Original Paper

A Study on the Impact of Self-Efficacy on College Students' Acceptance of Generative AI-empowered English Learning: Based on the Technology Acceptance Model

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Abstract

This study, grounded in the Technology Acceptance Model (TAM), analyzes questionnaire data from 226 university students using Structural Equation Modeling (SEM). It investigates the predictive effects of self-efficacy (SE) on students' perceived usefulness (PU), perceived ease of use (PEOU), attitude toward use (ATT), and behavioral intention (BI). Additionally, it explores the direct and indirect mediating roles of the aforementioned three variables between self-efficacy and behavioral intention. The results indicate that university students generally show a high level of acceptance toward generative artificial intelligence in English learning. The predictive relationships among the core variables of the Technology Acceptance Model are validated, with self-efficacy having a significant positive impact on all four variables. Furthermore, the mediating effects of perceived usefulness, perceived ease of use, and attitude toward use between self-efficacy and behavioral intention are significant, with a continuous mediation path observed. Among these, the mediation effect of attitude toward use is the most prominent. These findings provide insights into how universities can optimize the implementation of generative artificial intelligence in English teaching practices and enhance learners' acceptance of technology.

Keywords

Technology Acceptance Model, Self-efficacy, Generative Artificial Intelligence, English Learning, Structural Equation Modeling

1. Introduction

Artificial intelligence (AI), with its vast data, powerful interactivity, and conversational capabilities,

has brought unprecedented opportunities to English language teaching. Teachers can leverage generative AI for targeted analysis of student learning conditions and generate multimodal teaching resources to enrich the content (Yang, 2025, p. 18). The application of AI in foreign language education has evolved from text-based assistance to co-creation of images and texts, and further to multimodal interaction and competency assessment. Its role has shifted from a mere tool to a generator of teaching resources, a collaborator in meaning construction, and an evaluator of cross-cultural competence. This evolution is driving foreign language teaching toward a new paradigm that is visualized, generative, and learner-centered (Fan et al., 2025, p. 48).

Numerous studies have confirmed the positive impact of AI on English learning (Zhang et al., 2023, p. 39). For instance, in AI-assisted English writing, generative AI, as a formative feedback tool, significantly improves students' writing quality, with its positive effects on content generation and structural organization lasting up to two months post-intervention. This demonstrates its long-term benefits in developing learners' writing abilities (Mahapatra, 2024, p. 8). In autonomous learning, generative AI can generate adaptive learning materials based on learners' progress and style, significantly enhancing learning efficiency (Liu et al., 2024, p. 16).

Although the positive effects of AI on English learning have been repeatedly verified (Jin et al., 2025, p. 101; Sun et al., 2025, p. 30), whether the technological value can translate into sustained learner usage in real classroom settings still depends on individual acceptance. The Technology Acceptance Model (TAM) provides a classic explanatory framework for this issue. In this model, perceived ease of use and perceived usefulness influence.

1.1 Technological Acceptance Model and Research on Generative Artificial Intelligence

The Technology Acceptance Model (TAM) was first proposed by Davis et al. (1989). The model suggests that users' attitudes towards and behavioral intentions to use new technologies are influenced by two core variables: perceived usefulness and perceived ease of use. Perceived ease of use refers to the degree to which a user believes that using a particular technology is easy; perceived usefulness refers to the user's judgment of the technology's value; attitude towards use refers to the user's evaluation of the technology; and behavioral intention refers to the user's tendency to use the technology (Scherer et al., 2019, p. 53). The relationships between these variables are illustrated in Figure 1.
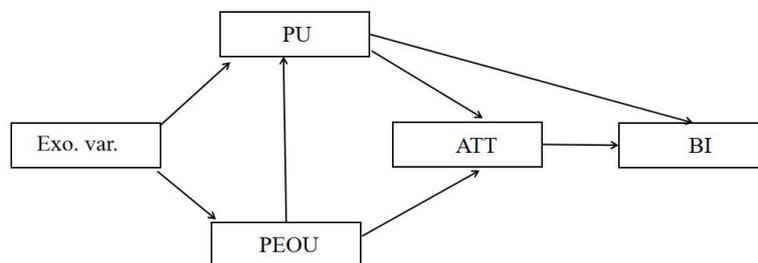

Figure 1. Technology Acceptance Model (Davis *et al.*, 1989)

