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Modeling the Impact of AI Features on Writing Performance: A TAM–SRL Integrated Framework

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Abstract

AI writing tools are becoming more crucial in helping university students with their English writing as generative AI in education continues to grow. This study explores how essential system features affect students' writing performance through technology acceptance routes. And it also researches the moderating function of self-regulated learning. This study used a questionnaire survey to gather data from 531 English major students using a quantitative design. We used partial least squares structural equation modeling to examine the links between system features, perceived usefulness, perceived ease of use, attitudes, behavioral intentions, and writing performance. The findings demonstrate that perceived utility and perceived ease of use, which in turn affect attitudes and behavioral intentions, are highly predicted by AI system attributes. Behavioral intention positively affects writing performance, and self-regulated learning strengthens this relationship. This study contributes to understanding the mechanisms through which AI tools enhance writing development and provide practical implications for improving AI tool design and integrating them into writing instruction. Future research should further examine long-term effects using longitudinal or process-based data.

Keywords: AI features, Technology Acceptance Model, self-regulated learning, EFL writing, learning outcomes, PLS-SEM

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Introduction

The educational landscape has been drastically altered by the quick development of artificial intelligence technology, especially in writing instruction and language acquisition. Automated Writing Evaluation, Intelligent Tutoring Systems, and emerging Generative AI are examples of AI-assisted writing tools that support learners' English writing development. These tools based on natural language processing and large language models (Fleckenstein et al., 2023). Compared with traditional writing instruction, AI tools give immediate feedback, personalized guidance, multi-turn interaction, and high-quality language generation, thereby addressing limitations such as delayed teacher feedback and insufficient individualized support (Zhai & Ma, 2023). As AI writing tools are increasingly integrated into higher education, understanding how learners perceive, accept, and effectively utilize these technologies has become an essential topic in language education research.

Whether or not technology can effectively improve learning outcomes in technology-enhanced learning environments depends critically on how well learners accept and use the technology. Perceived Usefulness (PU) and perceived ease of use (PEOU) significantly influence users' attitudes and behavioral intentions, according to the Technology Acceptance Model (TAM), which has been extensively used in educational technology research (Davis, 1989). However, current research on AI writing tools primarily focuses on their effectiveness while paying less attention to how specific features of AI tools influence learners' acceptance processes. At the same time, individual learner differences, particularly Self-Regulated Learning (SRL), may affect how students use AI tools during writing. Yet, this relationship still remains underexplored empirically (Fleckenstein et al., 2023). Therefore, an integrated approach that simultaneously considers AI tool features, technology acceptance pathways, and SRL is necessary.

Although AI writing tools have become increasingly prevalent in educational practice, the mechanisms underlying their use remain insufficiently understood. First, many existing studies conceptualize AI writing tools as a single construct and lack detailed analysis of how key system features, such as perceived intelligence, personalization, interactivity, and feedback quality, influence students' PU and PEOU. As a result, it remains unclear which features truly drive students' initial judgments about the tools (Zhai & Ma, 2023). Second, while numerous studies have examined students' behaviors when using AI tools, few have systematically explored how AI features operate through the complete psychological pathway emphasized in TAM, from PU and PEOU to attitudes, behavioral intention, and eventually learning outcomes(Venkatesh et al., 2003). Moreover, in highly technologized writing environments, learners exhibit substantial differences in SRL ability, and it remains uncertain whether this critical individual characteristic influences the extent to which AI tools improve learning outcomes—a gap that current empirical evidence has yet to address sufficiently (Panadero, 2017). These issues represent key concerns for current research and affect the sustainable adoption and effective implementation of AI writing tools in English education.

This study offers a more thorough understanding by combining the essential components of TAM, SRL, and AI writing tools into a single analytical framework of the internal mechanisms through which learners form cognitive evaluations, attitudinal tendencies, and usage behaviors in AI-assisted writing environments. The findings contribute to the theoretical development of educational technology and learner behavior research. Specifically, the results help identify the AI system features that most strongly influence students' technology acceptance and writing experience, offering empirical support for improving system functionality, interface design, and

feedback mechanisms. Additionally, the study emphasizes the significance of learners' SRL abilities, providing implications for instructors to strengthen strategy instruction and enhance students' capacity to use AI resources effectively. From a practical perspective, this study offers decision-making support for higher education institutions seeking to promote AI writing tools, facilitating deeper integration between technology and writing instruction, and ultimately improving students' English writing proficiency and learning outcomes.

