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Adopting GenAI-Assisted Writing Feedback in L2 Learning: A UTAUT Study of Medical Students

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Abstract. The use of generative artificial intelligence (GenAI) in English as a Foreign Language (EFL) writing instruction has created new opportunities to support students' English language writing. Yet little is known about the factors that influence medical students' acceptance of GenAI-assisted writing feedback. This study modified the Unified Theory of Acceptance and Use of Technology (UTAUT) to examine the determinants of medical students' adoption of GenAI-assisted English language writing feedback. A cross-sectional survey was conducted among 357 medical students at a Chinese medical university. The data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The proposed model showed satisfactory explanatory power (R^2 = 0.475 for use behaviour) and predictive relevance (Q^2 > 0.41). All hypothesised relationships were significant. Social influence was the strongest predictor of use behaviour (β = 0.274, p < .001), followed by performance expectancy. Intention to use significantly mediated the relationships between the antecedent variables and use behaviour, indicating partial mediation. Social influence and performance expectancy also had stronger total effects than effort expectancy and facilitating conditions. The findings extend the application of the UTAUT model to medical students' English language education. They suggest that successful implementation of GenAI-assisted writing feedback depends on both clear educational value and strong support from

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teachers and peers. These factors may encourage continued student use of the technology.

Keywords: English Writing Feedback; Generative Artificial Intelligence (GenAI); Medical Students; Technology Acceptance; UTAUT

1. Introduction

Generative artificial intelligence (GenAI) is reshaping teaching and learning in higher education. One such use case that's become increasingly popular is GenAI-assisted writing feedback. This system can offer students timely, personalized, and scalable assistance across the writing process. In English as a Foreign Language (EFL) education in China, this can enhance formative assessment, promote learner autonomy, and ease the workload associated with providing written feedback.

English language proficiency is a must for medical students for both their academic and professional progression. It increases access to international medical literature, supports participation in global health communication, and job prospects (Alkhaaldi et al., 2023). Accordingly, English language writing has taken on the role of preclinical training in many Chinese medical universities (Lin et al., 2025; Pan & Chen, 2026). Providing valid English language written feedback remains an ongoing challenge in China, despite its importance.

Because instructors often work under such limited and time-poor conditions (large class sizes, limited instructional time, and staffing constraints), they fall short of responding personally but timely to students' specific learning needs through effective feedback (Alsofyani & Barzanji, 2025; Cheng et al., 2025). In this vein, GenAI-assisted writing tools have also become a boon in addition to teachers' commentaries. They can give suggestions on grammar, vocabulary, coherence, and style right now, while supporting students going through the revision process (Abduljawad, 2024; Aladini et al., 2025).

While the educational appeal of GenAI has been widely recognized, its successful integration is contingent on students' openness to the use of these tools in their learning. The literature has focused on the impact of GenAI-assisted writing feedback on writing performance (Jembu & Balang, 2025; Rong & Yao, 2026). However, the psychological and social factors that have a significant impact on learners' acceptance of these technologies, especially for medical students, have received less attention. In several respects, medical students are distinct from the general university population.

As a group, they are typically subject to significant academic demands, well-defined professional goals, and emphasis on efficiency in the learning process (Khojasteh et al., 2025). These features can affect their view and acceptance of newly developed tools in education. It is therefore critical to understand what factors shape their acceptance. Even the most promising technologies are unlikely to improve learning outcomes if students are not willing to use them consistently (Adabor et al., 2025； Luo & Day, 2026).

To this end, the current study has used the Unified Theory of Acceptance and Use of Technology (UTAUT) as its theoretical framework (Venkatesh, 2022). The UTAUT model assumes that technology use is influenced by four key factors: performance expectancy, effort expectancy, social influence, and facilitating conditions. These factors predict behavioural intention, and this subsequently affects people's use of technology. While UTAUT is a widely used framework in educational technology research, the implications of it for medical students accepting GenAI-assisted English language writing feedback have yet to be considered.

The nature of medical education is diverse in that it involves intensive curricula, a regular interplay with instructors, and a real emphasis on goal-directed learning. These characteristics can impact how students view and accommodate new products. Thus, it is uncertain that the relationships put forth by UTAUT work in the same manner in this context (Chu et al., 2025). Exploring such relationships could yield important clues about how GenAI-assisted writing feedback might be integrated successfully into medical students' English language teaching.

1.1 Significance of the Study

Accordingly, this study examines the factors that influence medical students' adoption of GenAI-assisted feedback for English language writing. To achieve this goal, the UTAUT model is modified and tested in the context of medical students' English language education. The study addresses the following research questions:
1. To what extent do performance expectancy, effort expectancy, social influence, and facilitating conditions predict medical students' intention to use GenAI-assisted English writing feedback?
2. Does intention to use mediate the relationships between these factors and students' use behaviour?
3. Do these factors differ in their effects on use behaviour through the mediation of intention to use?

2. Literature Review

2.1 Language Learning Foundations: The Role of Feedback and Mediation in L2 Writing

The study also makes use of perspectives from applied linguistics and educational technology to identify reasons for learners' acceptance of GenAI-assisted writing feedback. This may indicate that the instructional merit of the technology is less a function of its mere presence and more a function of how learners use it and incorporate it into their learning processes (Asltaleb & Alavinia, 2024).

Further, the study is influenced by the process-oriented model of second language (L2) writing. This perspective sees writing as a sort of 'recursively planned, drafted, re-written and re-edited' process instead of a final output of a text (Jembu

& Balang, 2025; Asadi et al., 2025). Within this context, feedback is an essential component that supports learners in detecting language problems, revising their drafts, and updating the content in EFL writing. GenAI-assisted feedback can help in this process by quickly, as well as iteratively guiding grammar, words, organization and the use of language. Consequently, we can see that when students revise their writing it is more effective and efficient (Ahmed et al., 2024).

