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LLM-supported EFL writing: AI feedback literacy, revision behaviour, and writing self-efficacy among Vietnamese undergraduates

Quoc Khanh Nguyen[1], Nhat Quang Vo[2]*

[1]*The University of Da Nang, 41 Le Duan Street, Hai Chau Ward, Da Nang 550000, Vietnam*
[2]*Ho Chi Minh University of Banking, 36 Ton That Dam Street, Sai Gon Ward, Ho Chi Minh City 700000, Vietnam*
e-mail: [1]av32.1b2cva1d047@oncce.udn.vn, *[2]020401250009@st.buh.edu.vn

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A B S T R A C T

This cross-sectional survey examined whether AI feedback literacy and revision behaviour mediated the association between large language model (LLM) co-editing intensity and writing self-efficacy among 305 Vietnamese undergraduates with recent experience using LLM tools for English writing revision. The questionnaire measured LLM co-editing intensity, AI feedback literacy, revision behaviour, and writing self-efficacy. Reliability estimates were acceptable to good, and exploratory factor analysis supported the proposed four-factor structure. Serial mediation analysis with 5,000 bootstrap resamples showed significant indirect associations between LLM co-editing intensity and writing self-efficacy through AI feedback literacy, revision behaviour, and their sequential pathway. The serial indirect effect was 0.048, with a 95% bootstrap confidence interval of [0.024, 0.080], and the total indirect effect was 0.206, 95% CI [0.140, 0.283]. Given the cross-sectional and self-reported data, these findings are interpreted as associational rather than causal. Pedagogically, the results suggest that LLM-supported EFL writing instruction should focus not simply on increasing tool use but on helping students evaluate AI-generated feedback and translate it into purposeful revision decisions.

1. INTRODUCTION

Large language model (LLM) tools have rapidly entered the everyday writing practices of English as a foreign language (EFL) students and have become an increasingly important feature of technology-mediated writing and feedback. Unlike earlier automated writing evaluation (AWE) systems, tools such as ChatGPT, Gemini, Claude, and Microsoft Copilot can respond dialogically to students' drafts, explain suggested changes, provide alternative wordings, and answer follow-up questions. Technology reviews in language education have noted that generative AI can create new opportunities for interaction, feedback, and language practice, but they also emphasize the need for digital competence and ethical use (Kohnke et al., 2023). These affordances are particularly relevant to EFL writing, where students often need support not only with grammar and vocabulary but also with organization, coherence, academic tone, and revision decision-making. However, the pedagogical value of LLMs in writing instruction should not be assumed simply because these tools can generate fluent text. A more important question is how students use LLMs during revision and whether such use is associated with feedback-related capacities and writing self-efficacy.

Recent studies have begun to examine the role of generative AI in L2 and EFL writing feedback. Teng (2024) showed that EFL learners perceived ChatGPT as a useful companion for

writing feedback because it could provide timely support and explanations. Lin and Crosthwaite (2024) further demonstrated that GPT-assisted written corrective feedback can offer useful feedback, although its feedback practices differ from those of human teachers. This pattern is consistent with earlier AWE research, which has shown that automated feedback can support revision and accuracy when it is embedded within instruction, but that learners' engagement and contextual support remain crucial (Li et al., 2015; Link et al., 2022). At the same time, emerging reviews of generative AI and L2 written feedback suggest that the field still needs more evidence on learners' engagement, feedback uptake, revision behaviour, and the relationship between AI-generated feedback and human pedagogical support (Crosthwaite & Sun, 2026). Therefore, the issue is no longer simply whether LLMs can provide feedback. The more pressing question is how students evaluate and use that feedback in their own writing process.