This research aims to construct and validate an integrated model to systematically explore how key features of AI writing tools influence students' English writing achievement through technology acceptance pathways and further examine the moderating role of SRL in this process. Based on this overarching objective, we first try to identify the system features of AI writing tools that significantly affect learners' PU and PEOU, and to test the structural relationships among PU, PEOU, attitude, and behavioral intention. Second, the study investigates the mechanism through which behavioral intention affects learning outcomes and examines whether learners' SRL moderates the relationship between behavioral intention and learning achievement, as well as the strength of the relationships between AI features and technology acceptance variables. Guided by these aims, six research questions are proposed:

RQ1. How do AI features influence students' PU and PEOU of AI writing tools?

RQ2. What is the relationship between PU and PEOU?

RQ3. How do PU and PEOU further influence students' attitudes and behavioral intentions?

RQ4. Does behavioral intention positively predict students' English writing learning outcomes?

RQ5. Does self-regulated learning moderate the relationship between behavioral intention and English writing learning outcomes?

RQ6. Does self-regulated learning moderate the connection between AI features and PU/PEOU?

To answer these questions, the study proposes a series of testable hypotheses grounded in TAM and SRL theory. First, it is predicted that the system features of AI writing tools have a substantial impact on students' PU and PEOU, which is where the process of technological acceptance begins. Second, according to the TAM core pathway, PU is anticipated to be positively impacted by PEOU; together, these two perceptions shape students' attitudes toward using AI, which in turn strengthens behavioral intention. Based on the established relationship between behavioral intention and learning outcomes, the study hypothesizes that behavioral intention enhances students' English writing achievement. Furthermore, considering the critical role of individual differences, the study proposes that SRL exerts moderating effects along multiple pathways: it may strengthen the positive influence of behavioral intention on learning outcomes and may also amplify the impact of AI features on PU and PEOU. This work aims to offer a more thorough explanation of the mechanisms connecting AI writing tools, technological acceptability, and learning performance by methodically evaluating these assumptions.

Literature Review

In recent years, AI writing tools have been widely applied in the field of language learning, demonstrating substantial potential, particularly in the writing training of English-major students. AI-assisted writing has been shown to effectively enhance learners' linguistic accuracy, textual coherence, and organizational skills, while also positively affecting on writing motivation, writing

anxiety, and writing confidence. Empirical studies with EFL learners have found that after receiving feedback generated by AI-based systems, students exhibit significant improvements in writing quality, content organization, and language fluency; compared with traditional teacher feedback groups, learners supported by AI show statistically significant gains in writing scores, increased revision frequency, and heightened writing confidence (Mekheimer, 2025). In addition, other studies have highlighted that the instant feedback, multi-turn interaction, and semantic processing capabilities of AI writing tools enable learners to obtain personalized assistance within a short period of time, leading to substantial improvements in writing performance (Mohammed & Khalid, 2025). However, despite the consistent evidence confirming the effectiveness of AI tools in improving writing outcomes, the underlying mechanisms remain insufficiently understood. Questions concerning differences in learners' usage experiences, the specific effects of various tool features on learning outcomes, and the psychological processes mediating these effects still require further investigation.

As AI writing tools become increasingly prevalent in educational practice, researchers have begun to explore how specific tool features shape students' writing experiences and technology acceptance. Recent studies have reached a growing consensus that learners' perceptions of AI tools are heavily influenced by system attributes such as intelligence, personalization, interactivity, and feedback quality (Fleckenstein et al., 2023). When a system demonstrates strong linguistic understanding, grammar diagnosis, and text-generation capabilities, students are more inclined to trust its feedback and perceive the tool as valuable for improving their writing (Wilson et al., 2021). Tools that offer personalized suggestions, adaptive difficulty, or task-specific support appear to benefit learners across proficiency levels; likewise, tools with high interactivity, multi-turn dialogue, or real-time feedback are more likely to be perceived as easy to use, thereby increasing user acceptance. These system features form the cognitive foundation upon which learners evaluate AI writing tools and represent key factors in understanding why, how, and under what conditions students choose to engage with such tools (Mekheimer, 2025).

Meanwhile, TAM has played a central role in explaining user behavior related to AI writing tools. Studies with higher education students have shown that PU is the strongest predictor of attitudes and intentions to use AI tools; when students believe that AI applications can provide actual convenience for writing, research, or learning tasks, they tend to demonstrate higher intention to use them (Kim et al., 2025). Other research has incorporated additional variables such as multimodal literacy, self-efficacy, and university support into extended TAM frameworks, revealing that these factors significantly shape students' cognitive evaluations and behavioral intentions in higher education contexts (Z. Zhao et al., 2025). However, despite the extensive application of TAM in educational technology research, systematic model validations specifically situated in AI writing contexts, as well as studies integrating external tool features, psychological mechanisms, and writing outcomes, remain limited. Existing studies have tended to focus on internal TAM constructs such as PU, PEOU, attitude, and intention, while overlooking how tool features influence these variables and how behavioral intention ultimately translates into writing achievement.

