

PAPER

Mobile Generative AI Literacy and English Writing Self-Efficacy: The Role of AI Feedback Engagement in Higher Education

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ABSTRACT

This study examines the relationship between mobile Generative Artificial Intelligence (GenAI) literacy and English writing self-efficacy (EWSE) among university students, with AI feedback engagement (AFE) proposed as a mediating mechanism. Using a quantitative cross-sectional design, data were collected from 312 university students in China through validated self-report measures. Partial least squares structural equation modelling (PLS-SEM) was employed to test the proposed relationships and mediation effects. The results show that mobile GenAI literacy (MGL) significantly predicts AFE ($\beta = 0.563, p < 0.001$) and EWSE ($\beta = 0.182, p = 0.003$), while AFE significantly predicts writing self-efficacy ($\beta = 0.478, p < 0.001$). AFE partially mediates the relationship between MGL and writing self-efficacy, accounting for approximately 59.6% of the total effect. The model explains 41.2% of the variance in writing self-efficacy. These findings indicate that the educational value of MGL extends beyond technological competence, with active engagement in AI-generated feedback serving as an important mechanism for strengthening writing confidence. The study highlights the importance of pedagogical approaches that promote critical evaluation, reflective use, and meaningful engagement with AI feedback.

KEYWORDS

mobile generative AI literacy (MGL), AI feedback engagement (AFE), English writing self-efficacy (EWSE), higher education, partial least squares structural equation modelling (PLS-SEM)

1 INTRODUCTION

Generative artificial intelligence (GenAI) technologies have transformed higher education, particularly in English as a Second Language (ESL) and academic writing instruction [1]. Advanced large language models (LLMs), such as GPT-4, Claude, and Gemini, provide students with immediate, context-aware feedback on written work.

Liu, D., Hasim, Z., Lim, J. W. (2026). Mobile Generative AI Literacy and English Writing Self-Efficacy: The Role of AI Feedback Engagement in Higher Education. *International Journal of Interactive Mobile Technologies (iJIM)*, 20(19), pp. 19–30. <https://doi.org/10.3991/ijim.v20i19.63209>

Article submitted 2026-07-13. Revision uploaded 2026-08-19. Final acceptance 2026-08-20.

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At the same time, the widespread use of mobile computing devices, including smartphones, tablets, and portable laptops, has expanded learning beyond the boundaries of traditional classrooms and computer laboratories [2]. The convergence of GenAI capabilities and mobile technologies has therefore created new opportunities for mobile GenAI-supported language learning.

The COVID-19 pandemic accelerated the adoption of digital and mobile learning, making mobile devices increasingly commonplace across diverse educational contexts [3]. In higher education, online platforms and mobile applications are increasingly used by students to support academic writing, brainstorm ideas, check grammatical accuracy, and improve coherence. These tools may help address persistent challenges in English writing instruction, including diverse levels of English proficiency, large class sizes, and the limited capacity of instructors to provide timely and individualised feedback [4].

However, access to mobile AI writing tools does not necessarily translate into effective learning. A persistent gap remains between the availability of educational technologies and their meaningful pedagogical integration. Students may engage with AI tools superficially by accepting generated suggestions without critical evaluation or ignoring feedback when they do not understand, trust, or know how to apply it effectively [5]. This raises broader concerns about assumptions of “digital nativity” and the actual levels of digital and AI literacy among university students. Therefore, the critical issue is not simply whether AI writing tools are available on mobile devices but which cognitive and behavioural factors determine their pedagogical value for learners [6].

Despite the growing adoption of mobile GenAI tools in higher education writing instruction, an important gap remains between their technological capabilities and the educational outcomes associated with their use. Mobile AI writing assistants can provide sophisticated and immediate feedback, yet how students engage with such feedback and how this engagement relates to English writing self-efficacy (EWSE) remain insufficiently understood. Writing self-efficacy refers to students’ confidence in their ability to successfully perform writing-related tasks [7]. This issue is particularly relevant in China’s higher education context, where English plays an important role, and students increasingly engage with mobile and AI-enabled learning technologies. Students may also demonstrate varying levels of mobile GenAI literacy (MGL), encompassing technical understanding, critical evaluation, practical use, and ethical awareness, which may shape how effectively they engage with AI-generated feedback. Consequently, greater empirical attention is needed to understand whether and how AI feedback engagement (AFE) serves as a mechanism linking MGL with EWSE [8].