This issue is particularly relevant in EFL higher education contexts, including Vietnam, where students increasingly encounter generative AI as part of their writing and revision practices. Recent evidence from Vietnamese university EFL learners indicates that ChatGPT feedback is already being used and evaluated alongside teacher and peer feedback in writing revision (Nguyen & Nguyen, 2026). The pedagogical issue is therefore not simply whether students have access to LLM tools, but how they engage with the feedback these tools provide. If LLMs are used mainly for surface correction or ready-made rewriting, opportunities for learning may remain limited. By contrast, asking for explanations, comparing alternatives, questioning feedback, and revising strategically may position LLMs as interactive feedback resources rather than as substitutes for students' own writing decisions (Teng, 2024; Lin & Crosthwaite, 2024).

This study uses the term LLM co-editing intensity to describe students' active and repeated use of LLM tools as feedback partners during English writing revision. This construct differs from general technology acceptance or perceived usefulness. It focuses on what students report doing with LLMs after producing a draft: asking for suggestions, requesting explanations, posing follow-up questions, and using feedback without surrendering authorship. This distinction is necessary because LLM use alone does not indicate meaningful learning. A student may use ChatGPT frequently but remain dependent on AI-generated text, whereas another may use the same tool as a dialogic feedback source to strengthen revision control.

To explain why LLM co-editing may be associated with writing self-efficacy, this study draws on two mediating constructs: AI feedback literacy and revision behaviour. Feedback literacy refers to students' capacity to understand, evaluate, manage, and act on feedback (Carless & Boud, 2018). In L2 writing, Yu et al. (2022) showed that student writing feedback literacy involves appreciating feedback, acknowledging different feedback sources, making judgments, managing affect, and taking action. These dimensions are highly relevant to AI-generated feedback because LLM suggestions may be useful, but they may also be inaccurate, too general, or misaligned with task requirements. Revision behaviour is the second mechanism because feedback becomes meaningful only when it is transformed into action (Ranalli, 2021; Zhang & Hyland, 2018).

The outcome variable in this study is writing self-efficacy. Writing self-efficacy refers to students' beliefs about their capability to perform writing tasks. This construct is grounded in social cognitive theory, in which self-efficacy is task-specific rather than a general feeling of confidence (Bandura, 1997; Pajares, 2003). Bruning et al. (2013) conceptualized writing self-efficacy as multidimensional, involving ideation, conventions, and self-regulation. More recent EFL research also treats academic writing self-efficacy as multidimensional and linked to writing performance and engagement with feedback (Teng & Wang, 2023; Tsao et al., 2021). This

construct is appropriate for the present study because the research does not measure actual writing performance through essay scores. Instead, it investigates whether students' LLM-supported revision practices are associated with their writing self-efficacy in managing English academic writing tasks.

Against this background, the present study tests a serial mediation model among Vietnamese EFL undergraduates. Its contribution lies not in showing that students use LLMs for writing, but in explaining how LLM-supported revision may become pedagogically meaningful for English language teaching through AI feedback literacy and revision behaviour. First, it conceptualizes LLM use as co-editing rather than simple tool adoption. Second, it extends L2 writing feedback literacy research to the context of AI-generated feedback. Third, it identifies revision behaviour as a behavioural mechanism connecting feedback literacy with writing self-efficacy. This framing is directly relevant to LLM-supported EFL writing because it shifts attention from tool access to guided, critical, and revision-oriented use of AI in writing classrooms.

The study addresses the following research questions:

RQ1. To what extent is LLM co-editing intensity associated with Vietnamese EFL undergraduates' writing self-efficacy?

RQ2. Does AI feedback literacy mediate the relationship between LLM co-editing intensity and writing self-efficacy?

RQ3. Do AI feedback literacy and revision behaviour serially mediate the relationship between LLM co-editing intensity and writing self-efficacy?

2. LITERATURE REVIEW

2.1. LLM Co-Editing in EFL Writing

In EFL writing, LLM tools can provide feedback on grammar, vocabulary, organization, coherence, and academic tone. Yet LLM use should not be treated simply as automated correction or text generation. The more relevant issue is how students position LLMs within the revision process: whether they use them passively to receive ready-made text or interactively to question, evaluate, and revise their own drafts. This distinction echoes broader discussions in language education, where ChatGPT is described as potentially useful for language teaching and learning only when users possess the digital competencies needed to use it ethically and effectively (Kohnke et al., 2023).