Similarly, the study is guided by sociocultural theory, as it considers that cultural and technological tools mediate learning processes (Acosta-Enriquez et al., 2025). In this regard, GenAI writing assistants may come across as digital tools that facilitate learning throughout the writing process (Fränken et al., 2023). Their educational value is dependent on learners' active and ongoing engagement, however. If students do not use these tools, they are unlikely to make a meaningful contribution to learning (Ali et al., 2024). For explaining technology-mediated learning in EFL writing contexts (Cammarano et al., 2024), therefore, it is important to understand the acceptance of GenAI by learners.

Taken together, these perspectives suggest that the benefits of GenAI-assisted writing feedback depend not only on the capabilities of the technology but also on learners' willingness to use it. For this reason, technology acceptance has become an important area of research in second language acquisition (Cai, 2025). If learners are unwilling to adopt GenAI-assisted feedback, its potential to support writing development will remain limited. This highlights the need to examine the factors that influence medical students' acceptance and use of GenAI-assisted English writing feedback (Butler & Jiang, 2025).

2.2 Generative AI in Language Learning for Medical Students

The use of GenAI in medical education has grown rapidly in recent years. Its applications now include clinical simulation, diagnostic training, and personalised learning support (Adiyono et al., 2024). More recently, attention has turned to the potential of GenAI in language learning, particularly in supporting the development of English writing skills among medical students. Powered by large language models, GenAI systems can understand and generate natural language. This capability makes them useful learning tools that provide timely, context-sensitive feedback throughout the writing process (Rodway & Schepman, 2023).

For medical students, writing in English is a key academic skill. It facilitates access to the international medical literature, research writing, clinical documentation, and communication in global healthcare settings (Wu et al., 2023). Hence, English writing has been integrated into many types of medical English coursework (Lewis et al., 2024). It has been proved to be important, but it is difficult to offer high quality written feedback. That's especially the case in major classes where instructors have limited time to respond to single students. GenAI-enabled writing feedback provides a pragmatic replacement by instantly giving students advice on grammar, vocabulary, sentence structure, and text organisation (Barrot, 2023). Such feedback allows students to revise their work more independently and continue learning outside of school. It may also help reduce delays in the feedback process (Annamalai et al., 2025).

While previous work has shown bright prospects, there have so far been no more than two areas of academic investigation. The first assesses the accuracy and utility of GenAI-generated feedback, often by comparison with feedback provided by human instructors. The second examines whether GenAI feedback enhances students' writing performance under controlled experimental conditions (Bannister et al., 2024). Moreover, relatively few studies have explored whether students are willing to use these technologies or what affects their continued use in authentic learning contexts. This is particularly important because of learner acceptance being essential for successful implementation and further studies about the factors that encourage or hinder medical students' adoption of GenAI-assisted writing feedback in everyday English language learning are required.

2.3 Theoretical Adoption Framework: The Unified Theory of Acceptance and Use of Technology (UTAUT)

Using the research findings to determine the factors that influence medical students' acceptance of GenAI-assisted English writing feedback, this study will apply the Unified Theory of Acceptance and Use of Technology (UTAUT) as its theoretical background (Venkatesh et al., 2003). UTAUT, which was created by combining eight of the earlier models of user acceptance of technology, has emerged as one of the most applied theoretical perspectives explaining how students adopt and maintain new technologies.

UTAUT suggests that acceptance of technology is affected by four primary factors: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy refers to learners' perceptions of learning outcomes or task performance as being improved because of technology and effort expectancy, in turn, concerns the perceived ease of using the technology. Social influence, which is the degree to which key others support or promote technology use, and facilitating conditions, which are the technical resources and institutional support to use the technology. These four factors influence users' intention to use a technology, which then predicts their actual use behaviour (Venkatesh et al., 2003). As a result of its strong explanatory power, UTAUT is commonly used in educational technology research, for instance, in online learning, mobile learning, and AI-supported learning environments.

Despite its extensive application, relatively few studies have examined the applicability of UTAUT to GenAI-assisted English writing feedback among medical students. Compared with general university students, medical students often experience heavier academic workloads, stronger professional goals, and greater demands for English proficiency. These characteristics may shape their perceptions of the usefulness, ease of use, and practical value of GenAI-assisted writing tools (Chu et al., 2025). Examining technology acceptance in this population may therefore provide deeper insights into the factors that encourage or hinder the adoption of GenAI-assisted writing feedback in medical students' English language education (Lucas et al., 2024).

2.4 Research Model and Hypotheses Development

2.4.1 Performance Expectancy (PE)

Medical students may perceive GenAI-assisted writing feedback as a tool that can improve their academic performance in English courses, help them achieve higher grades, increase the efficiency of writing tasks, and prepare them for future language requirements, such as the College English Test (CET) (Fu & Li, 2022). Given their strong focus on academic achievement and goal-oriented learning, medical students may be more likely to adopt technologies that they perceive as providing clear benefits for their academic outcomes.

H1A: Performance expectancy positively influences medical students' intention to use GenAI-assisted English writing feedback.

H1B: Performance expectancy positively influences medical students' use of GenAI-assisted English writing feedback.

2.4.2 Effort expectancy (EE)

Effort expectancy refers to users' perceptions of the ease of using a GenAI feedback system. For medical students, who often face demanding academic schedules, technologies that are intuitive and time-efficient may be more likely to be accepted (Abbad, 2021). If the processes of submitting written work, interpreting feedback, and applying suggested revisions are perceived as overly complex or cognitively demanding, these challenges may become barriers to adoption, even when the technology offers potential benefits.