This study aims to develop and empirically test a conceptual model examining the relationships among MGL, AFE, and EWSE among university students. Specifically, it investigates the direct effects of MGL on AFE and EWSE, examines the relationship between AFE and writing self-efficacy, and assesses the mediating role of AFE in the relationship between MGL and EWSE.

2 LITERATURE REVIEW

2.1 Mobile learning

The introduction of AI in mobile learning is an important development in education technology, as it moves beyond rule-based systems and introduces more powerful and complex generative models that can generate contextually appropriate,

human-like answers [9]. The use of mobile applications in the field of education has been revolutionised by the adoption of GenAI, specifically LLMs, which have made it possible to develop apps that can interact with users through natural language, generate text responses, give feedback and align to the needs of each learner. This technological improvement has important consequences for language education, where the need for immediate personalised and scalable feedback has been recognised as a key pedagogical issue for some time now [10]. The architecture of mobile learning has developed to incorporate increasingly sophisticated AI capabilities, enabled by the progress made in the fields of cloud computing, edge processing and device-native AI capabilities. Today, mobile AI writing tools can be divided into paradigms, with some being standalone apps with embedded language models and others being mobile interfaces to cloud-based AI services. Mobile devices add to these factors the challenges of small screens, touch screen interaction, intermittent connectivity and physical environment effects on user interactions with AI-generated content [11]. Studies have shown that the use of a mobile platform affects the frequency of interaction with educational content, as well as the length of interaction, with mobile users having more frequent but shorter interactions with the educational content than desktop users. Mobile language learning (MLL) has great potential and received a lot of attention in the field of second language learning (SLL) in recent years, and it has been reported that GenAI has improved vocabulary acquisition, grammar learning, and writing skills [12].

2.2 AI literacy

AI literacy has become a vital skill in the digital era, which includes comprehending, assessing, and utilising AI technologies effectively [13]. In general, there are several dimensions that are intertwined in conceptualisations of AI literacy, including technical knowledge about what AI is and can do, evaluating the outcomes of AI, and ethical awareness about the use of AI and how to use AI tools. AI literacy has become a crucial part of digital citizenship and academic success in educational environments and is being viewed as a key form of literacy rather than a standalone skill to acquire. There have been multiple stages in AI literacy research. Focusing on general awareness and attitudes toward AI, the initial studies often showed that students and educators had a lot to learn and needed to fill in their knowledge gaps and misconceptions about AI [14]. There is a complex and context-dependent relationship between AI literacy and learning outcomes. However, there have been several studies that have detected positive linkages between AI literacy and the proper use of AI instruments, and a few others that have detected more complicated linkages, such as a hyperlink between higher AI literacy and both greater scepticism and lower use of AI tools [15].

2.3 Writing self-efficacy

Self-efficacy is a person's confidence in the ability to perform specific tasks effectively. For the academic context, writing self-efficacy involves self-confidence regarding the abilities to plan, organise, produce and revise written texts effectively [16]. Self-efficacy in writing has been consistently shown as one of the most important writing outcome variables, the persistence in writing tasks, and willingness to undertake difficult writing tasks. Multiple sources have been shown to contribute

to self-efficacy for writing, such as enactive mastery experiences, or successful writing experiences; vicarious experiences, or observing others do well; verbal persuasion, or encouragement from others, including instructors and peers; and emotional arousal, or managing writing anxiety [17]. Writing self-efficacy is also important in ESL/EFL settings because learners may face extra difficulties in aspects of writing competence, cultural aspects of writing, and academic demands. Self-efficacy beliefs and technology use have been the subject of a large body of research in education. The technology-enhanced learning environment can help to develop self-efficacy through instant feedback, practice opportunities, and scaffolding of complex tasks [18].