Empirical research on GenAI feedback in L2 writing has grown quickly. Teng (2024), for example, found that EFL learners generally perceived ChatGPT as a useful writing companion because it provided timely feedback and helped students notice problems in their drafts. Lin and Crosthwaite (2024) compared teacher and GPT-assisted written corrective feedback and showed that ChatGPT can generate useful feedback, but its feedback practices differ from those of teachers. These findings suggest that LLM feedback should be studied not only in terms of availability or convenience but also in terms of how students engage with it as part of the writing process.

Recent reviews also indicate that the field needs more focused empirical work on mechanisms rather than further descriptions of general tool use. Crosthwaite and Sun (2026) mapped 51 studies on GenAI and L2 written feedback and reported that current research often examines writing quality, perceptions, feedback uptake, and revision behaviour. Their review calls for stronger attention to how learners process AI-generated feedback and how AI feedback interacts with human pedagogical support. This need is also supported by AWE research syntheses, which show that students' engagement with automated feedback is complex, multi-

layered, and shaped by individual and contextual factors (Fu & Liu, 2022; Karatay & Karatay, 2024).

2.2. AI Feedback Literacy

Feedback does not lead to learning automatically. Students need the capacity to understand what feedback means, judge whether it is useful, and transform it into action. Carless and Boud (2018) define student feedback literacy as the understandings, capacities, and dispositions needed to make sense of information and use it to enhance work or learning strategies. This learner-centred view of feedback is consistent with L2 writing research showing that students' engagement with feedback includes cognitive, behavioural, and affective dimensions (Han & Hyland, 2015; Zhang & Hyland, 2018). This perspective is especially relevant to LLM-supported writing because AI-generated feedback can be immediate and detailed, but not always accurate, task-sensitive, or pedagogically appropriate.

In L2 writing, Yu et al. (2022) developed and validated the L2 Student Writing Feedback Literacy Scale. Their model includes appreciating feedback, acknowledging different feedback sources, making judgments, managing affect, and taking action. This provides a strong foundation for the present study because LLM feedback creates a new feedback source that students must learn to handle. Unlike teacher feedback, LLM feedback is available on demand and can be repeatedly prompted. However, it does not carry the same pedagogical authority, contextual awareness, or accountability as teacher feedback. Students therefore need AI feedback literacy: the ability to elicit, interpret, evaluate, question, and ethically use LLM-generated feedback.

In this study, AI feedback literacy is treated as the first mediator between LLM co-editing intensity and writing self-efficacy. The assumption is that frequent LLM use alone is not necessarily associated with stronger writing self-efficacy. Students may use LLMs frequently but still copy suggestions uncritically, misunderstand feedback, or become dependent on AI-generated revisions. By contrast, students with stronger AI feedback literacy are more likely to ask follow-up questions, identify unclear or inaccurate feedback, compare suggestions with task requirements, and decide which suggestions to accept, modify, or reject.

2.3. Revision Behaviour

Revision behaviour represents the behavioural link between feedback and writing development. Feedback has limited value if students do not use it to revise their drafts. This is particularly important in LLM-supported writing because students may receive many suggestions without necessarily engaging in meaningful revision. Some may copy AI-generated sentences directly, while others may use feedback as a starting point for rethinking organization, coherence, meaning, and language accuracy. Earlier AWE studies have similarly shown that automated feedback can encourage revision, but its value depends on how students interpret and incorporate suggestions (Li et al., 2015; Link et al., 2022).