H2A: Effort expectancy positively influences medical students' intention to use GenAI-assisted English writing feedback.

H2B: Effort expectancy positively influences medical students' use of GenAI-assisted English writing feedback.

2.4.3 Social Influence (SI)

Social influence is the degree to which a person perceives that important others encourage or support the use of a technology. Sources of social influence: In medical education, possible sources for social influence may be English course instructors, peers, and senior students (Acosta-Enriquez et al., 2025). When instructors officially recommend or integrate GenAI-assisted writing feedback tools into teaching activities, or students notice others use such tools effectively, they may well see GenAI adoption as being positive and socially accepted. Such perceptions can bolster their intention to use the technology (Korchak et al., 2025).

H3A: Social influence positively influences medical students' intention to use GenAI-assisted English writing feedback.

H3B: Social influence positively influences medical students' use of GenAI-assisted English writing feedback.

2.2.4 Facilitating Conditions (FC)

Facilitating conditions refer to the resources, infrastructure, and support available to enable technology use (Rumangkit et al., 2023). These conditions include reliable internet access, compatible digital devices, the availability and affordability of GenAI tools, and the digital skills required to use them effectively. Although basic access to technology may be common in university settings, variations in device quality, familiarity with relevant software, and institutional support may still influence students' perceptions of facilitating conditions.

H4A: Facilitating conditions positively influence medical students' intention to use GenAI-assisted English writing feedback.
H4B: Facilitating conditions positively influence medical students' use of GenAI-assisted English writing feedback.

2.4.5 The Mediating Role of Intention to Use
According to the UTAUT framework and established behavioural theories, behavioural intention is the most immediate cognitive predictor of actual behaviour (Venkatesh et al., 2003). In this study, medical students' intention to use GenAI-assisted writing feedback represents the final cognitive step before actual use behaviour occurs. Therefore, behavioural intention is expected to mediate the effects of the four antecedent constructs on use behaviour.
H5: Medical students' intention to use GenAI-assisted English writing feedback positively influences their use behaviour.
Implicit Mediation Hypothesis: Intention to use mediates the relationships between performance expectancy, effort expectancy, social influence, facilitating conditions, and use behaviour.

Based on the modified UTAUT model and previous empirical studies, the present study proposes the conceptual framework shown in Figure 1.

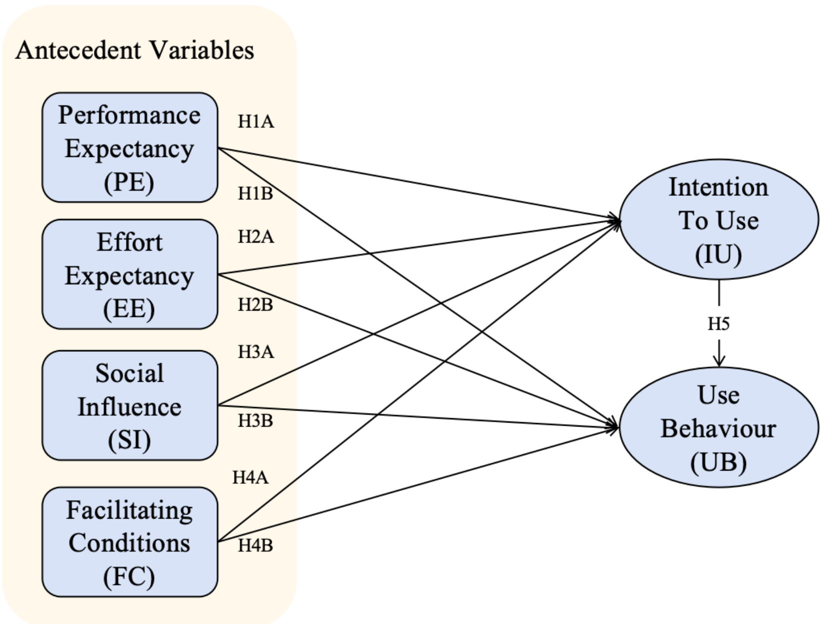

Figure 1: Proposed conceptual framework based on the modified Unified Theory of Acceptance and Use of Technology (UTAUT) model

3. Methodology

3.1 Research Design

This study adopted a quantitative survey design to collect data and test the proposed hypotheses (Creswell, 2003). A structured online questionnaire was developed and administered by the research team. To ensure contextual relevance, the sample consisted of undergraduate medical students enrolled at a medical university in China. The proposed hypotheses were examined using

Partial Least Squares Structural Equation Modelling (PLS-SEM), which is appropriate for analysing complex relationships among multiple latent constructs (Hair et al., 2017).

3.2 Research Procedure

A pilot study was conducted with 50 medical students from the same university to assess the clarity and reliability of the questionnaire before the main survey. Based on the pilot findings, minor modifications were made to improve the wording of several items. The revised questionnaire was then distributed online to undergraduate medical students from different academic years. A total of 389 responses were collected. After excluding incomplete questionnaires, duplicate submissions, and responses showing logical inconsistencies, 357 valid responses were retained for the final analysis.

3.3 Participants

The target population consisted of undergraduate medical students enrolled at a medical university in China. A purposive convenience sampling approach was adopted. Participants were recruited from several medical disciplines, including clinical medicine, dentistry, and preventive medicine.

3.4 Research instruments

All constructs in the research model were measured using reflective indicators adapted from the validated UTAUT scale (Venkatesh et al., 2003). The questionnaire consisted of three sections. The first section collected participants' demographic information. The second section measured the four antecedent constructs of the UTAUT model: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), as well as the mediating construct of intention to use (IU). The final section assessed use behaviour (UB).