In the field of education, the Technology Acceptance Model has been applied to explore learners' acceptance of various technology-assisted learning tools, such as generative artificial intelligence (Chen et al., 2024, p. 2), automated English writing evaluation systems (Zhai et al., 2021, p. 3), and online teaching platforms (Alfadda et al., 2021, p. 884). Sharma et al. (2024) found that, in their study of AI acceptance in Indian universities, students exhibited the highest acceptance of artificial intelligence. A possible reason for this is that university students are more concerned with the improvements in learning efficiency AI can offer and are willing to integrate AI into their daily learning activities. Similarly, Chen et al. (2025) found that Chinese university students generally display a high level of acceptance towards artificial intelligence, with this tendency being influenced by factors such as technological perception, environmental support, and individual characteristics. However, Oc et al. (2025) pointed out that some learners are less willing to accept AI due to concerns over academic integrity, data privacy, and other risks. In contrast, technologically proficient learners are better at avoiding the potential risks of AI, leading to significantly higher acceptance compared to those with lower technological skills. Further research by Sergeeva et al. (2025) confirmed that while learners acknowledge the benefits of generative AI, there are concerns regarding its accuracy, impact on academic integrity, and creativity development. Additionally, a lack of environmental support can negatively affect students' willingness to accept AI.

In summary, while existing studies confirm that university students generally have a high acceptance of generative artificial intelligence, research on its acceptance in English learning contexts remains scarce. Therefore, the article proposes Hypothesis 1: University students have a high level of acceptance of generative AI in English learning (H1).

1.2 The Relationship between Perceived Ease of Use, Perceived Usefulness, Attitude toward Use, Self-Efficacy, and Behavioral Intention

Perceived usefulness and perceived ease of use are two core variables in the Technology Acceptance Model (TAM), both of which significantly predict behavioral intention (Davis et al., 1989, p. 985). In their extended study of the TAM model, Venkatesh et al. (2000) further validated the central role of perceived ease of use and perceived usefulness in driving users' acceptance of technology and their behavioral intentions. This provides a theoretical foundation for exploring the relationship between these variables and attitude toward use. Subsequent studies expanded the TAM model, demonstrating that perceived ease of use can indirectly influence behavioral intention through perceived usefulness as a mediator (Martínez-Torres et al., 2008, p. 498). Based on these findings, the following hypotheses are proposed:

H2: Perceived ease of use has a significant positive effect on university students' behavioral intention to use generative artificial intelligence for English learning.

H3: Perceived usefulness has a significant positive effect on university students' behavioral intention to use generative artificial intelligence for English learning.

H4: Perceived ease of use has a significant positive effect on university students' attitude toward using

generative artificial intelligence for English learning.

H5: Perceived usefulness has a significant positive effect on university students' attitude toward using generative artificial intelligence for English learning.

H6: Perceived ease of use has a significant positive effect on the perceived usefulness of generative artificial intelligence for English learning.

In the classical framework of the Technology Acceptance Model, attitude toward use is the mediator that links users' perceptions of technology with their behavioral tendencies and is recognized as a key variable for predicting behavioral intention. Its positive influence on behavioral influence on behavioral intention has been confirmed in earlier research on technology acceptance (Davis, 1989, p. 334). Zhang et al. (2018) pointed out that teachers' attitudes toward applying information technology in teaching directly influence their intention to use it and indirectly affect actual usage behavior through intention. Scherer et al. (2019) conducted a meta-analysis of 114 empirical studies on teacher technology acceptance and confirmed that, regardless of the type of technology or application scenario, attitude toward use remains a key variable in predicting behavioral intention. While existing studies have thoroughly confirmed the pathway from attitude toward use to behavioral intention, most focus on teachers, lacking perspectives from learners, and few address emerging educational technologies such as generative artificial intelligence. Therefore, based on the characteristics of generative AI in empowering university students' English learning, the following hypothesis is proposed:

H7: Attitude toward use has a significant positive effect on university students' behavioral intention to use generative artificial intelligence for English learning.

Self-efficacy refers to an individual's subjective assessment of their ability to successfully perform a behavior (Bandura, 1977, p. 191). Dehghani et al. (2024) found that self-efficacy has a positive effect on perceived ease of use and perceived usefulness, both of which significantly predict attitude toward use. This result not only validates the Technology Acceptance Model but also supports the idea that self-efficacy significantly predicts perceived usefulness, perceived ease of use, and attitude toward use. Chen (2019) pointed out that self-efficacy has a significant positive predictive effect on classroom oral participation motivation. The stronger a learner's confidence in their language ability, the more active their participation in classroom activities. Although this study focused on traditional classroom settings, its conclusion aligns with Bandura's (1997) core theory of self-efficacy, which suggests that self-efficacy enhances individuals' willingness to act and promotes actual participation. Based on the above, the following hypotheses are proposed:

H8: Self-efficacy has a significant positive effect on university students' behavioral intention to use generative artificial intelligence for English learning.

