturers or institutions reduced initial uncertainty and equipped them with the necessary skills to use GenAI effectively. Practical demonstrations, such as how to construct prompts, paraphrase, or integrate GenAI into academic writing, were particularly valued. As S1 recalled: *"I once joined a training session on how to create good prompts. We were given explanations and practiced implementing them."* Similarly, S4 noted: *"The lecturer showed us in class how to make prompts for paraphrasing or summarizing."* Workshops and seminars organized at the institutional level further reinforced this support. S14 shared: *"There was a campus seminar on AI use ... from there I immediately tried it for my assignments."* Likewise, S6 explained: *"Actually, there have been several trainings on using ChatGPT for article writing from the university."* These demonstrate that both formal training and informal classroom guidance-built confidence, reduced technical barriers, and increased AI literacy. This combination not only motivated students to experiment with GenAI but also encouraged them to embed it into their daily study routines.

Beyond skills, the availability of devices and stable internet access emerged as critical for sustained use. EFL students described how laptops, smartphones, and flexible platform design enabled them to access ChatGPT anywhere. For instance, S8 shared: *"ChatGPT is easy in terms of its interface and flexibility since it can be used on both HP and laptop, and even if I make a typo, ChatGPT still understands what I want."* However, barriers such as unstable connections and usage limits in the free version also shaped experiences. S4 reported: *"Sometimes the network is down, so I can't use ChatGPT because of limited access."* Similarly, S10 highlighted: "*I don't use premium, so my usage is limited. I have to wait before I can use it again."*

These indicate that infrastructure and access acted as both enablers and constraints. While adequate facilities strengthened behavioral intention by ensuring readiness and convenience, constraints such as free-version limits did not reduce intention but instead motivated adaptive strategies, like switching accounts or exploring alternative platforms.

Institutional regulations and lecturers' attitudes also shaped EFL students' sense of legitimacy in using GenAI. Rules such as AI detection thresholds, guidelines for "responsible use," or explicit recommendations provided the normative framework for adoption. S12 explained: "*Lecturers allow us to use AI, but the AI detection must not exceed 20%."* Others described the absence of strict rules as an opportunity for autonomy. As S3 noted: *"There are no rules yet. Just advice to use ChatGPT wisely ... so I feel freer."* Meanwhile, encouragement from lecturers directly strengthened students' confidence. S13 emphasized: *"The push from lecturers ... they suggested opening ChatGPT to do assignments."* Similarly, S7 highlighted: *"GenAI has no strict regulations, so there are no barriers stopping me from using it."* These show that permissive or supportive policies legitimized the use of GenAI, while technical constraints such as detection checks created pressure but did not deter adoption.

The interviews also confirmed the relationship between behavioral intention and actual use. Some EFL students highlighted how their intention to use ChatGPT was expressed in a targeted and selective way. For example, S8 noted: *"My intention is to keep using ChatGPT, especially to support my microteaching lesson plan, but mainly for generating activities for each material. The rest, I design on my own."* This indicates that ChatGPT was adopted to enhance efficiency in activity design, while students maintained creative and pedagogical control. Other participants revealed ambivalence, balancing usefulness with concerns about dependence. As S16 explained: *"I want to use it because it is helpful, but I also worry that using it too often might lead to dependence."* This indicates that intention was filtered through self-regulation, with students deliberately limiting use to preserve their independence and learning capacity. Workload also influenced how behavioral intention translated into actual use. As S9 explained: *"My intention to use AI becomes stronger when assignment demands are high ... but if the workload is lighter, I usually complete the tasks on my own."* This shows that intention was not constant but adapted to academic pressures, functioning as a coping strategy under heavy workloads.