In the process of using AI writing tools, learners' SRL ability has increasingly been recognized as a key factor influencing learning outcomes. Research has shown that in AI-assisted writing contexts, learners with high SRL can use AI-generated feedback more critically and strategically. They actively interpret and evaluate the suggestions provided by AI, selectively adopt and revise them based on their own writing goals and task requirements, thereby achieving genuine

improvement in writing skills (H. Yang et al., 2024). In contrast, low-SRL learners tend to rely more heavily on AI-generated content, engage in less active thinking, and demonstrate limited use of writing strategies. When AI support is removed, these learners often experience declines in the quality of their independent writing. This evidence suggests that SRL not only influences how learners utilize AI tools but may also moderate the effects of tool features on their cognitive evaluations and final writing outcomes, providing a theoretical foundation for developing integrated models that account for learner differences (L. F. Yang & Zhang, 2023).

Despite recent advancements in research on AI-assisted writing, several gaps remain that warrant further investigation. First, many studies treat AI writing tools as a unified construct, failing to differentiate their specific features. As a result, it remains unclear which functions are most effective and why. Second, although researchers have frequently applied TAM to examine students' attitudes toward AI and their intentions to use it, few studies have systematically examined the complete relationships among tool features, technology acceptance pathways, and writing outcomes. There is also a lack of clear theoretical models that explain how these variables interact. Third, learner differences, especially SRL, have rarely been incorporated into existing models. Moreover, writing outcomes have often been narrowly assessed in terms of linguistic accuracy or grammatical correction, with limited attention to higher-order writing abilities, e.g., argumentative structure, depth of ideas, critical expression, or long-term development. Furthermore, although AI writing tools are increasingly used by English-major students, systematic research focusing on this population remains limited, particularly studies integrating tool features, psychological mechanisms, and writing outcomes into a comprehensive framework.

Finally, this study proposes an integrated model that incorporates key features of AI writing tools, including intelligence, personalization, interactivity, and feedback quality, as exogenous variables; includes PU, PEOU, attitude, and behavioral intention from the TAM as mediating variables; and introduces learners' SRL as a moderating variable. This model provides a systematic explanation of how AI writing tools influence English-major students' writing development. Specifically, the model reveals how different system features shape learners' cognitive evaluations of AI tools, how attitudes and behavioral intentions are translated into actual writing outcomes, and how individual differences play a critical role in this procedure. By constructing and validating this model, the study aims to offer theoretical foundations and empirical evidence for optimizing AI tool design, improving writing pedagogy, and enhancing learners' strategy development. Accordingly, the following conceptual model is proposed, as shown in Figure 1.

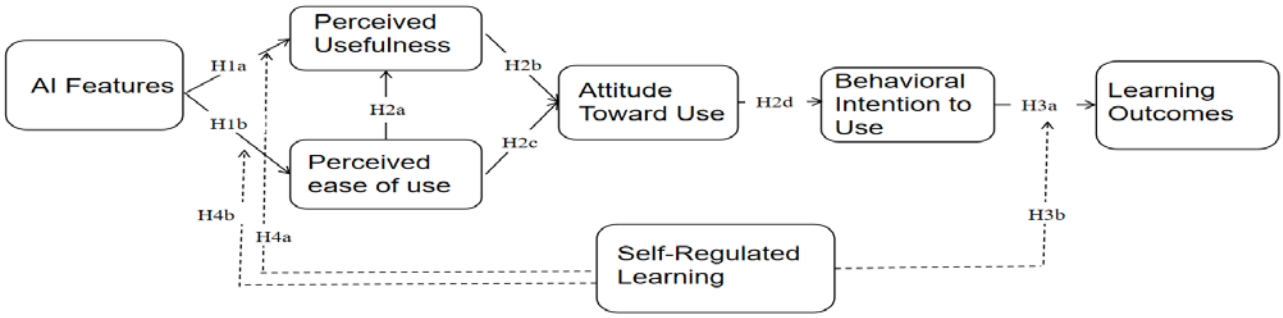


Figure 1. Conceptual Model of this Study

Research Methodology

Research Design

To investigate the links empirically, this study used a quantitative research approach among the seven core variables in the proposed research model through a questionnaire survey. A cross-sectional survey approach was used to collect data, and every measurement item used a Likert scale with five points.