H9: Self-efficacy has a significant positive effect on university students' perceived ease of use of generative artificial intelligence for English learning.

H10: Self-efficacy has a significant positive effect on university students' perceived usefulness of generative artificial intelligence for English learning.

34

H11: Self-efficacy has a significant positive effect on university students' attitude toward using generative artificial intelligence for English learning.

1.3 The Mediating Role of Perceived Ease of Use, Perceived Usefulness, and Attitude toward Use in the Relationship between Self-Efficacy and Behavioral Intention

Perceived ease of use, perceived usefulness, and attitude toward use play mediating roles in the process by which self-efficacy influences behavioral intention. This mechanism has been consistently supported across various studies. Chen et al. (2024) found that although self-efficacy can directly and positively predict usage behavior, its more central role lies in enhancing attitude toward use, which indirectly drives the formation of behavioral intention. Yang et al. (2020), in their study on Web 2.0 technology-assisted foreign language learning, highlighted the mediating role of perceived ease of use and perceived usefulness. They clarified that Web 2.0 self-efficacy must first positively predict perceived ease of use, which in turn affects perceived usefulness, indirectly strengthening usage intention, forming a complete chain: "self-efficacy → perceived ease of use → perceived usefulness → usage intention." Liang Yu et al. (2023) emphasized that self-efficacy does not directly affect behavioral intention, but instead operates through the mediating paths of perceived usefulness, perceived ease of use, and attitude toward use to effect this transformation. Wu et al. (2025) further supplemented this from a teacher's perspective, showing that self-efficacy not only works through the aforementioned indirect path but also relies on the chain of mediating effects of perceived ease of use and perceived usefulness to influence behavioral intention.

In summary, while existing studies have verified the mediating roles of these three variables in the relationship between self-efficacy and behavioral intention across different technology application scenarios, research from the learner's perspective regarding generative artificial intelligence empowering English learning remains lacking. Based on this, the article proposes Hypothesis 12: Perceived ease of use, perceived usefulness, and attitude toward use mediate the relationship between self-efficacy and behavioral intention (H12).

Thus, the article constructs the hypothetical model shown in Figure 1 based on the Technology Acceptance Model, aiming to explore the mechanism of behavioral intention formation among university students using generative artificial intelligence for English learning. It also analyzes in depth the key roles and mediating pathways played by perceived usefulness, perceived ease of use, and attitude toward use. Furthermore, the article incorporates self-efficacy, an important individual characteristic variable, aiming to reveal the psychological transformation path from learners' internal belief in their abilities to their external willingness to use technology, providing insights for universities to optimize English teaching through technology empowerment.
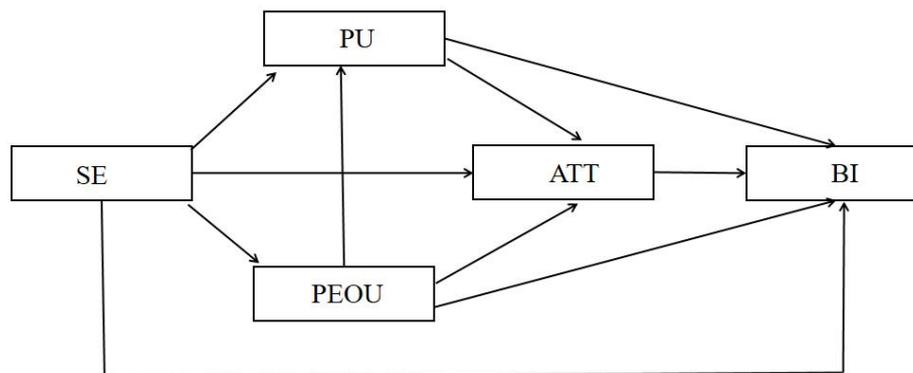
Figure 1. Model of Learners' Acceptance of Generative AI-empowered English Learning

2. Research Design

2.1 Participants

This study adopted a convenience sampling method. The participants were undergraduate students from a university in Henan Province, ranging from first-year to fourth-year students. All participants were required to engage in English learning, such as College English courses and preparation for English proficiency examinations. Their learning needs are highly aligned with the technological features of generative artificial intelligence in English learning.

A total of 226 students participated in the study. Among them, 30 were male (13.27%) and 196 were female (86.73%). Their majors included Translation, Chemical Engineering, Accounting, Law, Aquaculture, and English Education.