Furthermore, the qualitative findings reinforced the quantitative results, indicating that perceived autonomy, perceived competence, and perceived relatedness were not significant predictors of students' behavioral intention to adopt GenAI. Instead, their intention was primarily shaped by considerations of utility and efficiency. Perceived autonomy did not act as a trigger for adoption but rather influenced how students positioned GenAI within their learning process. As S3 noted: *"I still want to learn on my own; AI is only a companion."* This suggests that while students valued maintaining independence, perceived autonomy did not motivate their initial decision to use GenAI; it only regulated the way they engaged with it once adopted. Similarly, perceived competence was described as something cultivated through the use of

GenAI rather than a prerequisite for adoption. S6 explained: *"I don't just copy the answer; I try to understand and rewrite it in my own way."* Likewise, S11 added: *"I don't copy-paste; I usually rewrite it to match my own style."* These reflections highlight that GenAI supported the development of competence during use, but such competence was not a factor influencing students' initial BI. Perceived relatedness also played little role in adoption decisions. Students consistently clarified that their intention stemmed from the practical benefits of GenAI rather than from emotions or peer influence. As S14 emphasized: *"I don't decide to use AI because of my feelings or friends; I use it because it helps me finish tasks faster."* This illustrates that social belonging or relatedness did not significantly determine students' intention to use the tool.

Discussion

This explanatory sequential mixed-methods study employed UTAUT2 and SDT to investigate EFL students' behavioral intention and actual use of GenAI for English learning. These results highlight that while UTAUT2 explains initial intention, the motivational mechanisms of SDT are crucial for understanding actual and sustained usage. The result revealed that performance expectancy emerged as the strongest predictor of students' behavioral intention, indicating that their intention to use GenAI tools is primarily shaped by tangible academic performance gains. This supports Zheng et al. (2024), who highlighted performance expectancy as a central factor in GenAI adoption for English learning. In the same vein, Foroughi et al. (2024) confirmed performance expectancy as the most influential determinant of ChatGPT use in educational settings, noting that its adaptive and personalized feedback allows students to overcome barriers and reach their goals more effectively. The strong influence of performance expectancy in this study shows that EFL students perceived GenAI tools such as ChatGPT as valuable resources that streamline their learning process by facilitating idea development, improving writing clarity and accuracy, optimizing time use, easing task completion, and enriching language expression. These perceived gains enhance students' confidence and reinforce their readiness to integrate GenAI into their regular learning activities.

Behavioral intention was also a significant positive predictor of actual use, with a medium effect size. This suggests that although EFL students' intentions led to the adoption of GenAI tools, actual use was shaped by contextual and adaptive factors, including the type of tasks, assignment demands, and the need for self-regulation. Similar results have been reported in technology adoption studies, where behavioral intention consistently predicts actual use (Surachmi et al., 2025; Venkatesh et al., 2012; Zheng et al., 2024). For example, Amin et al. (2024) found that students with intention and interest in using ChatGPT were more likely to adopt it regularly in their studies.

The effect of habit on behavioral intention was also moderate but statistically significant. This result is consistent with prior studies on GenAI acceptance in higher education (e.g., Grassini et al., 2024; Salifu et al., 2024; Zheng et al., 2024), which identified habit as a positive predictor of intention. Strzelecki (2024) also emphasized that habit, developed through repeated engagement with AI-powered tools fosters sustained routines that strengthen intention. Interview data further support this evidence, as EFL students reported that frequent use of GenAI for academic tasks gradually developed into a routine, which over time reinforced their willingness to continue using the technology. This result indicates that while habit is not the strongest determinant, it plays a meaningful role in transforming short-term adoption into long-term integration in EFL students' learning practices.

Effort expectancy showed a statistically significantly effect on behavioral intention, though with moderate effect on EFL students' intention to use GenAI for English learning. The moderate influence in this study can be explained by the fact that EFL students were already technologically adaptive and regarded ease of use as a default expectation, which made perceived usefulness a more decisive factor in shaping intention. Qualitative results support this view, as students highlighted that GenAI required no tutorials, resembled familiar applications, and provided immediate responses through its conversational format. These features of simplicity, familiarity, and user-friendliness lowered adoption barriers, built confidence, and encouraged routine engagement. This result is consistent with previous research that identified effort expectancy as a relevant predictor of technology adoption (Lai et al., 2024; Surachmi et al., 2025; Xu & Thien, 2025). In line with this, Strzelecki (2024) highlighted that ChatGPT was widely perceived as easy and practical, thereby eliminating technical challenges in its adoption.