Use behaviour was measured based on participants' self-reported use of GenAI-assisted English writing feedback in their English writing activities. As objective usage data, such as system logs, were not available, use behaviour in this study reflects perceived behavioural engagement rather than actual recorded usage. All measurement items were rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The measurement items are presented in Table 1, and the complete list is provided in Appendix 1.

Table 1: Measurement items examples and sources

Construct	Code	Example Item	Description (Contextualized for Medical Students use GenAI-assisted English Writing)	Adapted Source
Performance Expectancy	PE	PE1	PE1: I find GenAI useful in my English language writing.	Venkatesh et al. (2003) Al-Qeisi et al. (2015)
Effort Expectancy	EE	EE1	EE1: I can quickly adapt to using GenAI assisted English writing feedback.	
Social Influence	SI	SI1	SI1: My classmates and friends think that I should use GenAI assisted English language writing.	
Facilitating Conditions	FC	FC1	FC1: I have the necessary resources to use GenAI-assisted English language writing.	
Intention to Use	IU	IU1	IU1: I intend to use GenAI-assisted English language writing in the future.	
Use Behaviour	UB	UB1	UB1: I consider myself a regular user of GenAI-assisted English language writing.	

3.5 Data Collection

In the initial phase of the study, 389 completed questionnaires were collected. After excluding 32 responses that failed to meet the predefined screening criteria, 357 valid responses from medical undergraduates were retained for analysis. This sample size satisfies the recommended minimum requirement for structural equation modelling, which suggests a minimum of ten observations per estimated parameter, and provides sufficient statistical power (Stefanus, 2023). The demographic characteristics of the participants are presented in Table 2.

Table 2: Demographic profile of participants (N=357)

Name	Options	Frequency	Percentage (%)
Gender	male	194	54.34
	female	163	45.66
Highest Education Level	undergraduate	357	100
Total		357	100

3.6 Data Analysis

Data were analysed using SPSS 27.0 and SmartPLS 4.0. SPSS was used for data screening, descriptive statistics, reliability analysis, and Harman's single-factor test to examine common method bias. SmartPLS 4.0 was employed to evaluate the measurement and structural models using Partial Least Squares Structural Equation Modelling (PLS-SEM). Reliability, convergent validity, and discriminant validity were assessed before testing the hypothesised relationships and mediation effects through bootstrapping with 5,000 resamples.

3.7 Ethical Considerations

This anonymous survey study did not require formal ethical approval in line with the guidelines of the participating medical university in China. The study adhered to the ethical principles of the Declaration of Helsinki. The purpose of the study was explained to the participants, who provided electronic informed consent and participated voluntarily. They were informed that they could withdraw from the study at any time without penalty. No personally identifiable information was collected, and all data were securely stored and used solely for academic purposes.

4. Results and Findings

4.1 Preliminary Analysis

4.1.1 Descriptive Statistics and Correlation Analysis

Before hypothesis testing, descriptive statistics and intercorrelations among the key study variables were examined. Table 3 shows the means, standard deviations, skewness, kurtosis, and Pearson correlation coefficients of the six latent constructs.

The mean scores on all constructs ranged from 3.062 to 3.262 on a five-point scale, reflecting a generally positive attitude among medical students towards GenAI-assisted writing feedback and related factors. The standard deviations varied between 0.871 and 1.037, indicating sufficient variability among measures. The absolute values of skewness and kurtosis were below the recommended cut-offs of 3 and 10, respectively (Baffour et al., 2023). These estimates indicate that the data conform to univariate normality.

The correlation analysis showed that all variables were significantly and positively correlated at the $p < .01$ level, with correlation coefficients ranging from 0.404 to 0.557. Intention to Use and Use Behaviour showed the strongest correlation ($r = 0.557$), providing initial support for the hypothesised relationship between intention and actual use behaviour reported in the UTAUT model (H5). In addition, all the correlation coefficients were below 0.85, indicating the lack of substantial multicollinearity as well as the appropriateness of the data for subsequent regression and path analyses (Hair et al., 2021).

Table 3: Means, Standard Deviations, and Correlations among Study Variables

Name	Mean	SD	Skew.	Kurt.	1	2	3	4	5	6
Performance Expectancy	3.225	0.979	-0.121	-1.056	1					
Effort Expectancy	3.260	1.037	-0.043	-1.058	0.451**	1				
Social Influence	3.250	0.958	-0.037	-0.979	0.507**	0.460**	1			
Facilitating Conditions	3.062	1.023	0.08	-0.956	0.404**	0.467**	0.477**	1		
Intention To Use	3.262	0.871	0.054	-0.888	0.507**	0.495**	0.528**	0.481**	1	
Use Behaviour	3.121	1.034	0.091	-1.083	0.520**	0.497**	0.557**	0.487**	0.556**	1

4.1.2 Common Method Bias Assessment

Because the data were collected using self-reported questionnaires, Harman's single-factor test was conducted to examine the potential presence of common method bias. An unrotated principal component analysis of all measurement items showed that the first factor accounted for 38.36% of the total variance, which was below the commonly recommended threshold of 50% (Podsakoff et al., 2003). These results suggest that common method bias was unlikely to substantially affect the validity of the findings.

4.1.3 Measurement Model Assessment

This model of reflective measurement was evaluated for its reliability and convergent validity. All constructs exhibited promising psychometric properties, as indicated in Table 4. Internal consistency reliability was validated, with Cronbach's alpha ranging from 0.762 to 0.855 and composite reliability (CR) values between 0.848 and 0.902. All values were above the 0.70 threshold. Additionally, convergent validity was also confirmed, all standardised factor loadings being statistically significant ranging between 0.75 and 0.87 with a value greater than the 0.70 recommended value. AVE values ranged from 0.583 to 0.709, exceeding the acceptable limit value of 0.50. All the corrected item-total correlations (CITC) also exceeded 0.50.