2.4 AFE

Feedback engagement has been studied quite a bit in the field of educational psychology and SLL. Feedback engagement is the cognitive, behavioural and affective process of receiving, processing, and responding to feedback information [19]. There are multiple dimensions in feedback engagement: cognitive processing (understand and evaluate feedback), behavioural response (revise work based on feedback), and emotional management (manage affective responses to feedback).

Feedback engagement has unique characteristics when it comes to AI-assisted writing. In comparison to feedback provided by human teachers, AI feedback is often very timely, detailed, and accessible [20]. But sometimes it also has a lack of context, nuance and personal connection that is found in human feedback. This means that students need to learn how to work with the AI-generated feedback, such as by checking its accuracy, understanding the suggestions within their context, and determining which ones to follow [21]. Several key dimensions of AFE have been identified in previous research to be relevant to writing instruction.

2.5 Conceptual framework and hypotheses

Based on the reviewed literature, this study proposes that MGL is positively associated with EWSE both directly and indirectly through AFE. MGL is expected to facilitate students' active engagement with AI-generated feedback, which in turn is associated with greater confidence in academic writing. Accordingly, Figure 1 presents AFE as a mediating mechanism linking MGL and EWSE.

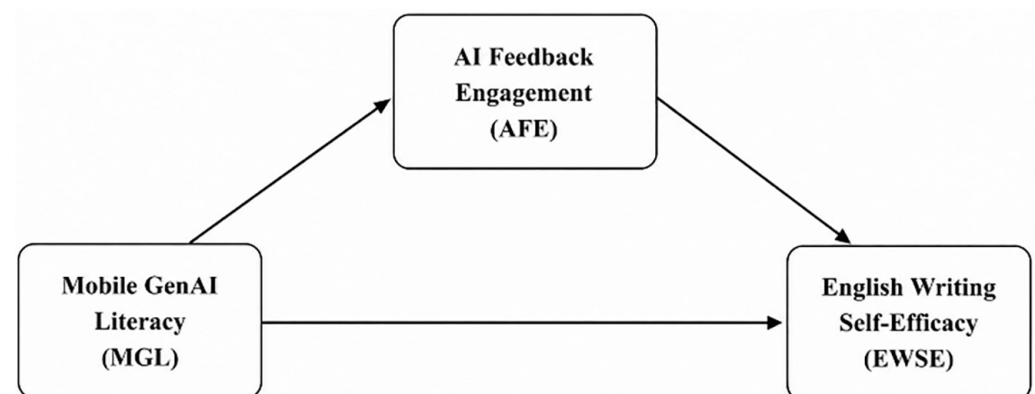


Fig. 1. Proposed conceptual model

H1: MGL is significantly related with EWSE.

H2: MGL is positively associated with AFE.

H3: AFE is positively associated with EWSE.

H4: AFE influences the association between MGL and English writing perceived ability.

3 METHODOLOGY

3.1 Research design

This study employed a quantitative cross-sectional survey design to examine the relationships among MGL, AFE, and EWSE. The design enabled the measurement of latent constructs and testing of direct and mediating relationships using structural equation modelling (SEM).

3.2 Population and sample

The study involved undergraduate and postgraduate students from public and private universities in China who used mobile AI tools for academic writing. A stratified random sampling approach was adopted across academic disciplines and study levels. Of 350 responses collected, 312 valid responses were retained for Partial Least Squares Structural Equation Modelling (PLS-SEM) analysis, yielding an 89.1% response rate.

3.3 Instrument design

Data were collected using a structured questionnaire comprising demographics and three validated scales adapted for mobile GenAI-assisted academic writing. MGL comprised 18 items covering technical understanding, critical evaluation, ethical awareness, and practical AI-use skills [12]. AFE comprised 15 items assessing cognitive, behavioural, and affective engagement with AI-generated feedback [21]. EWSE comprised 12 items assessing confidence in planning, organising, drafting, revising, and editing academic writing [22]. All constructs were measured using five-point Likert scales, resulting in 45 measurement items in total.