Perceived autonomy was found to have a significant but weak effect on actual use. This result is consistent with Osei et al. (2022), who identified perceived autonomy as a significant factor influencing actual use. This significance can be explained by the role of autonomy in sustaining and regulating EFL students continued use of GenAI. The interviews showed that EFL students positioned GenAI as a supportive companion rather than as a replacement for their learning, using it to complement rather than substitute their efforts. The freedom to decide when and how to use the tool, for instance checking their work at any time or writing independently before seeking AI feedback, reinforced their sense of control and ownership over the learning process. This autonomy allowed students to integrate GenAI flexibly into their study routines, thereby maintaining their motivation to keep using it. Thus, while autonomy did not drive initial adoption, it became essential for sustaining actual use, as it enabled students to balance the advantages of GenAI with their commitment to independent learning.

Moreover, perceived competence showed a statistically significant but small effect on actual use, confirming earlier findings by Osei et al. (2022). This result can be explained by the way EFL students perceived competence as something that gradually developed through continued use of GenAI rather than as a prerequisite for adoption. Interview findings supported this interpretation, as students explained that ChatGPT helped them improve sentence structure, expand vocabulary, and refine academic arguments, which in turn enhanced their confidence and motivation to continue using the tool. However, the relatively small effect size suggests that while competence reinforced ongoing engagement, it was not the primary driver of continued adoption, as practical benefits such as efficiency and usefulness still carried greater weight in shaping actual use.

Social influence had a statistically significant but small impact on behavioral intention to adopt GenAI for English learning. This suggests that peers, lecturers, and social media serve mainly as initial sources of encouragement that introduced EFL students to GenAI and shaped their early willingness to use it. The small relationship can be explained by the fact that once EFL students became familiar with GenAI, their continued intention to use it was driven more by internal factors such as perceived usefulness and personal learning experiences rather than ongoing social influence. This result is supported by Amin et al. (2024), who showed that recommendations from peers, relatives, and teachers increased students' trust and initial confidence in ChatGPT, indicating the role of social influence during early adoption. Similarly, Strzelecki (2024) found that social influence played a weaker role, as GenAI adoption was more prevalent among early adopters with educated backgrounds who were less influenced by external pressures, partly due to the novelty and limited diffusion of the technology. In line with this, Grassini et al. (2024) reported that university students are generally less affected by external societal pressures due to their confidence and familiarity with digital technologies. Consistent with these results, Foroughi et al. (2024) emphasized that students tend to rely more on their personal perceptions of usefulness and ease of use than on peer or social influence.

Facilitation conditions were identified as a significant factor influencing EFL students' intention to use GenAI tools for English learning, consistent with previous studies that identified a positive association between facilitating conditions and behavioral intention in the adoption of ChatGPT (Arthur et al., 2024; Surachmi et al., 2025; Zheng et al., 2024). This relationship was also evident in the interview data, where EFL students highlighted that lecturers and institutions contributed to their readiness, skills, and sense of legitimacy by offering training sessions, classroom demonstrations, and campus seminars. However, the effect was small because external support primarily assisted the initial stage of adoption, while long-term intention was more strongly driven by internal factors. EFL students demonstrated high digital adaptability, overcame technical limitations with personal strategies, and relied more on the direct benefits of GenAI than on institutional support. This result contrasts with Foroughi et al. (2024), who argued that ChatGPT requires only basic access to a computer and the internet, features a user-friendly interface similar to familiar search engines, and does not demand advanced technical infrastructure, thereby minimizing the role of facilitating conditions in shaping intention.