In general, these results suggest that the model for measurement has sufficient degree of reliability and convergent validity for the structural analysis going forward. Discriminant validity was evaluated according to the Fornell–Larcker criterion. The square roots of the average variance extracted (AVE) values across the constructs from Table 5 (the bold diagonal values) was greater than its correlations with the respective other constructs (off-diagonal values). For instance, the square root of the AVE for Use Behaviour (0.835) was above its correlations with all other constructs (between 0.488 and 0.560 Hair et al., 2021). This was seen across all constructs, suggesting that each latent variable had a larger variance with its own indicators than with other constructs. Hence, discriminant validity was established.

Table 4: Reliability Analysis of Measurement Scales

Construct	Number of Items	Cronbach's α	Loadings Range	Composite Reliability (CR)	Average Variance Extracted (AVE)	Range of CITC	Conclusion
Performance Expectancy (PE)	4	0.833	0.79- 0.83	0.889	0.666	0.639 - 0.679	Good
Effort Expectancy (EE)	4	0.845	0.81 - 0.84	0.896	0.683	0.656 - 0.706	Good
Social Influence (SI)	4	0.810	0.77 - 0.82	0.875	0.636	0.596 - 0.655	Good
Facilitating Conditions (FC)	3	0.795	0.82 - 0.87	0.88	0.709	0.609 - 0.664	Acceptable
Intention to Use (IU)	4	0.762	0.75 - 0.78	0.848	0.583	0.548 - 0.579	Acceptable
Use Behaviour (UB)	4	0.855	0.82 - 0.85	0.902	0.698	0.677 - .720	Good

Note: CR = Composite Reliability (reported as rho_a or Dijkstra-Henseler 's rho_a is recommended for PLS-SEM); AVE = Average Variance Extracted; CITC = Corrected Item-Total Correlation. All indicators meet the recommended thresholds (α/CR > .70; AVE > .50; loadings > .70; CITC > .50).

Table 5: Fornell-Larcker criterion for discriminant validity

	UB	EE	FC	IU	PE	SI
UB	0.835					
EE	0.497	0.826				
FC	0.488	0.466	0.842			
IU	0.557	0.496	0.483	0.764		
PE	0.52	0.451	0.404	0.509	0.816	
SI	0.56	0.463	0.478	0.53	0.51	0.798

Discriminant validity was further examined using the Heterotrait–Monotrait Ratio (HTMT). As presented in Table 6, all HTMT values ranged from 0.497 to 0.688, remaining below the recommended threshold of 0.85 (Hair et al., 2021). These results indicate that the constructs are empirically distinct and demonstrate satisfactory discriminant validity.

Table 6: Heterotrait–Monotrait Ratio (HTMT) of construct correlations

	UB	EE	FC	IU	PE	SI
UB						
EE	0.585					
FC	0.589	0.569				
IU	0.688	0.616	0.617			
PE	0.614	0.538	0.497	0.637		
SI	0.669	0.557	0.594	0.671	0.616	

4.1.4 Structural Model Assessment

The structural model was assessed for collinearity, explanatory power and predictive relevance before analysing the respective path coefficients. As indicated in Table 6, the inner VIF values ranged from 1.527 to 1.746 for the predictor paths targeting Use Behaviour and from 1.465 to 1.605 for those targeting Intention to Use. None of these values exceeded the recommended threshold of 3.0 (Hair et al., 2021), so multicollinearity was not of concern.

The model proved to have good explanatory power which accounted for 47.5% of the variance in Use Behaviour ($R^2 = 0.475$, Adjusted $R^2 = 0.467$) and 42.7% of the variance in Intention to Use ($R^2 = 0.427$, Adjusted $R^2 = 0.421$). The model also had predictive relevance: Stone–Geisser's Q^2 predict values = 0.436 for Use Behaviour and 0.411 for Intention to Use. Both of these values were above the recommended threshold of 0.25.

Table 7 : Assessment of the structural model: explanatory power, predictive relevance, and collinearity

	Q^2predict	RMSE	MAE	R^2	Adjusted R^2	Inner Model VIF Range
Use Behaviour (UB)	0.436	0.755	0.618	0.475	0.467	1.527 – 1.746
Intention to Use (IU)	0.411	0.771	0.653	0.427	0.421	1.465 – 1.605

Note. R^2 = coefficient of determination; adjusted R^2 = adjusted coefficient of determination; Q^2_predict = predictive relevance obtained using the PLSpredict procedure; RMSE = root mean square error; MAE = mean absolute error; VIF = variance inflation factor. The reported inner-model VIF values represent the range across all predictor paths targeting each endogenous construct.

Overall, this finding suggests the structural model is an adequate explanatory and predictive model and suitable for further hypothesis testing.

4.2 Predictors of Medical Students' Intention to Use GenAI-Assisted English Writing Feedback

To address Research Question 1, the structural model was examined to determine the effects of performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC) on medical students' intention to use (IU) GenAI-assisted English writing feedback. Path coefficients were estimated using bootstrapping with 5,000 resamples. The results are presented in Table 8.

Regarding the predictors of Intention to Use (H1A–H4A), all four UTAUT antecedents showed significant positive effects. Social Influence ($\beta = 0.234$, $t = 4.971$, $p < 0.001$) and Performance Expectancy ($\beta = 0.224$, $t = 4.509$, $p < 0.001$) were the strongest predictors. Effort Expectancy ($\beta = 0.199$, $t = 4.141$, $p < 0.001$) and Facilitating Conditions ($\beta = 0.188$, $t = 3.900$, $p < 0.001$) also had significant positive effects.