Participants and Setting

The participants of this study were English-major students recruited through purposive sampling. The questionnaires were distributed in university classrooms and online learning groups to reach students at different stages of study. Nine invalid responses were eliminated from the 540 questionnaires that were gathered, leaving 531 valid questionnaires for analysis.

In terms of demographics, Table 1 indicates that 25% of the participants were men and 75% were women. 52.4% of students were undergraduates, 39.4% of students were master's, and 8.2% were PhD students. Overall, the sample demonstrated reasonable representativeness and captured the perspectives and attitudes of English-major students across various academic stages.

The study was conducted in higher education settings, including face-to-face classrooms and online learning platforms, ensuring that participants completed the survey in familiar instructional environments, thereby enhancing the authenticity and validity of their responses.

Research Instruments

The primary tool was a self-administered, anonymous questionnaire. It consisted of 48 items representing seven core research variables. Every item was modified to fit the study's setting after being taken from well-known scales in the literature.

Three field experts reviewed the questionnaire before formal administration. Thirty students was subsequently conducted to assess item clarity and comprehensibility in pilot study. The pilot results indicated that the items were clearly worded and understandable, and no further revisions were required.

Research Procedures

The research procedures followed three stages. The first stage involved preliminary preparation, including selecting and adapting validated scales based on the research model, constructing the initial questionnaire, and submitting it for expert review to assess content validity. The second stage was the pilot test, during which 30 target-group students completed the questionnaire to confirm that the wording and structure were free of significant problems. The final stage was formal data collection, where both online and paper-based questionnaires were distributed to English-major students. Five hundred thirty-one valid samples were kept out of the 540 responses that were gathered after incomplete or inconsistent responses were eliminated. To guarantee participant confidentiality and voluntary involvement, the entire procedure closely followed ethical research guidelines.

Data Analysis

Two phases of data analysis were carried out. To acquire an overview of the sample characteristics and to assess frequencies and percentages for demographic variables, descriptive statistics were first carried out using SPSS. Second, the measurement model, structural model, and

both moderate effects, and mediating effects were tested using PLS-SEM with SmartPLS 4.

Table 1. *Student demographic data*

Variables	Item	Frequency	Effective percentage	Cumulative percentage
Gender	Male	133	25	25
	Female	398	75	100
Grade	Undergraduate	278	52.4	52.4
	Master student	209	39.4	91.8
	PhD student	44	8.2	100

Results

Measurement Model

Three second-order reflective constructs and some first-order reflective constructs are included in this study's measuring approach. The analysis was conducted in two stages (Sarstedt et al., 2019). Latent variable scores were computed for each first-order dimension in the first stage. These scores are manifest indicators of the appropriate second-order constructs.

Evaluation of First-Order Reflective Constructs

All item loadings for the first-order reflective constructs were significant and higher than the suggested cutoff of 0.70, as Appendix 1 illustrates, implying that the observable variables accurately reflect their underlying latent constructs (Hair et al., 2017). In terms of internal consistency, all constructs' Cronbach's alpha and composite reliability (CR) values were above the widely recognized cutoff point of 0.70, with the majority above 0.80, indicating the scales' good reliability (Hair et al., 2019).

AVE values are all greater than 0.50, with the majority lying between 0.72 and 0.82, according to the convergent validity evaluation results, which further supported the constructs' good convergent validity (Fornell & Larcker, 1981). All things considered, the measuring model for the first-order constructs demonstrated convergent validity, internal consistency, and strong factor loadings.

Evaluation of Second-Order Constructs

After confirming the measurement quality of the lower-order dimensions, this study further assessed the three second-order constructs (see Table 2): AI Features, Learning Outcomes, and SRL. The path loadings of the second-order constructs on their respective lower-order dimensions were all significant. They exceeded 0.70, indicating that the lower-order dimensions effectively represent their corresponding higher-order latent variables.

Excellent internal consistency was shown by the three second-order constructions' CR and Cronbach's α values, which were all over 0.90. Additionally, their AVE values were higher than 0.50, supporting the second-order constructs' excellent convergent validity. (Hair et al., 2019).