Hedonic motivation also showed a small but significant effect on behavioral intention. This result is consistent with previous studies (Foroughi et al., 2024; Strzelecki, 2024; Surachmi et al., 2025; Zheng et al., 2024), which identified hedonic motivation as an important factor in predicting GenAI acceptance. The interviews provide supporting evidence, as EFL students described how enjoyment, a sense of safety, and satisfaction when using GenAI encouraged them to adopt the technology. They highlighted that ChatGPT's non-intimidating nature, instant feedback, and conversational quality reduced stress and made learning more engaging, thereby explaining the significant role of hedonic motivation in shaping behavioral intention. However, the relatively weak effect size can be understood in the academic context, where enjoyment played only a secondary role compared to practical considerations. The novelty of GenAI's enjoyable features diminished over time, its hedonic value was not unique for digital natives already familiar with interactive technologies, and some students deliberately regulated their use to avoid dependency. These results indicate that while enjoyment encouraged initial adoption, sustained intention was shaped more strongly by utilitarian factors such as usefulness and efficiency.

Perceived relatedness was found to have a small but significant effect on actual use, consistent with Osei et al. (2022). This indicates that while relatedness supported continued use of GenAI through collaborative practices, such as exchanging prompts and comparing responses with peers, it was not the main factor driving sustained engagement. The interview findings confirmed that students appreciated the sense of belonging and peer interaction GenAI fostered, which complemented their learning and encouraged repeated use. However, the relatively weak effect can be explained by the fact that students' actual use was shaped more strongly by internal drivers, including perceived usefulness, efficiency in completing tasks, and competence development, than by social influence. As a result, relatedness acted as a supportive motivator but not the primary determinant of continued adoption.

In contrast, perceived autonomy was found to have a negligible and non-significant effect on behavioral intention, which contrasts with prior studies (Alharbi, 2023; Cortez et al., 2024; Wang & Reynolds, 2024). One possible explanation is that EFL students' intention was shaped more by practical benefits such as efficiency, ease of access, and task completion rather than by psychological needs for autonomy. The insignificance of perceived autonomy may be attributed to the fact that autonomy did not act as a trigger for initial adoption. Instead, it functioned as a regulatory factor after adoption, guiding how students positioned GenAI in their learning process and how they balanced its use with independent learning goals. This indicates that while autonomy remained an important value for students, it did not play a decisive role in motivating their initial intention to adopt GenAI.

Perceived competence also showed negligible, non-significant effect on behavioral intention, consistent with Alowayr and Al-Azawei (2021), who also found that the relationship between perceived competence and behavioral intention was not significantly significant. This non significance was further supported by interview results, which revealed that EFL students did not feel the need to possess prior competence or confidence before using GenAI. Instead, they perceived competence as something cultivated through its use, for example by improving sentence structure, expanding vocabulary, constructing academic arguments, and refining outputs through rewriting and adaptation. Thus, competence appeared more as a consequence of GenAI use rather than as a determinant of initial adoption. This result suggests that GenAI adoption in English learning is highly task-driven, where the demands of completing academic assignments outweigh psychological factors related to self-perceived competence.

In contrast with earlier studies that emphasized perceived relatedness as a significant predictor of technology adoption (Alharbi, 2023; Cortez et al., 2024; Şahin & Yıldız, 2024), this study found that perceived relatedness did not have a direct and significant effect on EFL students' behavioral intention to use GenAI for English learning. One possible explanation is that while peers and lecturers introduced students to GenAI and reduced initial uncertainty, their influence was limited to the early stage of adoption. The insignificance of perceived relatedness may be explained by the fact that EFL students' sustained intention was more strongly driven by internal factors such as practical usefulness, efficiency in completing academic tasks, and individual learning needs, rather than by ongoing social pressure or external encouragement.

Implications

This study offers both theoretical and practical implications. Theoretically, it enriches the literature on GenAI adoption in language education by offering four key contributions;

First, it integrates UTAUT2 and SDT into a unified explanatory model, advancing current understanding of how technological expectations and psychological needs jointly influence students' adoption of GenAI for English learning.

Second, the study highlights performance expectancy as a critical factor in the technology acceptance process, emphasizing that EFL students perceive GenAI as beneficial for enhancing idea generation, improving writing quality and vocabulary, increasing efficiency, and managing academic workload more effectively. Such perceived benefits not only drive students' initial willingness to engage with GenAI but also support their continued reliance on the technology as a valuable tool for achieving learning outcomes in English education.