These results indicate that all four UTAUT antecedents significantly predicted medical students' intention to use GenAI-assisted English writing feedback. Therefore, H1A–H4A were supported, providing a positive answer to Research Question 1.

Table 8: Results of Hypothesis Testing for Predictors of Intention to Use

Hypothesis	Path	Original Sample (β)	Sample Mean	Std. Dev.	t-Statistic	p-Value	Supported or not
H1A	PE -> IU	0.224	0.225	0.050	4.509	<.001	Yes
H2A	EE -> IU	0.199	0.200	0.048	4.141	<.001	Yes
H3A	SI -> IU	0.234	0.233	0.047	4.971	<.001	Yes
H4A	FC -> IU	0.188	0.189	0.048	3.900	<.001	Yes

4.3 Relationship between these antecedent factors and students' use behaviour

To address Research Question 2, the relationships among the four UTAUT antecedents, intention to use (IU), and use behaviour (UB) were examined. The direct effects on use behaviour were first assessed, followed by an analysis of the mediating role of intention to use. The results are presented in Tables 9 and 10.

As shown in Table 9, intention to use had a significant positive effect on use behaviour ($\beta = 0.208$, $t = 4.236$, $p < .001$), supporting H5. In addition, all four antecedent variables showed significant direct effects on use behaviour. Social influence was the strongest predictor ($\beta = 0.274$, $t = 5.159$, $p < .001$), followed by performance expectancy ($\beta = 0.225$, $t = 4.391$, $p < .001$), effort expectancy ($\beta = 0.185$, $t = 3.802$, $p < .001$), and facilitating conditions ($\beta = 0.180$, $t = 3.808$, $p < .001$). Therefore, H1B, H2B, H3B, and H4B were supported.

Table 9: Results of Hypothesis Testing for Predictors of Use Behaviour

Hypothesis	Path	Original Sample (β)	Sample Mean	Std. Dev.	t-Statistic	p-Value	Supported or not
H1B	PE -> UB	0.225	0.225	0.051	4.391	<.001	Yes
H2B	EE -> UB	0.185	0.187	0.049	3.802	<.001	Yes
H3B	SI -> UB	0.274	0.273	0.053	5.159	<.001	Yes
H4B	FC -> UB	0.180	0.180	0.047	3.808	<.001	Yes
H5	IU -> UB	0.208	0.208	0.049	4.236	<.001	Yes

To further examine the mediating role of intention to use, the specific indirect effects of the four antecedent variables on use behaviour were estimated using bootstrapping with 5,000 resamples. As presented in Table 9, all indirect effects were statistically significant ($p < .01$), indicating that intention to use significantly mediated the relationships between the four UTAUT antecedents and use behaviour. Among the indirect effects, social influence showed the strongest mediated effect ($\beta = 0.049$), followed by performance expectancy ($\beta = 0.047$), effort expectancy ($\beta = 0.041$), and facilitating conditions ($\beta = 0.039$). Since both the direct and indirect effects remained significant, the mediation effects identified in this study can be interpreted as partial mediation.

Table 10: Specific Indirect Effects (Mediation) via Intention to Use

Indirect Path	Original Sample (β)	Sample Mean	Std. Dev.	t-Statistic	p-value
PE -> IU -> UB	0.047	0.047	0.015	3.082	0.002
SI -> IU -> UB	0.049	0.049	0.016	3.075	0.002
EE -> IU -> UB	0.041	0.042	0.015	2.833	0.005
FC -> IU -> UB	0.039	0.039	0.014	2.828	0.005