Table 2. *Convergent validity and dependability of second-order structures*

	Loadings	Cronbach's alpha	CR (rho_a)	CR(rho_c)	AVE
AIF-FQ <- AIF	0.879	0.943	1.041	0.955	0.841
AIF-I <- AIF	0.944				
AIF-P <- AIF	0.939				
AIF-PI <- AIF	0.904				
SRL-GS <- SRL	0.923	0.937	0.941	0.955	0.841
SRL-SE <- SRL	0.919				

SRL-TM <- SRL	0.911				
SRL-TS <- SRL	0.915				
LO-ITCU <- LO	0.928				
LO-LS <- LO	0.936	0.915	0.931	0.946	0.854
LO-PLP <- LO	0.908				

Discriminant validity includes the HTMT index and the Fornell-Larcker criterion. The square root of each construct's AVE is greater than its correlations with other constructs, as Table 3 illustrates, demonstrating acceptable discriminant validity among the latent variables (Fornell & Larcker, 1981). Furthermore, all HTMT values are much less than the stringent threshold of 0.85, as seen in Table 4, further demonstrating the lack of significant construct overlap (Henseler et al., 2015). When combined, these findings show that strong discriminant validity appears in the measurement model, which satisfies the prerequisites for further structural model research.

Table 3. *Fornell and Larcker's standards of discriminant validity*

	AIF	ATU	BITU	OL	PEOU	PU	SRL
AIF	0.924						
ATU	0.414	0.893					
BITU	0.436	0.547	0.900				
OL	0.163	0.221	0.418	0.925			
PEOU	0.528	0.456	0.509	0.206	0.886		
PU	0.612	0.526	0.639	0.326	0.557	0.886	
SRL	-0.024	0.005	-0.033	0.216	0.004	-0.006	0.917

Table 4. *Discriminant validity using the HTMT*

	AIF	ATU	BITU	OL	PEOU	PU	SRL
AIF							
ATU	0.455						
BITU	0.479	0.620					
OL	0.174	0.246	0.465				
PEOU	0.570	0.512	0.568	0.226			
PU	0.660	0.588	0.713	0.358	0.612		
SRL	0.035	0.026	0.038	0.231	0.026	0.035	

Structural Model

Multicollinearity was initially investigated and ruled out in the structural model assessment because, as Table 5 illustrates, all VIF values were below 3.3, indicating no substantial collinearity problems among the independent variables (Diamantopoulos & Siguaw, 2006). Subsequently, the path coefficients obtained through 5,000 bootstrap resamples showed that all hypothesized direct effects reached statistical significance (Hair Jr et al., 2023)

AI Features exerted significant positive effects on students' PEOU and PU, and PEOU also significantly enhanced students' perceptions of usefulness. Both PU and PEOU had good impacts on students' attitudes toward using the system (ATU), which in turn significantly predicted behavioral intention (BITU). Finally, behavioral intention significantly promoted students' English writing learning performance. This sequence of significant relationships clearly illustrates the causal chain extending from AI features, technology perceptions, and attitudes to behavioral intentions and ultimately learning performance, aligning well with the Technology Acceptance Model (TAM) and its extended frameworks.

The model demonstrated moderate explanatory power (Hair et al., 2019) (see Table 6): the R^2 values for PEOU, PU, ATU, BITU, and learning performance ranged between 0.28 and 0.45, with PU showing the strongest explanatory power, highlighting its pivotal role in the overall model. The f^2 effect sizes further confirmed the substantive influence of key paths (Hair et al., 2017) (see Table 7). For example, AI Features exhibited medium to large effect sizes on PEOU and PU. At the same time, attitude toward use showed an effect size approaching a significant effect on behavioral intention, underscoring its central role in the technology acceptance process.

Moreover, all endogenous variables had positive Q^2 values, indicating that the model possesses satisfactory predictive relevance (Doleck et al., 2017) (see Table 6).

Table 5. *Multicollinearity diagnostics for structural model paths (VIF Values)*

AIF -> PEOU	AIF -> PU	ATU -> BITU	BITU -> OL	PEOU -> ATU	PEOU -> PU	PU -> ATU	SRL x AIF -> PEOU	SRL x AIF -> PU	SRL x BITU -> OL
1.001	1.390	1.000	1.010	1.450	1.398	1.450	1.004	1.011	1.022

Table 6. *Coefficient of determination (R^2) and predictive relevance (Q^2)*

	R^2	R^2 adjusted	Q^2
ATU	0.315	0.312	0.247
BITU	0.300	0.298	0.239
OL	0.288	0.284	0.242
PEOU	0.284	0.280	0.220
PU	0.451	0.447	0.351