Third, the psychological needs of perceived autonomy, perceived competence, and perceived relatedness emerge as stronger predictors of actual use, underscoring the importance of motivational mechanisms in sustaining engagement with GenAI. This distinction advances theoretical understanding by clarifying that the drivers of adoption are not identical to the drivers of sustained engagement, thereby extending acceptance theory and positioning SDT as a necessary complement to UTAUT2 in explaining long-term use of GenAI in education.

Finally, the study contributes methodologically through its explanatory sequential mixed-methods design, which combines statistical analysis with qualitative evidence. While quantitative results confirmed the relationships among UTAUT2 and SDT constructs, qualitative insights revealed how students experienced GenAI as a learning partner that enhanced efficiency, built confidence in writing, and supported self-directed practice. This integration not only validates the model but also refines theoretical assumptions about how GenAI adoption unfolds specifically in the context of English learning.

In practice, this study offers several important implications for educators, curriculum developers, and educational institutions in integrating GenAI effectively into English instruction. For educators, professional training should prepare them with the pedagogical skills to guide students in GenAI use, including how to design prompts, critically evaluate AI outputs, and integrate GenAI into language learning activities. Such preparation ensures that educators are not only technologically literate but also able to scaffold students' effective and ethical use of GenAI. By embedding GenAI into writing, speaking, and reading tasks, teachers can help students see the practical usefulness of these tools while also fostering autonomy, critical thinking, and responsible adoption. This approach can further reduce overreliance on GenAI by equipping students with strategies to balance AI assistance with their own independent learning. From a curriculum perspective, GenAI-based activities should be embedded into formal learning frameworks and linked to clear learning outcomes, such as vocabulary enrichment, improved writing coherence, or collaborative tasks for constructing arguments. Providing task exemplars, structured templates, and assessment systems that evaluate both final products and processes (e.g., prompt logs, tracked revisions, and reflective statements) ensures that GenAI is used as a learning partner that supports competence, rather than as a shortcut for completing assignments.

At the institutional level, educational institutions need to provide balanced support between access and accountability. Beyond ensuring adequate infrastructure such as stable connectivity, cross-device accessibility, and official licensing, institutions should establish clear policies that define acceptable forms and boundaries of GenAI use. Such policies should cover academic integrity, transparency in the disclosure of AI use, and monitoring mechanisms that are educative rather than punitive. Furthermore, institutions can establish learning communities, peer mentoring, or professional learning communities (PLCs) that encourage students to share strategies, experiences, and best practices in ethical GenAI use. In this way, students' psychological needs for autonomy, competence, and relatedness will be optimally facilitated, ensuring that GenAI adoption does not stop at initial intention but develops into sustainable, meaningful, and responsible practices in English language learning.

Conclusion

Using UTAUT2 and SDT frameworks, this explanatory sequential mixed-method study explored the determinants influencing EFL students' intention to use GenAI for English learning. Quantitative results revealed that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit were significant predictors of behavioral intention with performance expectancy emerging as the strongest predictor, whereas autonomy, competence, and relatedness did not directly influence intention. However, these motivational factors and behavioral intention significantly predicted actual usage, underscoring their importance in sustaining continued engagement. The qualitative analysis further illuminated students' experiences, which centered on five themes: perceived performance gains, ease of use and habitual practices, social influence, motivational experiences, and supportive learning environments and efficiency. These results highlight that while UTAUT2 explains initial intention, the motivational mechanisms of SDT are crucial for understanding actual and sustained usage. By integrating acceptance and motivation perspectives, this study advances knowledge on technology adoption in language learning and underscores the importance of fostering both technological readiness and motivational support to ensure long-term, responsible engagement with GenAI.

Limitations and Future Research

This study has some limitations. First, the quantitative data were obtained through a cross-sectional design, which captures learners' behavioral tendencies only at a single point in time.