3.4 Data collection procedure

Data were collected from January to April 2026 following ethical approval and institutional permission. Participants were informed about the study purpose, voluntary participation, and confidentiality, and informed consent was obtained before participation.

Questionnaires were administered both in person and online through Wenjuanxing, the most commonly used online survey platform in China.

3.5 Data analysis techniques

Data were analysed using PLS-SEM in SmartPLS 4. The adequacy of the measurement model was examined through a series of reliability and validity assessments.

Internal reliability was established using Cronbach's alpha and reliability, whereas convergent validity was evaluated from indicator loadings and AVE. (≥ 0.70) for composite reliability and (≥ 0.50) for AVE was adopted. The structural model was evaluated using path coefficients, coefficient of determination (R^2), and effect sizes (f^2). The significance of both direct and indirect relationships was determined using 5,000 bootstrap samples and a 95% confidence level, including assessment of the mediating role of AFE.

4 RESULTS AND DISCUSSION

4.1 Descriptive analysis

Results in Table 1 present the demographic characteristics of the 312 university students who participated in the study. The respondents were aged 18–35 years ($M = 22.4$, $SD = 3.2$), with the majority (66.7%) aged 18–22 years. The sample has 164 males (52.6%) and 148 females (47.4%), indicating a relatively balanced gender distribution. Most respondents were undergraduates (75.9%), with representation across different academic disciplines and years of study. Overall, the demographic profile reflects a diverse student sample suitable for examining mobile GenAI use in higher education.

Table 1. Demographic profile of the participants

Demographic Variable	Category	Frequency	Percentage (%)
Gender	Male	164	52.56
	Female	148	47.44
Age Group	18–22 years	208	66.67
	23–27 years	78	25.00
	28–35 years	26	8.33
Academic Level	Undergraduate	237	75.96
	Postgraduate	75	24.04
Discipline	Humanities/Social Sciences	98	31.41
	Engineering/Technology	76	24.36
	Natural Sciences	67	21.47
	Business/Management	71	22.76
Year of Study	First Year	69	22.12
	Second Year	85	27.24
	Third Year	83	26.60
	Final Year	75	24.04
AI Tool Used	Doubao	195	62.50
	ChatGPT	171	54.81
	Deepseek	119	38.14
	Others	67	21.47
Usage Frequency	Daily	89	28.53
	Several times per week	129	41.35
	Weekly	63	20.19
	Occasionally	31	9.94

Table 2 presents the descriptive statistics for the three study constructs. EWSE recorded the highest mean ($M = 3.76$, $SD = 0.73$), followed by AFE ($M = 3.58$, $SD = 0.79$) and MGL ($M = 3.42$, $SD = 0.87$). Overall, the results indicate moderately positive levels across all three constructs among the respondents.

Table 2. Descriptive statistics

Construct	Number of Items	Mean	Standard Deviation
MGL	18	3.42	0.87
AFE	15	3.58	0.79
EWSE	12	3.76	0.73

4.2 Evaluation of the measurement model quality

The measurement model was assessed for Construct reliability and convergent validity was assessed as part of the measurement model evaluation. As indicated in Table 3, all constructs exceeded the recommended thresholds for Cronbach's alpha and composite reliability (>0.70) and average variance extracted ($AVE > 0.50$), confirming satisfactory reliable and convergent measurement.

Table 3. Reliability and convergent validity

Construct	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
MGL	0.892	0.914	0.586
AFE	0.879	0.906	0.563
EWSE	0.861	0.895	0.549

Figure 2 shows the measurement model, which indicates all the variables used in this study along with the dimensions of the variables and their respective indicators.