Research on automated writing feedback suggests that learner engagement is complex. Zhang and Hyland (2018) showed that engagement with teacher and AWE feedback is a crucial mediating factor in how students use feedback in L2 writing. Further studies have shown that engagement with automated feedback differs across learners and is affected by trust, perceived usefulness, feedback clarity, and contextual mediation (Koltovskaia, 2020; Ranalli, 2021; Tian & Zhou, 2020; Zhang, 2020). Reviews of AWE engagement further suggest that behavioural, cognitive, and affective engagement jointly shape whether automated feedback is taken up

productively (Fu & Liu, 2022; Karatay & Karatay, 2024). LLM feedback may be more dialogic than traditional AWE because students can ask for explanations, request alternatives, and continue the interaction. However, this flexibility also increases the need for strategic revision behaviour.

Revision behaviour in this study refers to **students' self-reported tendency to transform LLM feedback into local and global revisions**. Local revisions include changes in grammar, vocabulary, and sentence clarity. Global revisions include paragraph organization, coherence, meaning, and alignment with the writer's intended message. This distinction between local language-level revision and broader meaning- or discourse-level revision is consistent with previous research on learners' engagement with writing feedback and revision (Link et al., 2022; Zhang & Hyland, 2018). Revision behaviour is positioned as the second mediator in the model. The theoretical logic is sequential: students who use LLMs more actively may develop stronger AI feedback literacy; students with stronger AI feedback literacy may then be more likely to revise strategically; and strategic revision behaviour may be associated with stronger writing self-efficacy.

2.4. Writing Self-Efficacy

Writing self-efficacy refers to students' beliefs about their ability to perform writing tasks successfully. In general self-efficacy theory, self-efficacy is task-specific rather than a general feeling of confidence (Bandura, 1997; Pajares, 2003). In writing, this means that students may feel confident in some aspects of writing, such as grammar or vocabulary, but less confident in others, such as organizing ideas or revising a draft. Bruning et al. (2013) conceptualized writing self-efficacy through three dimensions: ideation, conventions, and self-regulation. In EFL academic writing, Teng and Wang (2023) further validated academic writing self-efficacy as a multidimensional construct and found that its dimensions predicted writing performance. Writing self-efficacy is therefore suitable for the present study because academic writing requires students not only to produce accurate sentences but also to generate ideas, organize them logically, revise drafts, and respond to feedback.

Writing self-efficacy is an appropriate outcome for the present study for two reasons. First, the study uses self-reported survey data rather than direct writing performance measures. Therefore, it should not claim that LLM co-editing improves actual writing quality. Second, writing self-efficacy is pedagogically meaningful because students who believe they can manage writing tasks may be more willing to revise, persist, and respond constructively to feedback. Research on written corrective feedback has also suggested that self-efficacy is connected to learners' engagement with feedback in L2 writing (Tsao et al., 2021). In the context of LLM-supported writing, self-efficacy may be shaped by students' experiences of receiving feedback, understanding it, and successfully applying it to their drafts.

Taken together, the literature provides a theoretical basis for the proposed sequence among the four constructs. Repeated engagement with feedback can create opportunities for learners to develop the evaluative capacities associated with feedback literacy (Carless & Boud, 2018; Yu et al., 2022). Feedback literacy becomes educationally consequential when learners use those evaluative capacities to make decisions and act on feedback during revision (Zhang & Hyland, 2018). In GenAI-supported writing specifically, emerging evidence indicates that structured engagement with AI-generated feedback can strengthen learners' ability to interpret, evaluate, and act on feedback (Liu et al., 2026; Lu et al., 2026). Revision behaviour may, in turn, be associated with writing self-efficacy because self-efficacy reflects learners' task-specific beliefs about their capability to manage writing processes successfully (Bruning et al., 2013; Teng &

Wang, 2023). However, these relationships have rarely been integrated and tested as a sequential mechanism linking active LLM co-editing with writing self-efficacy, particularly among Vietnamese EFL undergraduates. The present study therefore examines AI feedback literacy and revision behaviour as sequential mediators of the association between LLM co-editing intensity and writing self-efficacy.