2.2 Research Methods

The questionnaire was distributed through the online survey platform Wenjuanxing. A total of 248 questionnaires were collected. After removing responses with straight-line answering patterns and those completed in less than one minute, 226 valid questionnaires were retained.

After data collection, SmartPLS 4 was first used to examine the reliability and validity of the instrument to ensure measurement quality. Next, a structural equation model was constructed in AMOS 29 to test model fit. SPSS 27.0 was then employed to conduct descriptive statistics and normality tests to assess English learners' acceptance of generative artificial intelligence. Finally, SmartPLS 4 was used to construct the structural equation model to examine the direct effects and the indirect mediating effects among the variables.

2.3 Instrument and Reliability and Validity Testing

A questionnaire survey was employed as the research instrument. The first part of the questionnaire collected demographic information, including gender, grade level, and major. The second part measured acceptance and consisted of 18 items.

A five-point Likert scale was used to assess acceptance, with responses ranging from 1 (strongly disagree) to 5 (strongly agree). The scale comprised five dimensions: perceived usefulness (Items 1–4,

36

four items), perceived ease of use (Items 5–8, four items), attitude toward use (Items 9–11, three items), behavioral intention (Items 12–14, three items), and self-efficacy (Items 15–18, four items).

As shown in Table 1, the overall Cronbach's alpha coefficient of the questionnaire was 0.92. The Cronbach's alpha coefficients for all constructs ranged from 0.806 to 0.854. These results indicate good internal consistency across all dimensions. All factor loadings exceeded 0.70, and the average variance extracted (AVE) for each construct was above 0.50, demonstrating satisfactory convergent validity. In addition, the composite reliability values for all constructs were greater than 0.70, further confirming internal consistency.

In the structural model constructed in AMOS 29, the fit indices were as follows: $\chi^2/df = 1.703$, RMSEA = 0.056, CFI = 0.961, and TLI = 0.953. These results indicate a good model fit.

Table 1. Results of Reliability and Validity Testing

Construct	Cronbach's α	Factor loading	AVE	CR
Attitude toward use	0.819	0.785	0.736	0.893
Behavioral intention	0.84	0.791	0.756	0.903
Perceived ease of use	0.854	0.772	0.696	0.902
Perceived usefulness	0.88	0.805	0.737	0.918
Self-efficacy	0.815	0.725	0.644	0.878

3. Results

3.1 Descriptive Statistical Analysis

As shown in Table 2, the mean values of all variables range from 3.62 to 4.00. All means are above the midpoint of 3 on the five-point Likert scale. This indicates a relatively high overall level of acceptance of generative artificial intelligence in English learning among students.

The variance ranges from 0.25 to 0.32, and the standard deviation ranges from 0.50 to 0.57. These values suggest a low degree of dispersion. The results indicate that students generally recognize the value of generative artificial intelligence in English learning contexts.

Regarding distribution shape, skewness values range from −0.57 to 0.88, and kurtosis values range from 0.13 to 3.01. The kurtosis value for perceived usefulness is slightly above 3. This suggests that most students assigned high scores and that the scores are highly concentrated. The skewness and kurtosis values of the remaining variables fall within acceptable ranges. The data are approximately normally distributed and meet the assumptions required for subsequent parametric statistical analyses.

Table 2. Descriptive Statistical Results

Construct	Mean	Variance	SD	Skewness (SE)	Kurtosis (SE)
Perceived usefulness	4.00	0.26	0.51	-0.57(0.16)	3.01(0.32)
Perceived ease of use	3.62	0.27	0.52	0.88(0.16)	0.67(0.32)
Attitude toward use	3.80	0.32	0.57	0.20(0.16)	0.13(0.32)
Behavioral intention	3.85	0.27	0.52	0.08(0.16)	0.62(0.32)
Self-efficacy	3.76	0.25	0.50	0.16(0.16)	0.85(0.32)