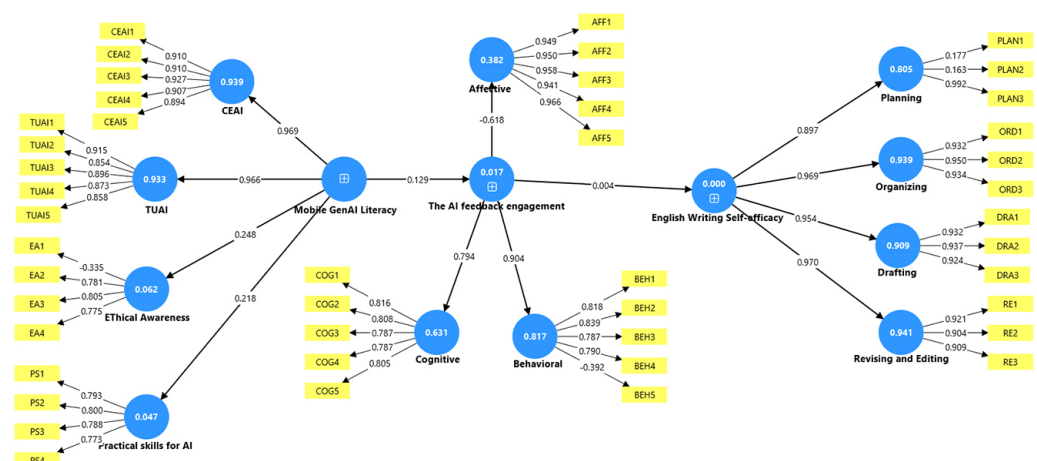


Fig. 2. Measurement model

Table 4 presents the Fornell-Larcker criterion for discriminant validity. The square root of AVE for each construct (diagonal values) exceeded its correlations with the other constructs, indicating satisfactory discriminant validity. Specifically, the

diagonal values were 0.765 for MGL, 0.750 for AFE, and 0.741 for EWSE, all exceeding their respective inter-construct correlations.

Table 4. Discriminant validity – Fornell-Larcker criterion

Construct	MGL	AFE	EWSE
MGL	0.765		
AFE	0.563	0.750	
EWSE	0.478	0.601	0.741

4.3 Assessment of the structural model

Following the confirmation of adequate measurement model properties, the structural model was assessed to test the hypothesised relationships. The structural model evaluation included examination of path coefficients, coefficient of determination (R^2), effect sizes (f^2), and predictive relevance (Q^2).

Table 5. Structural model path analysis and hypothesis assessment

Hypothesis	Path	Path Coefficient	Standard Error	t-Value	p-Value	95% CI Lower	95% CI Upper	Supported
H1	MGL → EWSE	0.182	0.061	2.986	0.003	0.058	0.305	Yes
H2	MGL → AFE	0.563	0.045	12.431	<0.001	0.476	0.652	Yes
H3	AFE → EWSE	0.478	0.054	8.926	<0.001	0.374	0.585	Yes
H4	MGL → AFE → EWSE	0.269	0.038	7.152	<0.001	0.195	0.348	Yes

Table 5 shows that all four hypotheses were supported. MGL significantly predicted EWSE ($\beta = 0.182$, $p = 0.003$) and AFE ($\beta = 0.563$, $p < 0.001$). AFE also significantly predicted EWSE ($\beta = 0.478$, $p < 0.001$). The indirect effect of MGL on EWSE through AFE was significant ($\beta = 0.269$, $p < 0.001$), supporting the mediating role of AFE. AFE accounted for approximately 59.6% of the total effect of MGL on EWSE, indicating partial mediation.

Table 6. Coefficient of determination and effect sizes

Endogenous Construct	R^2	Adjusted R^2	Predictor Construct	f^2	Effect Size Interpretation
AFE	0.317	0.314	MGL	0.464	Large
EWSE	0.412	0.408	MGL	0.062	Small
			AFE	0.278	Medium

Table 6 shows that MGL explained 31.7% of the variance in AFE ($R^2 = 0.317$), while MGL and AFE jointly explained 41.2% of the variance in EWSE ($R^2 = 0.412$). Regarding effect sizes, MGL had a large effect on AFE ($f^2 = 0.464$), while its effect on EWSE was small ($f^2 = 0.062$). AFE demonstrated a medium effect on EWSE ($f^2 = 0.278$).