2.5. Conceptual Model and Hypotheses

The theoretical framework integrates student feedback literacy, engagement with automated writing feedback, and writing self-efficacy. Student feedback literacy explains why learners need evaluative capacity when working with feedback. Automated feedback engagement explains why revision behaviour matters as the behavioural realization of feedback use. Writing self-efficacy provides a psychological outcome that reflects students' beliefs about their capability to manage English academic writing tasks. Together, these strands allow the study to move beyond a tool-use perspective and examine a feedback-mediated learning mechanism.

The model begins with LLM co-editing intensity. Students who use LLM tools more actively for writing revision are more likely to encounter different types of feedback, ask follow-up questions, and compare alternative revision suggestions. This repeated interaction may be associated with stronger AI feedback literacy because students gain more opportunities to evaluate feedback quality, identify limitations, and make decisions about feedback use. Students with stronger AI feedback literacy may then be more likely to revise strategically. When students revise actively and see that they can improve their drafts through feedback-informed action, they may report stronger writing self-efficacy in managing writing tasks.

Based on this framework, the following hypotheses were tested:

H1. LLM co-editing intensity is positively associated with AI feedback literacy.
H2. AI feedback literacy is positively associated with revision behaviour.
H3. Revision behaviour is positively associated with writing self-efficacy.
H4. LLM co-editing intensity is positively associated with writing self-efficacy.
H5. AI feedback literacy mediates the relationship between LLM co-editing intensity and writing self-efficacy.
H6. AI feedback literacy and revision behaviour serially mediate the relationship between LLM co-editing intensity and writing self-efficacy.

The hypothesized model is illustrated in Figure 1.

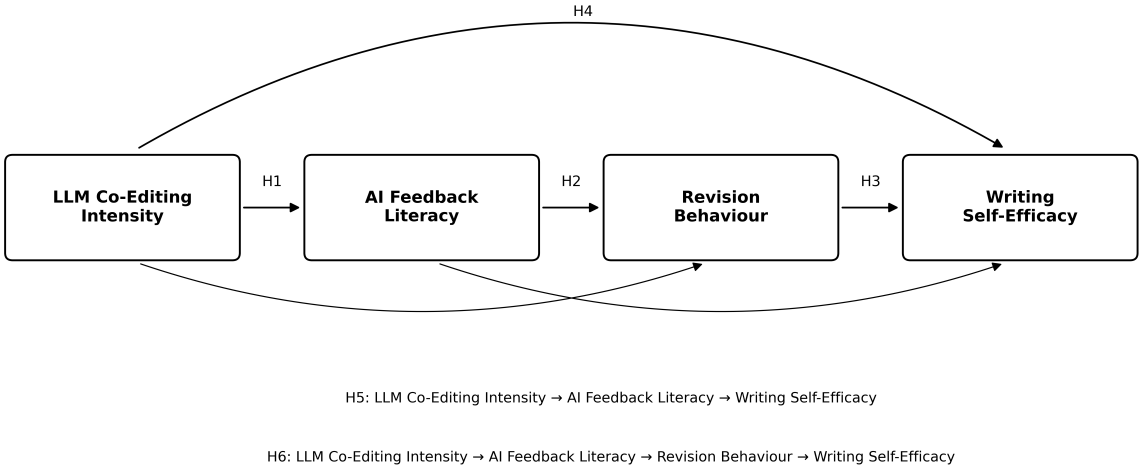

Figure 1. Hypothesized serial mediation model of LLM-supported EFL writing.

Note. H5 represents the indirect pathway through AI feedback literacy. H6 represents the serial indirect pathway through AI feedback literacy and revision behaviour. Unlabelled arrows represent additional paths estimated in the serial mediation model.