3.2 Structural Equation Model

The hypothesis testing results for each path are presented in Table 3, and the results of the structural equation model are shown in Figure 2. Perceived ease of use had significant positive effects on perceived usefulness ($\beta = 0.276$, $p < 0.01$), attitude toward use ($\beta = 0.228$, $p < 0.001$), and behavioral intention ($\beta = 0.116$, $p < 0.05$). Perceived usefulness had significant positive effects on attitude toward use ($\beta = 0.590$, $p < 0.001$) and behavioral intention ($\beta = 0.160$, $p < 0.05$). Attitude toward use had a significant positive effect on behavioral intention ($\beta = 0.490$, $p < 0.001$). In addition, self-efficacy had significant positive predictive effects on perceived usefulness ($\beta = 0.282$, $p < 0.05$), perceived ease of use ($\beta = 0.638$, $p < 0.001$), attitude toward use ($\beta = 0.219$, $p < 0.05$), and behavioral intention ($\beta = 0.136$, $p < 0.05$).
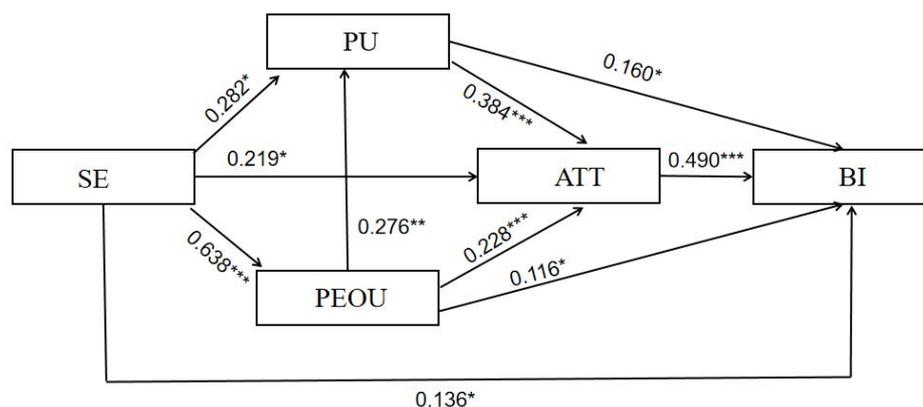

Figure 2. Structural Model of University Students' Acceptance of Generative Artificial Intelligence for English Learning

*Note. *p < .05; **p < .01; ***p < .001.*

Table 3. Hypothesis Testing Results of the Research Model

Hypothesis	β	Result
H2 Perceived ease of use → Behavioral intention	0.116*	Supported
H3 Perceived usefulness → Behavioral intention	0.160*	Supported
H4 Perceived ease of use → Attitude toward use	0.228*	Supported
H5 Perceived usefulness → Attitude toward use	0.384***	Supported
H6 Perceived ease of use → Perceived usefulness	0.276**	Supported
H7 Attitude toward use → Behavioral intention	0.490***	Supported
H8 Self-efficacy → Behavioral intention	0.136*	Supported
H9 Self-efficacy → Perceived ease of use	0.638***	Supported
H10 Self-efficacy → Perceived usefulness	0.282*	Supported
H11 Self-efficacy → Attitude toward use	0.219*	Supported

3.3 Mediation Effect Analysis

As shown in Table 4, the majority of the indirect mediation paths between self-efficacy and behavioral intention are significant. Specifically, the mediation effect of attitude toward use (β = 0.107, p < 0.05) between self-efficacy and behavioral intention is significant and has the highest path coefficient, indicating that Path 3, with attitude toward use as the sole mediator, performs the most prominently. Path 5 (β = 0.071, p < 0.05) and Path 6 (β = 0.053, p < 0.05), both involving multi-stage mediation through attitude toward use, also show significant effects, with their coefficient values being quite similar. Path 2, which uses perceived usefulness (β = 0.074, p < 0.05) as a single mediator, similarly shows significant indirect effects. Path 7 (β = 0.033, p < 0.05), a three-stage chain mediation path involving "perceived ease of use → perceived usefulness → attitude toward use," shows a significant indirect effect but has the smallest path coefficient among all significant paths. In contrast, Path 1 (β = 0.045, p > 0.05), using perceived usefulness as a single mediator, and Path 4 (β = 0.028, p > 0.05), which involves the "perceived ease of use → perceived usefulness" chain mediation, do not reach a significant level for their mediation effects.

Table 4. Mediation Effect Test Results

Path	β	t	p
1. Self-efficacy → Perceived usefulness → Behavioral intention	0.045	1.577	0.115
2. Self-efficacy → Perceived ease of use → Behavioral intention	0.074	2.08	0.038

3. Self-efficacy → Attitude toward use → Behavioral intention	0.107	2.468	0.014
4. Self-efficacy → Perceived ease of use → Perceived usefulness → Behavioral intention	0.028	1.777	0.076
5. Self-efficacy → Perceived ease of use → Attitude toward use → Behavioral intention	0.071	3.088	0.002
6. Self-efficacy → Perceived usefulness → Attitude toward use → Behavioral intention	0.053	2.18	0.029
7. Self-efficacy → Perceived ease of use → Perceived usefulness → Attitude toward use → Behavioral intention	0.033	2.689	0.007