Table 7. *Effect size (f^2) of the Structural Model Paths*

AIF -> PEOU	AIF -> PU	ATU -> BITU	BITU -> OL	PEOU -> ATU	PEOU -> PU	PU -> ATU
0.389	0.255	0.428	0.225	0.056	0.135	0.156

Mediation Effects

In examining the model's internal mechanisms, several theoretically meaningful but previously unspecified mediation effects were found to be significant (X. Zhao et al., 2010). PEOU influences PU directly, but it also indirectly influences behavioral intention through attitude toward use (ATU), as Table 8 illustrates. Similarly, PU indirectly influences behavioral intention via ATU. Moreover, the effect of AI Features on PU is partially mediated by PEOU and further transmitted through PU to affect students' attitudes and intentions, forming a coherent psychological pathway. Longer mediation chains, such as AI Features → PEOU → PU → ATU → BITU, have also reached significance.

Overall, these results underscore the central mediating role of technology perception variables. Rather than directly affecting learning outcomes, AI Features exert their influence through learners' perceptions, attitudes, and behavioral intentions in a cascading process. Since these mediating effects were not part of the original hypotheses, they are considered exploratory but theoretically supported, and their implications are elaborated in the discussion section.

Table 8. *Bootstrapping results for indirect effects*

	Original sample	Standard deviation	T	P	2.5%	97.5%
AIF -> PEOU -> PU -> ATU -> BITU -> OL	0.015	0.003	4.612	0.000	0.010	0.023
PEOU -> ATU -> BITU	0.129	0.025	5.150	0.000	0.083	0.181
PU -> ATU -> BITU	0.216	0.029	7.376	0.000	0.159	0.272
AIF -> PEOU -> PU	0.170	0.022	7.567	0.000	0.129	0.217
AIF -> PU -> ATU -> BITU	0.095	0.016	5.872	0.000	0.065	0.129

Moderation Effects

The moderation effects were examined using the bootstrap method with 5,000 resamples (Hair et al., 2017; Henseler et al., 2015). As shown in Table 9, self-regulated learning significantly strengthens the relationship between behavioral intention and learning outcomes, indicating that students with higher SRL convert their intention to use AI tools into greater writing improvements. SRL, on the other hand, does not significantly mitigate the impact of AI features on PU or PEOU, indicating that students' fundamental opinions of AI tools are largely unaffected by variations in SRL.

Overall, the results highlight SRL's critical role in enhancing learning outcomes, while showing limited moderating influence during the formation of technology perceptions. To further illustrate the significant moderation, a simple slopes analysis was conducted (Aiken & West, 2010).

Table 9. *Bootstrapping results for moderating effects*

	Original sample	Standard deviation	T	P	2.5%	97.5%
SRL x AIF -> PEOU	0.068	0.038	1.760	0.078	-0.007	0.143
SRL x AIF -> PU	0.023	0.028	0.818	0.413	-0.033	0.078
SRL x BITU -> OL	0.240	0.033	7.220	0.000	0.175	0.307

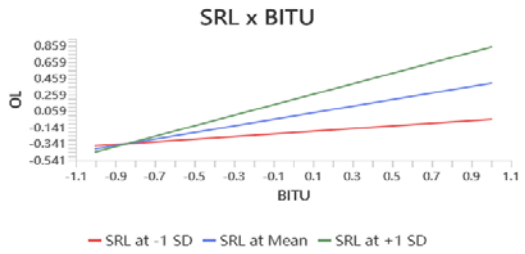


Figure 2: Moderating effect of SRL on the BITU–OL relationship

In summary, all the direct-effect hypotheses proposed in this study were supported. Among the moderation hypotheses, only the moderating effect of self-regulated learning on the relationship between behavioral intention and learning outcomes was significant, whereas the other two moderating hypotheses were not supported. The exploratory mediation analysis revealed several theoretically meaningful mediation pathways, further enriching the explanation of the psychological mechanisms through which AI Features influence learning outcomes. These findings provide a more detailed evidential chain for understanding the behavioral logic underlying students' use of AI-supported learning tools.

Discussion

Based on TAM and SRL theory, this article systematically examined the mechanism linking features of AI writing tools to English writing learning outcomes. Regarding Research Question 1, our findings indicate that the perceived intelligence, personalization, interactivity, and feedback quality of AI writing tools significantly enhanced students' PEOU and PU. This suggests that students' initial judgments about AI tools are not abstract or intuitive but are directly shaped by system features. More precise, more targeted, and more actionable the feedback provided by the tool is, the more likely students are to perceive it as beneficial to improving their writing, and the more easily they can understand how to operate the system with minimal cognitive effort. The study further confirms the path from PEOU to PU proposed in TAM: when students perceive an AI tool as easy to use, they are more likely to recognize its value in supporting writing tasks. This address is Research Question 2.