3. METHOD

3.1. Research Design

This study employed a quantitative cross-sectional survey design to examine the relationship between LLM co-editing intensity and writing self-efficacy among Vietnamese EFL undergraduates. A survey design was appropriate because the study aimed to investigate students' self-reported experiences of using LLM tools for English writing revision and to test a mediation model involving AI feedback literacy and revision behaviour. The study did not measure actual writing improvement through essay scores. Instead, writing self-efficacy was treated as a psychological outcome reflecting students' beliefs about their capability to generate, organize, revise, and respond to feedback in English academic writing.

3.2. Participants and Sampling

A criterion-based purposive sampling strategy was adopted because the study required participants with direct experience of LLM-supported English writing revision. Participants were recruited through social media and online student groups in Vietnam. The survey was administered using Google Forms, and the recruitment message invited undergraduate students with relevant English writing and LLM-use experience to participate voluntarily.

Eligibility was verified through screening questions at the beginning of the questionnaire. To be included, respondents had to be undergraduate students in Vietnam, be English majors or students enrolled in English writing-related courses, and have used at least one LLM tool for English writing revision within the previous three months. Year 2, Year 3, and Year 4 students were prioritized because they were more likely to have completed paragraph writing, essay writing, academic writing, or research writing courses.

A total of 348 responses were initially received. After screening, 43 responses were excluded because respondents either did not meet one or more of the eligibility criteria or failed the response-quality check. Specifically, eligible respondents had to be undergraduate students in Vietnam, be English majors or enrolled in English writing-related courses, and have used at least one LLM tool for English writing revision within the previous three months. Responses failing these screening requirements or the questionnaire's quality-check item were removed before analysis.

The final dataset included 305 Vietnamese EFL undergraduates who met the inclusion criteria and reported using LLM tools for English writing revision. As shown in Table 1, most participants were female (n = 207, 67.9%), followed by male students (n = 89, 29.2%) and students who preferred not to report their gender (n = 9, 3.0%). The sample included Year 2 students (n = 96, 31.5%), Year 3 students (n = 118, 38.7%), and Year 4 students (n = 91, 29.8%). Most participants rated their writing ability as moderate (n = 168, 55.1%) or high (n = 91, 29.8%). ChatGPT was the most commonly used LLM tool (n = 228, 74.8%), and most students reported using LLMs for writing revision often (n = 139, 45.6%) or very often (n = 62, 20.3%).

Table 1. Participant demographics, N = 305

Variable	Category	n	%
Gender	Female	207	67.9
	Male	89	29.2
	Prefer not to say	9	3.0
Year of study	Year 2	96	31.5
	Year 3	118	38.7
	Year 4	91	29.8
Self-rated writing proficiency	Low	34	11.1
	Moderate	168	55.1
	High	91	29.8
	Very high	12	3.9
Main LLM tool	ChatGPT	228	74.8
	Gemini	45	14.8
	Claude	17	5.6
	Microsoft Copilot	15	4.9
LLM use frequency for writing revision	Sometimes	84	27.5
	Often	139	45.6
	Very often	62	20.3
	Always	20	6.6

Note. Percentages may not total 100 because of rounding.

3.3. Data Collection and Ethics

Data were collected through an anonymous online questionnaire administered using Google Forms. The survey link was distributed through social media and online student groups in Vietnam. The questionnaire consisted of screening questions, demographic items, 25 main Likert-scale items, one response-quality check item, and one optional open-ended question. Only the quantitative Likert-scale data were used in the present analysis. All main items were rated on a five-point scale ranging from 1 = strongly disagree to 5 = strongly agree.

The 25 main items measured four constructs. LLM co-editing intensity was measured using five items and referred to the extent to which students used LLM tools interactively as co-editors during English writing revision. AI feedback literacy was measured using eight items and referred to students' capacity to understand, evaluate, question, and use LLM-generated feedback responsibly. This construct was conceptually informed by feedback literacy research (Carless & Boud, 2018; Yu et al., 2022). Revision behaviour was measured using six items and referred to students' self-reported tendency to transform LLM feedback into local and global revisions. Writing self-efficacy was measured using six items and referred to students' beliefs about their capability to perform English academic writing tasks, including idea generation, logical organization, grammatical accuracy, vocabulary choice, revision for clarity and coherence, and response to feedback (Bruning et al., 2013). Because LLM co-editing intensity and AI feedback literacy are emerging constructs in GenAI-supported writing research, their items were developed in alignment with the study's operational definitions and informed by recent work on GenAI feedback, L2 writing feedback literacy, automated feedback engagement, and writing self-efficacy.