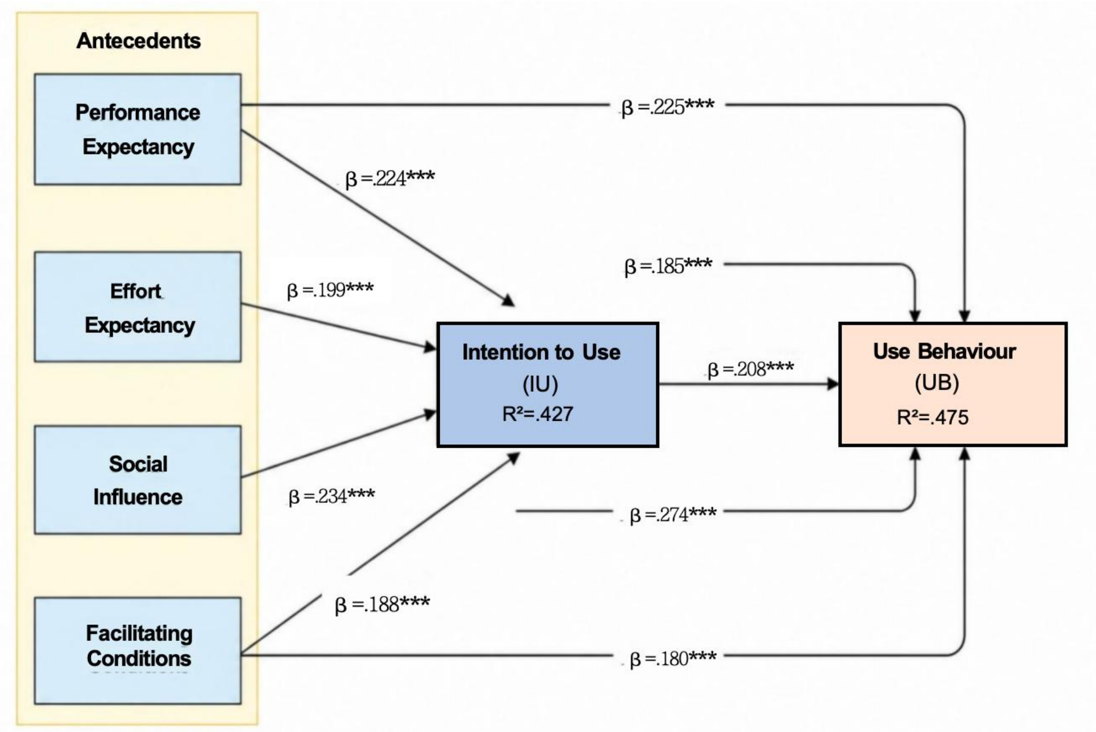

Figure 2: Structural Model with Standardized Path Coefficients

Overall, the findings indicate that intention to use plays a significant mediating role in the relationships between the four UTAUT antecedents and use behaviour. Moreover, the significant direct effects suggest that use behaviour is jointly influenced by both behavioural intention and the four antecedent variables.

4.4 Differences in the predictive strengths of antecedents on use behaviour through the mediation of intention

To address Research Question 3, the relative predictive strengths of the four antecedent variables were compared by examining their total effects on use behaviour. The total effect of each antecedent was calculated as the sum of its direct effect on use behaviour and its indirect effect through intention to use. Pairwise comparisons were then conducted to determine whether significant differences existed among these total effects. The results are presented in Table 11.

As shown in Table 11, social influence had the largest total effect on use behaviour ($\beta = 0.323$), followed by performance expectancy ($\beta = 0.272$), effort expectancy ($\beta = 0.226$), and facilitating conditions ($\beta = 0.219$). Descriptively, the total effect of social influence was 0.051 greater than that of performance expectancy, 0.097 greater than that of effort expectancy, and 0.104 greater than that of facilitating conditions.

Table 11: Comparison of Total Effects on Use Behaviour

Antecedent	Direct	Indirect	Total
PE	0.225	0.047	0.272
SI	0.274	0.049	0.323
EE	0.185	0.041	0.226
FC	0.180	0.039	0.219

Overall, the findings indicate that the four antecedent variables differed in their overall effects on use behaviour. Social influence had the strongest total effect, followed by performance expectancy, whereas effort expectancy and facilitating conditions showed relatively weaker effects. These results suggest that, in the context of GenAI-assisted English writing feedback, social support and perceived performance benefits may play a more important role than perceived ease of use and facilitating resources in encouraging sustained technology use among medical students.

5. Discussion

This study modified the UTAUT model to investigate the adoption of GenAI-assisted English language writing feedback among medical students. The PLS-SEM analysis provided empirical evidence addressing the three research questions. All hypothesised direct paths were statistically significant, supporting the applicability of the modified model in this context. Accordingly, the discussion focuses on the determinants of intention to use, the relationships between antecedent factors and use behaviour, and the comparative predictive strengths of these factors through the mediating role of intention to use.

5.1 Medical students' intention to use GenAI-assisted English writing feedback

Regarding RQ1, which examined the predictors of intention to use, the results showed that Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions were all significant positive predictors of medical students' intention to use GenAI-assisted feedback tools. Social Influence (β = 0.234) and Performance Expectancy (β = 0.224) showed relatively stronger effects, slightly exceeding the effect of Effort Expectancy (β = 0.199). Notably, unlike some previous studies, Facilitating Conditions also had a significant, although weaker, effect (β = 0.188) in the medical education context.

The prominent role of Social Influence suggests that medical students may place considerable value on peer recommendations, instructor support, and shared norms within professional learning environments. The significant effect of Performance Expectancy indicates that students are particularly concerned with whether GenAI-assisted feedback can improve the quality and efficiency of their English language writing.

In the context of the highly structured environment of medical education, these findings suggest that normative strength may be an important factor within the UTAUT framework. When group norms are strong, social factors may become more influential than utilitarian considerations in shaping individual behaviour. This implies that learners may be more likely to adopt GenAI-assisted writing feedback when it is actively recommended or modelled by peers and instructors, particularly when its efficiency and convenience are emphasised. These findings differ from those reported by Yang (2025) among general second-language learners, where social influence and performance expectancy showed similar or slightly weaker effects. This difference may be related to the stronger normative pressures embedded in medical education, which could increase the influence of social factors.

However, Xing et al. (2025) found that performance expectancy remained a prominent factor among EMI students, suggesting that the relative importance of UTAUT factors may vary across learner groups. Future research should therefore further examine user heterogeneity. These findings extend previous UTAUT research by showing that social influence may outweigh utilitarian considerations in highly structured medical education settings. From a practical perspective, universities could strengthen instructor endorsement and peer support to facilitate the adoption of GenAI-assisted writing feedback.

5.2 Antecedent factors and students' use behaviour

Regarding RQ2, which examined the mediating role of intention to use, the results provided evidence that intention to use significantly mediated the relationships between the antecedent variables and use behaviour. However, this mediation was partial for Performance Expectancy and Social Influence, as both constructs maintained significant direct effects on use behaviour after the inclusion of intention to use. In contrast, the effect of Effort Expectancy on use behaviour was fully mediated by intention to use.

The partial mediation effects shows that students' use behaviour may be influenced not only by deliberate intention but also by perceived usefulness and social pressures. This finding is consistent with El Mehdi Chadli et al. (2024), who highlighted the role of habit as a significant predictor in MALL research, and with Wang (2025), who identified motivation as an important moderating factor. Together, these findings suggest that future technology acceptance models may benefit from incorporating perspectives from habit formation theory and motivational psychology to better explain automatic or affect-driven pathways from perception to behaviour. This result may also provide a useful framework for developing more comprehensive models of technology acceptance.