Such an approach does not account for potential changes in behavioral patterns that may occur as students continue to engage with GenAI tools over extended periods. Therefore, future research should adopt longitudinal designs to provide more robust and comprehensive explanations of EFL students' acceptance and sustained use of GenAI in English learning. Second, this study primarily focused on the perspectives of EFL students regarding the use of GenAI in language learning, while teachers' perspectives were not examined. Since teachers play a pivotal role in guiding classroom practices, shaping technology integration, and mediating students' engagement with GenAI tools, future studies should incorporate teachers' viewpoints to provide a more comprehensive understanding of GenAI adoption in higher education. Third, this study focused solely on undergraduate EFL students, limiting the generalizability of the findings. Further research should include EFL postgraduate students to provide a more comprehensive understanding. Finally, since this study was conducted in the Indonesian higher education context, its results may not be fully generalizable to international settings. Differences in educational systems, institutional support, levels of digital infrastructure, and cultural perspectives on technology can shape distinct patterns of GenAI adoption across countries. Future research should therefore include cross-national and cross-cultural comparisons to determine whether the trends observed here also apply globally. Such efforts would enhance the broader international significance of research on GenAI use in English learning.

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Appendix 1. Measurement Model Assessment

The UTAUT2 constructs were measured using items adapted from Zheng et al. (2024), and the SDT-based motivational factors were derived from the validated instrument developed by Hew and Kadir (2016).

Construct	Item	Factor Loading	Cronbach's Alpha	CR	AVE
BI	BI1	0.860	0.893	0.926	0.758
	BI2	0.896			
	BI3	0.896			
	BI4	0.879			
AU	AU1	0.839	0.859	0.905	0.703
	AU2	0.855			
	AU3	0.826			
	AU4	0.834			
PE	PE1	0.871	0.906	0.934	0.780
	PE2	0.906			
	PE3	0.904			
	PE4	0.890			
EE	EE1	0.896	0.911	0.937	0.789
	EE2	0.896			
	EE3	0.848			
	EE4	0.912			
SI	SI1	0.860	0.891	0.924	0.753
	SI2	0.879			
	SI3	0.892			
	SI4	0.840			
FC	FC1	0.865	0.893	0.934	0.824
	FC2	0.888			
	FC3	0.781			
HM	HM1	0.916	0.801	0.883	0.716
	HM2	0.925			
	HM3	0.882			
HT	HT1	0.864	0.881	0.918	0.738
	HT2	0.847			
	HT3	0.847			
	HT4	0.877			
PA	PA1	0.843	0.872	0.913	0.723
	PA2	0.858			
	PA3	0.869			
	PA4	0.831			
PC	PC1	0.813	0.826	0.896	0.742
	PC2	0.871			
	PC3	0.898			
PR	PR1	0.846	0.869	0.911	0.719
	PR2	0.868			
	PR3	0.864			
	PR4	0.813			

Note. BI: Behavioral Intention, AU: Actual Use, PE: Performance Expectancy, EE: Effort Expectancy, SI: Social Influence, FC: Facilitating Conditions; HM: Hedonic Motivation, HT: Habit, PA: Perceived Autonomy, PC: Perceived Competence, PR: Perceived Relatedness

Appendix 2. Discriminant Validity (HTMT)

	BI	AU	PE	EE	SI	FC	HM	HT	PA	PC	PR
BI											
AU	0.715										
PE	0.835	0.524									
EE	0.495	0.187	0.217								
SI	0.785	0.695	0.656	0.230							
FC	0.453	0.358	0.357	0.074	0.331						
HM	0.782	0.751	0.645	0.208	0.824	0.348					
HT	0.841	0.613	0.603	0.393	0.657	0.343	0.638				
PA	0.570	0.674	0.414	0.220	0.615	0.360	0.615	0.467			
PC	0.263	0.394	0.184	0.120	0.310	0.027	0.277	0.299	0.204		
PR	0.387	0.500	0.279	0.049	0.416	0.401	0.415	0.370	0.600	0.035	

Appendix 3. Collinearity Statistics (VIF)

	VIF
BI → AU	1.401
PE → BI	1.799
EE → BI	1.171
SI → BI	2.572
FC → BI	1.258
HM → BI	2.266
HT → BI	1.938
PA → BI	1.831
PA → AU	1.673
PC → BI	1.130
PC → AU	1.077
PR → BI	1.524
PR → AU	1.412