For Research Question 3, we found that PEOU and PU jointly influenced students' attitudes toward using AI tools, which in turn significantly predicted behavioral intention. Behavioral intention further contributed to improved writing performance. This complete pathway reveals the psychological mechanism through which AI tools enhance learning outcomes and directly addresses the core question concerning the relationship between technology acceptance and writing outcomes. With respect to individual differences, this research found that SRL played an important moderating role between behavioral intention and learning outcomes. Students with higher SRL abilities were better able to analyze AI feedback, plan writing strategies, and monitor their writing process, which enabled them to translate their intention to use AI tools into actual improvements in writing performance. This finding answers Research Question 4. In contrast, SRL did not exert a significant moderating effect during the perception stage, specifically on the relationship between AI tool features and PEOU/PU. This suggests that students' cognitive evaluations of the system itself are relatively universal and less influenced by individual strategy differences; SRL is more likely to shape the post-use strategizing process that determines how students internalize AI feedback and convert it into actual writing gains. This addresses Research Question 6. Overall, the study clearly responds to all six research questions and presents a coherent pathway linking system features, psychological perceptions, attitudes, behavioral intention, and learning outcomes, while clarifying the critical but bounded role of SRL within this mechanism.

From a theoretical perspective, situating these findings within existing research shows strong alignment with prior studies emphasizing the importance of AI writing tool features. Previous research has demonstrated that the quality of feedback, degree of interactivity, and personalization capabilities influence students' value judgments and writing improvement (Mekheimer, 2025; Mohammed & Khalid, 2025). By integrating these features into the TAM framework, the present study not only reaffirms their importance but also clarifies that they directly shape PU and PEOU, thereby enriching previous research that tended to conceptualize AI writing tools as a single undifferentiated construct. Furthermore, the mechanisms identified for PEOU and PU are consistent with existing literature on technology acceptance (Kim et al., 2025; Z. Zhao et al., 2025). However, this research found that PEOU exerts a more substantial influence in the AI writing tools context than in specific other instructional contexts. This may be attributed to the high interactivity, structural complexity, and firm reliance on feedback presentation inherent in writing tasks, suggesting that ease of use plays a particularly critical role in AI-supported writing environments.

The validation of the relationship between behavioral intention and learning outcomes contributes to existing evidence on the positive effects of AI tools on writing performance. While previous studies have frequently emphasized that AI tools support improvements in linguistic accuracy, content organization, and writing confidence, they have seldom explained these outcomes from the perspective of a behavioral-intention perspective. The findings indicate that when students are genuinely willing to use AI writing tools and actively engage with the system throughout the writing process, they are more likely to achieve gains in content development, logical organization, and language expression (Wilson et al., 2021). This provides a process-oriented explanation that complements earlier research, which tended to focus more on the manifestation of learning outcomes rather than the mechanisms through which these outcomes emerge. In addition, the findings related to SRL align with and extend theoretical perspectives in prior research. Students with higher SRL are more capable of planning, monitoring, and reflecting throughout the writing process, enabling them to strategically utilize AI-generated feedback (H. Yang et al., 2024). In contrast, students with low SRL may rely more on surface-level revisions or AI-generated content, making it difficult for them to achieve comparable growth. This study not only confirms the positive role of SRL but also reveals that its influence is concentrated primarily along the intention and performance path rather than the feature and perception path, offering a more nuanced theoretical explanation of how individual differences shape the use of AI writing tools.

About the overall theoretical contribution, this study proposes and validates an integrated three-layer model that incorporates AI tool characteristics, TAM variables, and SRL, providing a systematic account of how AI writing tools operate within the context of university English writing. Compared with prior research that primarily examined PU, PEOU, attitude, and intention, this study further clarifies how specific tool features progressively shape students' psychological evaluations and ultimately influence writing performance. The pathway from external system characteristics to psychological mechanisms and then to learning outcomes enriches the explanation of technology acceptance theory in learning contexts. Moreover, the study delineates the boundary conditions of SRL, demonstrating that while SRL plays a critical role in the gap between intention and performance, it does not substantially alter students' fundamental perceptions of the tool itself. This finding encourages future research to adopt a more process-oriented perspective on SRL, such as examining its real-time influence on feedback interpretation, strategy selection, and revision behaviors.