4. Discussion

4.1 University Students' Acceptance of Generative Artificial Intelligence for English Learning

The study found that university students have a relatively high overall acceptance of artificial intelligence (AI)-empowered English learning. This result aligns with the conclusions of studies by Wang et al. (2024) and Liu et al. (2024). In the context of the generative AI-assisted English learning scenario emphasized in this article, this high level of acceptance is closely related to the technical characteristics of AI. From the perspective of perceived ease of use, AI can be accessed and operated easily on mobile devices such as smartphones and tablets, with simple operation processes. Learners can engage in English learning and receive personalized feedback at any time. This convenience lowers the usage threshold and enhances learners' willingness to use the technology (Salam, 2025, p. 152).

Regarding perceived usefulness, generative AI can both reduce learners' anxiety and continuously stimulate their interest, making it an effective tool for personalized English learning (Kohnke et al., 2023, p. 3). AI can serve as a practical auxiliary tool for English learners, helping them to understand difficult points in input materials, enrich output content, and correct errors in language expression (Wen, 2024, p. 13). These functionalities directly enhance learners' perception of the value of

generative AI. Generative AI can instantly diagnose language errors, improve text organization and language quality, thereby strengthening learners' recognition of its value (Mekheimer, 2025, p. 12).

4.2 The Predictive Effects of Self-Efficacy, Perceived Usefulness, Perceived Ease of Use, and Attitude Toward Use on Behavioral Intention

The structural equation model showed that both external variables and core variables significantly predict behavioral intention. Self-efficacy also had significant effects on the other four variables. Among them, attitude toward use had the highest path coefficient. This finding is consistent with the results reported by Liu et al. (2024). One possible explanation is that attitude toward use reflects learners' subjective evaluation of whether the technology meets their learning needs. When learners develop a positive attitude toward use, they are more likely to recognize its value in improving their language competence. This internal value recognition can translate into a willingness to use the technology, thereby fostering behavioral intention. In contrast, a negative attitude may weaken learners' willingness to use the technology and inhibit the formation of behavioral intention due to perceived lack of value.

Perceived ease of use had the lowest predictive effect on behavioral intention. This result is inconsistent with the findings of Li (2023). This discrepancy may be attributed to learners' familiarity with generative artificial intelligence. As most learners are already familiar with the technology, ease of use may no longer be a key factor influencing behavioral intention.

4.3 The Mediating Roles of Perceived Usefulness, Perceived Ease of Use, and Attitude Toward Use

The mediation analysis showed that perceived usefulness, perceived ease of use, and attitude toward use played mediating roles of varying strength between self-efficacy and behavioral intention. This result can be attributed to the role of self-efficacy in shaping attitudes and the central position of attitude in behavioral decision-making. High self-efficacy reduces behavioral anxiety and strengthens individuals' beliefs in their abilities. This process promotes the formation of a positive attitude toward use. In addition, the results showed that attitude toward use had the strongest mediating effect (Path 3). One possible explanation is that attitude toward use serves as a critical bridge between beliefs and behavioral tendencies (Jia et al., 2022, p. 54). It more effectively translates self-efficacy into behavioral intention.

The results also indicated that perceived ease of use had a significant mediating effect between self-efficacy and behavioral intention (Path 2). In the context of this study, this finding may be explained by the influence of self-efficacy on learners' competence judgments. High self-efficacy encourages university students to form positive evaluations of their ability to use AI for English learning. This process indirectly enhances perceived ease of use and reduces psychological barriers during task performance (Curtis et al., 2018, p. 6). As a result, learners' behavioral intention to use generative AI for English learning is strengthened. In contrast, perceived usefulness did not show a significant mediating effect (Path 1). This may be because university students' perceptions of usefulness rely more on objective performance outcomes and external evaluations. These factors are

41

relatively independent of learners' subjective beliefs about their own abilities. Therefore, perceived usefulness is less likely to be significantly influenced by self-efficacy.

Self-efficacy can indirectly influence perceived usefulness and perceived ease of use, which in turn affect attitude toward use and ultimately behavioral intention (Paths 5 and 6). From the perspective of the relationship between self-efficacy and perceived usefulness, high self-efficacy encourages individuals to actively use the tool. When individuals directly experience the tool's value, their perceived usefulness is strengthened. This process promotes the formation of a positive attitude toward use and leads to clear behavioral intention. From the perspective of the relationship between self-efficacy and perceived ease of use, high self-efficacy strengthens individuals' positive expectations of their operational ability. This reduces anxiety associated with using the tool and enhances perceived ease of use. As a result, a positive attitude toward use is fostered, which provides a foundation for behavioral intention.