These findings indicate that enhancing students' intention to use GenAI tools alone may not be sufficient to encourage adoption. Universities should also improve students' perceptions of the usefulness of GenAI tools and foster supportive learning environments.

5.3 Predictive strengths of antecedents on usage behaviour through the mediation of intention

Regarding RQ3, the findings revealed clear differences in the predictive strengths of the antecedent variables. Social Influence exhibited the largest total effect on use behaviour, reflecting both its strong direct effect ($\beta = 0.274$) and its indirect effect through intention. Performance Expectancy ranked second, demonstrating substantial direct and indirect effects. Although Effort Expectancy and Facilitating

Conditions also significantly predicted use behaviour, their overall effects were comparatively weaker.

This finding suggests that social influence is the most influential determinant of medical students' adoption of GenAI-assisted English writing feedback. The strong effects of social influence on both intention and use behaviour indicate that students' technology adoption is shaped not only by individual evaluations of usefulness but also by the expectations of instructors, peers, and the broader educational environment. This finding is consistent with Yang (2025), who likewise identified social influence as a significant predictor of technology acceptance. However, unlike Xing et al. (2025), whose ecological model positioned social influence as an indirect influence through other antecedent variables, the present study demonstrates that Social Influence has the strongest direct and total effects on use behaviour. This discrepancy may reflect the collaborative nature of medical education, where students frequently rely on teacher guidance and peer recommendations when adopting new learning technologies.

5.4 Limitations and Future Research

This study has multiple limitations. The findings were first based on questionnaire data and on participants’ self-reported use behaviour as opposed to objective usage records. Thus, the reported use behaviour may not be representative of students’ true engagement with GenAI-assisted English language writing feedback. Next, future studies can use more objective usage data like system logs or learning analytics to provide more accurate assessments of technology use. Second, the cross-sectional nature of the data does not allow researchers to make causal inferences. Longitudinal research is needed to examine how students’ acceptance of GenAI-assisted writing feedback develops over time.

Third, participants were drawn from only one medical university in China, limiting the generalisability of findings. Future studies are encouraged to include multiple institutions and various educational contexts. Despite these shortcomings, the study demonstrated satisfactory reliability, validity, and explanatory power. The findings thus offer valuable insights into medical students’ adoption of GenAI-assisted English language writing feedback.

5.5 Practical Implications

The results offer practical guidelines for English language instructors, higher education institutions, and designers of GenAI-supported writing aids. Since the strongest predictor of technological use was social influence, teachers need to be actively trying to get students to adopt GenAI-assisted writing feedback as part of regular classroom activities and demonstrate its usefulness. Universities should provide training and establish clear guidelines to support the effective and ethical use of GenAI in English writing courses. Developers also should provide more usability to AI writing systems, with feedback specific to the discipline, to better serve the writing needs of medical students. This might aid better integration of GenAI-assisted writing feedback with medical students’ English language education.

6. Conclusion

This research modified and validated the UTAUT model to investigate factors affecting medical students' acceptance of GenAI-assisted feedback for EFL writing. All four antecedents of the UTAUT were found to be significant predictors of technology acceptance. Of these factors, social influence was the strongest predictor of use behaviour and the next was performance expectancy, emphasizing the role of both social support and perceived usefulness in motivating the adoption of writing feedback using GenAI.

The study also found that intention to use partially mediated the relationships of antecedent variables to use behaviour, suggesting that technology adoption is shaped by both deliberate intention and direct contextual influences. These results allow the UTAUT model to be applied to GenAI-assisted language learning in medical education and give empirical data regarding students' adoption of cutting-edge AI technologies.

On the practical side, the findings point to universities needing to bolster teacher and peer encouragement, but they must also articulate how the educational benefits of GenAI-assisted writing feedback. Our study adds to the current literature on AI-supported language learning, providing more concrete recommendations to incorporate GenAI technologies in medical students' English language education.

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Appendix 1

Measurement Items
All constructs were measured using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).
PE1: I find GenAI useful in my English language writing.
PE2: Using GenAI enables me to accomplish English language writing activities more quickly.
PE3: Using GenAI increases my English language writing output.
PE4: If I use GenAI, I will increase my chances of getting better marks in English language writing courses.
EE1: My interaction with GenAI is clear and understandable.
EE2: I am skillful at using GenAI-assisted English language writing.
EE3: I find it easy to learn how to use GenAI-assisted English language writing.
EE4: I find it easy to get GenAI to do what I want it to do.
SI1: My classmates and friends think that I should use GenAI-assisted English language writing.
SI2: My teachers think I should use GenAI-assisted English language writing.
SI3: The English teachers in my college actively support the use of GenAI for writing feedback.
SI4: In general, the university supports the use of GenAI-assisted English language writing.
FC1: I have the necessary resources to use GenAI-assisted English language writing.
FC2: I have the necessary knowledge to use GenAI-assisted English language writing.
FC3: It is easy for me to access and understand GenAI-generated writing feedback.
FC4: A specific person or group is always available for assistance with GenAI-assisted English language writing difficulties.
IU1: I intend to use GenAI-assisted English language writing in the future.
IU2: I believe I would use GenAI-assisted English language writing in the future.
IU3: I plan to use GenAI-assisted English language writing in the future.
IU4: I would recommend GenAI-assisted English language writing to my colleagues.
UB1: I consider myself a regular user of GenAI-assisted English language writing.
UB2: I prefer to use GenAI-assisted English language writing whenever possible.
UB3: I do most learning tasks by using GenAI-assisted English language writing.