Notwithstanding the noteworthy results, several limitations need to be noted. First, even though the structural model shows pathway linkages, the cross-sectional nature is not easy to draw firm conclusions on causality. To examine the suggested chain mediation mechanism more thoroughly, future studies should use experimental treatments or longitudinal approaches. Second, the measurement of SRL relied on self-report questionnaires, which may be affected subject to bias. Future studies could incorporate trace data, interaction logs, or writing process analysis to capture SRL behaviors more dynamically during tool use. Third, since only English writing learners made up the study's sample, it is still unclear whether the results can be applied to other academic fields, learning phases, or cultural situations. Finally, future study should examine how various kinds of AI systems, different forms of feedback, and more sophisticated intelligent functions may vary influence learning results given the quick advancement of AI authoring tools and the time-sensitive nature of their features.

Conclusion

This study, grounded in the Technology Acceptance Model and the concept of Self-Regulated Learning, offers a comprehensive account of how AI writing tools function within the context of university students' English writing development. By establishing and validating an integrated model that links AI system features with cognitive perceptions and learning behaviours, the study reveals that the intelligence, personalization, interactivity, and feedback quality of AI tools significantly shape students' PU and PEOU. These perceptions then operate through attitudes and behavioural intentions to enhance writing outcomes. The findings indicate that students' evaluations of AI tools are closely tied to the specific attributes of the system rather than abstract impressions, and that psychological mechanisms within the acceptance process play an essential role in translating tool engagement into learning gains.The results further show that Self-Regulated Learning moderates the relationship between behavioural intention and writing performance. Learners with stronger self-regulatory skills are more capable of turning their intention to use AI tools into improved writing performance, whereas those with lower self-regulation may struggle to benefit to the same extent. This highlights the crucial role of learning strategies and motivational management in AI-assisted writing environments.

From a practical perspective, the findings provide useful implications for both AI tool developers and writing instructors. Developers may consider enhancing the accuracy of intelligent feedback, strengthening personalization, and improving interactive features to reinforce students' positive perceptions of AI tools. Instructors can also guide students to use AI feedback more strategically by fostering planning, monitoring, and reflective skills, enabling them to make more effective use of the support provided by AI systems.

Overall, this study contributes a clearer understanding of how AI system features, cognitive evaluations, and learner strategies interact to influence writing performance. The findings not only enrich current knowledge of AI-assisted writing processes but also offer practical direction for integrating AI tools more effectively into higher education writing instruction.

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Appendices

Appendix A
Reliability and Convergent Validity of First-order Constructs

	Loadings	Cronbach's alpha	CR (rho_a)	CR (rho_c)	AVE
AIF-FQ1	0.878				
AIF-FQ2	0.918	0.880	0.881	0.926	0.807
AIF-FQ3	0.897				
AIF-I1	0.893				
AIF-I2	0.924	0.895	0.898	0.934	0.826
AIF-I3	0.909				
AIF-P1	0.891	0.892	0.894	0.933	0.823
AIF-P2	0.921				

AIF-P3	0.910				
AIF-PI1	0.891				
AIF-PI2	0.911	0.887	0.889	0.930	0.816
AIF-PI3	0.907				
PU1	0.881				
PU2	0.894	0.909	0.910	0.936	0.786
PU3	0.900				
PU4	0.871				
PEOU1	0.893				
PEOU2	0.900	0.909	0.909	0.936	0.786
PEOU3	0.890				
PEOU4	0.862				
ATU1	0.884				
ATU2	0.915	0.873	0.878	0.922	0.797
ATU3	0.879				
BITU1	0.887				
BITU2	0.896	0.883	0.886	0.928	0.811
BITU3	0.918				
SRL-GS1	0.888				
SRL-GS2	0.860	0.866	0.868	0.918	0.789
SRL-GS3	0.915				
SRL-SE1	0.903				
SRL-SE2	0.868	0.879	0.882	0.925	0.805
SRL-SE3	0.920				
SRL-TM1	0.894				
SRL-TM2	0.871	0.878	0.885	0.925	0.804
SRL-TM3	0.924				
SRL-TS1	0.899				
SRL-TS2	0.867	0.869	0.871	0.920	0.792
SRL-TS3	0.904				
LO-ITCU1	0.871				
LO-ITCU2	0.877	0.875	0.878	0.914	0.727
LO-ITCU3	0.821				
LO-ITCU4	0.841				
LO-LS1	0.909				
LO-LS2	0.854	0.857	0.861	0.913	0.778
LO-LS3	0.881				
LO-PLP1	0.864				
LO-PLP2	0.870	0.849	0.851	0.908	0.768
LO-PLP3	0.894				