It is noteworthy that self-efficacy cannot indirectly influence behavioral intention through the path of perceived ease of use to perceived usefulness (Path 4). This finding is inconsistent with the results of Xu et al. (2024). One possible explanation is that perceived usefulness depends more on objective performance outcomes and external evaluations. These factors are relatively independent of individual self-efficacy. Therefore, improvements in perceived ease of use resulting from higher self-efficacy may not be sufficient to change individuals' judgments of the tool's usefulness. This limitation disrupts the transmission chain and prevents it from influencing behavioral intention.

Finally, self-efficacy can indirectly influence perceived usefulness through perceived ease of use. It then affects attitude toward use and behavioral intention (Path 7). This result is consistent with the findings of Bailey et al. (2022). High self-efficacy reduces operational anxiety and facilitates the formation of perceived ease of use. A lower usage barrier allows individuals to focus on the tool's functions and recognize its practical value. This process strengthens perceived usefulness and ultimately translates into behavioral intention through attitude toward use.

5. Conclusion

This study adopted the Technology Acceptance Model as the theoretical framework and conducted an empirical investigation in the context of generative AI-assisted English learning. The study aimed to examine university students' acceptance of generative AI and its influencing factors. The results showed that learners demonstrated a relatively high level of overall acceptance of generative AI. In addition to the confirmed predictive relationships among the core variables of the Technology Acceptance Model, self-efficacy, as an external variable, had significant positive effects on perceived ease of use, perceived usefulness, attitude toward use, and behavioral intention. Furthermore, the other three core variables played mediating roles of varying strength between self-efficacy and behavioral intention.

From the perspective of pedagogical practice, teachers should actively enhance students' self-efficacy through instructional design. Simple and easy-to-operate tasks can help strengthen learners' perceptions of the ease of use of generative AI. Teachers can then gradually demonstrate the practical value of generative AI in vocabulary learning, writing, and speaking tasks. This process can foster positive attitudes and promote sustained usage behavior. Based on the overall path analysis, attitude toward use emerged as the most decisive factor influencing technology acceptance. This finding indicates that perceived ease of use and perceived usefulness must first be transformed into positive attitudes before they can effectively promote behavioral intention. Therefore, developers should focus not only on improving functional effectiveness but also on enhancing learners' emotional engagement through contextualized design. This approach can prevent an overemphasis on operational simplification alone.

This study has several limitations. The sample was drawn from a single university in Henan Province, which limits regional and disciplinary representativeness. In addition, the study used a cross-sectional questionnaire design and was unable to capture dynamic changes during actual use. Future research should expand the sampling scope and incorporate longitudinal designs or qualitative interviews. These approaches can provide deeper insights into the micro-level mechanisms underlying attitude formation and further enrich understanding of learners' acceptance of AI-assisted English learning.

References：

Alfadda, H. A., & Mahdi, H. S. (2021). Measuring students' use of Zoom application in language course based on the technology acceptance model (TAM). *Journal of Psycholinguistic Research*, *50*(4), 883-900.

Bailey, D. R., Almusharraf, N., & Almusharraf, A. (2022). Video conferencing in the e-learning context: Explaining learning outcome with the technology acceptance model. *Education and Information Technologies*, *27*(6), 7679-7698.

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191-215.

Chen, D., Liu, W., & Liu, X. (2024). What drives college students to use AI for L2 learning? Modeling the roles of self-efficacy, anxiety, and attitude based on an extended technology acceptance model. *Acta Psychologica*, *249*, 104442.

Chen, P., Wang, R., & Bai, J. L. (2025). What factors influence learners' adoption of generative AI? Evidence from fuzzy-set qualitative comparative analysis. *Modern Educational Technology*, *35*(6), 36-45.

Chen, Y. (2019). A study on the relationship among L2 motivational self-system, self-efficacy, language anxiety, and classroom oral participation. *Foreign Language Research*, (1), 63-70.

Curtis, R. G., & Windsor, T. D. (2019). Perceived ease of activity mediates the relationship between self-efficacy and activity engagement. *Aging & Mental Health*, *23*(10), 1367-1376.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340.

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, *35*(8), 982-1003.

Dehghani, H., & Mashhadi, A. (2024). Exploring Iranian EFL teachers' acceptance of ChatGPT in English language teaching. *Education and Information Technologies*, *29*(15), 19813-19834.