4.4 Mediating effect analysis

The mediating effect of AFE in the association between MGL and EWSE was further examined using a systematic mediation analysis.

Table 7. Mediation analysis results

Effect Type	Path	Coefficient	Standard Error	t-Value	p-Value	95% CI Lower	95% CI Upper
Direct Effect	MGL → EWSE	0.182	0.061	2.986	0.003	0.058	0.305
Indirect Effect	MGL → AFE → EWSE	0.269	0.038	7.152	<0.001	0.195	0.348
Total Effect	MGL → EWSE	0.451	0.056	8.124	<0.001	0.341	0.562

Table 7 confirms the partial mediating role of AFE. The indirect effect of MGL on EWSE through AFE was significant ($\beta = 0.269$, $p < 0.001$), while the direct effect remained significant ($\beta = 0.182$, $p = 0.003$). The total effect was $\beta = 0.451$ ($p < 0.001$), with the indirect pathway accounting for approximately 59.6% of the total effect, indicating that AFE serves as an important mechanism linking MGL with EWSE.

Table 8. Common method bias assessment – Harman's single-factor test

Model	Number of Factors Extracted	Total Variance Explained	Cumulative Variance	Comparison with Threshold	Interpretation
Single-Factor Model (All items loaded on one factor)	1	32.40%	32.40%	Below the threshold of 50%	No dominant single factor
Measurement Model (Three-factor model)	3	63.80%	63.80%	Substantially higher than the single-factor model	Constructs are empirically distinct

Table 8 presents the results of Harman's single-factor test for assessing potential common method bias. Results from the single-factor evaluation presented that the largest factor accounted for 32.40% of the overall variance, well below the 50% criterion. Therefore, the absence of a dominant factor offers a sign that common method bias was not a considerable concern in the dataset.

5 DISCUSSION

This study investigated the interactions between MGL, AFE, and EWSE among university students, with a specific focus on the mediating effect of AFE. The findings support the proposed conceptual model, showing that MGL is associated with writing self-efficacy both directly and indirectly through AFE. The significant indirect effect ($\beta = 0.269$, $p < 0.001$) accounted for approximately 59.6% of the total effect, indicating partial mediation. This finding indicates that AI literacy alone may not be adequate to strengthen writing confidence; rather, students need to actively evaluate, reflect on, and integrate AI-generated feedback into their writing practices.

Mobile GenAI literacy significantly predicted AFE ($\beta = 0.563$, $p < 0.001$), with a large effect size ($f^2 = 0.464$). This suggests that students with greater understanding of AI capabilities and limitations are more likely to engage meaningfully with AI-generated feedback. Similarly, AFE significantly predicted EWSE ($\beta = 0.478$, $p < 0.001$), representing that active engagement with AI feedback is associated with greater confidence in academic writing.

Importantly, the indirect effect through AFE ($\beta = 0.269$, $p < 0.001$) was stronger than the direct effect of MGL on writing self-efficacy ($\beta = 0.182$, $p = 0.003$). These findings support a process-orientated perspective in which the educational value of mobile GenAI depends not merely on access or AI literacy, but on how students actively engage with AI-generated feedback. This highlights AFE as an important mechanism linking MGL with EWSE.

6 CONCLUSION AND LIMITATIONS

This study examined the relationships among MGL, AFE, and EWSE among university students in China. The findings supported all four hypotheses and confirmed the partial mediating role of AFE. The model explained 31.7% of the variance in AFE and 41.2% in EWSE, highlighting the importance of active engagement with AI-generated feedback. However, the cross-sectional design limits causal inference, while self-reported data may be subject to response bias. Future studies should employ longitudinal designs, objective measures of AI use and writing performance, and cross-cultural samples to strengthen causal understanding and generalisability.

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