Fan, B. B., & Li, Z. Z. (2025). AIGC-assisted multimodal discourse teaching pathways. *Frontiers in Foreign Language Education Research*, *8*(2), 47-57.

Jia, L., Yang, L. R., & Zhang, W. Z. (2022). The effect of dynamic assessment on Chinese EFL learners' self-efficacy. *Foreign Language Teaching*, *43*(1), 50-56.

Jin, Y. X., & Sun, F. J. (2025). Generative AI-based intervention on college students' English speaking enjoyment. *Frontiers in Foreign Language Education Research*, *8*(3), 97-109.

Kohnke, L., Moorhouse, B. L., & Zou, D. (2023). ChatGPT for language teaching and learning. *RELC Journal*, *54*(2), 537-550.

Li, K. (2023). Determinants of college students' actual use of AI-based systems: An extension of the technology acceptance model. *Sustainability*, *15*(6), 1-16.

Liang, Y., & Li, N. E. (2023). Chinese digital learning resource usage intention based on TAM extension. *Applied Linguistics*, (2), 23-35.

Liu, G. L., Darvin, R., & Ma, C. (2024). Exploring AI-mediated informal digital learning of English. *Computer Assisted Language Learning*, *38*(77), 1-29.

Mahapatra, S. (2024). Impact of ChatGPT on ESL students' academic writing skills. *Smart Learning Environments*, *11*(1), 1-18.

Martínez-Torres, M. R., Toral Marín, S. L., & García, F. B. (2008). Technological acceptance of e-learning tools. *Behaviour & Information Technology*, *27*(6), 495-505.

Mekheimer, M. (2025). Generative AI-assisted feedback and EFL writing. *Discover Education*, *4*(1), 1-20.

Oc, Y., Gonsalves, C., & Quamina, L. T. (2025). Generative AI in higher education assessments. *Journal of Marketing Education*, *47*(2), 138-155.

Salam, U. (2025). Integration of ChatGPT in EFL courses. *Computers in the Schools*, *42*(2), 145-165.

Scherer, R., Siddiq, F., & Tondeur, J. (2019). Technology acceptance model meta-analysis. *Computers & Education*, *128*(1), 13-35.

Sergeeva, O. V., Zheltukhina, M. R., & Shoustikova, T. (2025). Adoption of generative AI technologies in higher education. *Contemporary Educational Technology*, *17*(2), 1-21.

Sharma, S., & Singh, G. (2024). Adoption of artificial intelligence in higher education. *International Journal of System Assurance Engineering and Management*.

Sun, P. J., Xu, J. Y., & Zhang, J. L. (2025). Generative AI feedback and English writing quality improvement. *Frontiers in Foreign Language Education Research*, *8*(4), 24-36.

44

Venkatesh, V., & Davis, F. D. (2000). Theoretical extension of the technology acceptance model. *Management Science*, *46*(2), 186-204.

Wang, S. S., & Wang, J. J. (2024). Motivation-driven AI acceptance in foreign language learning. *Computer-assisted Foreign Language Education*, (6), 23-29.

Wen, Q. F. (2024). English education in the age of artificial intelligence. *Foreign Languages in China*, *21*(3), 11-18.

Wu, C. X., Wang, Y. Y., & Wang, X. Y. (2025). Informal digital learning intention of international Chinese teachers. *Journal of Henan University (Social Sciences Edition)*, *65*(5), 112-120.

Xu, J. J. (2025). Implementation strategies for personalized foreign language education in the context of large language models. *Foreign Language Teaching and Research*, *57*(1), 81-91.

Xu, J. F., & Deng, Q. L. (2024). College English learners' acceptance of live-stream teaching platforms. *Foreign Language Teaching and Research*, *56*(2), 262-273.

Yang, S. X., & Mei, B. (2020). College students' intention to use Web 2.0 technologies. *Foreign Language Teaching Theory and Practice*, (4), 72-79.

Yang, S. E. (2025). Transformation of English teaching models in the digital intelligence era. *Foreign Language Research*, (3), 18-22.

Zhai, N., & Ma, X. (2021). Automated writing evaluation feedback acceptance. *Computer Assisted Language Learning*, *35*(9), 2817-2842.

Zhang, Z., Chen, X. H., & Wang, Y. N. (2018). Influencing factors on teachers' IT application behavior. *China Educational Technology*, (1), 118-125.

Zhang, Z. Y., & Hong, H. Q. (2023). ChatGPT-supported foreign language teaching. *Foreign Language World*, (2), 38-44.