Before accessing the main questionnaire, participants read an information and consent statement explaining the purpose of the study, the voluntary nature of participation, the approximate completion time, the anonymous use of responses for academic research, and their right to discontinue participation at any time without negative consequences. Respondents then completed the eligibility screening questions. Only those who consented and satisfied the

inclusion criteria proceeded to the main questionnaire. No names, student numbers, email addresses, or other personally identifying information were requested, and the data were stored confidentially and reported only in aggregated form.

No formal institutional ethics-board approval or exemption was sought or obtained for this study. The research involved an anonymous, voluntary online questionnaire and did not include an intervention, sensitive personal data, or identifiable student records. The study was conducted as low-risk educational survey research, with informed consent, voluntary participation, anonymity, confidentiality, and the right to discontinue participation incorporated into the data-collection procedure.

3.4. Data Analysis

The quantitative data were analysed in several stages. First, responses were screened for eligibility, completeness, and response quality. Responses that did not satisfy the inclusion criteria and/or the questionnaire's quality-check requirement were excluded before analysis. Composite scores were then calculated by averaging the items within each of the four constructs: LLM co-editing intensity, AI feedback literacy, revision behaviour, and writing self-efficacy.

Second, the measurement properties of the four scales were examined. Internal consistency was assessed using Cronbach's alpha. Skewness and kurtosis were inspected to identify substantial departures from normality in the composite variables. Exploratory factor analysis was conducted on the 25 Likert-scale items to examine whether their empirical structure was consistent with the proposed four-construct model. Principal axis factoring with oblimin rotation was used because the constructs were theoretically expected to be related. The Kaiser–Meyer–Olkin measure and Bartlett's test of sphericity were used to assess the suitability of the data for factor analysis.

Third, descriptive statistics and Pearson correlations were calculated to examine the distributions and bivariate associations among the four constructs. Finally, serial mediation analysis was conducted in R using the lavaan package (Rosseel, 2012) to examine whether AI feedback literacy and revision behaviour statistically mediated the association between LLM co-editing intensity and writing self-efficacy. Indirect effects were evaluated using 5,000 bootstrap resamples following Hayes (2022). Because the study was cross-sectional and based on self-reported data, all mediation results were interpreted as associational rather than causal.

3.5. Preliminary Measurement Assessment

Before addressing the research questions, the measurement properties of the four study scales were examined. Table 2 summarizes their reliability and distributional properties. Cronbach's alpha was .788 for LLM co-editing intensity, .850 for AI feedback literacy, .806 for revision behaviour, and .830 for writing self-efficacy. Skewness values ranged from −0.479 to −0.068 and kurtosis values from −0.389 to 0.553, indicating no substantial departures from normality in the composite variables.

Table 2. Reliability and distributional properties of the scales

Construct	Items	M	SD	Skewness	Kurtosis	Cronbach's α
LLM Co-Editing Intensity	5	3.517	0.636	−0.068	−0.389	.788
AI Feedback Literacy	8	3.607	0.619	−0.228	−0.316	.850
Revision Behaviour	6	3.564	0.616	−0.264	0.270	.806
Writing Self-Efficacy	6	3.653	0.621	−0.479	0.553	.830

Note. All variables were measured on a five-point Likert scale, from 1 = strongly disagree to 5 = strongly agree.

The exploratory factor analysis further supported the proposed four-construct structure. The Kaiser–Meyer–Olkin value was .91, and Bartlett's test of sphericity was significant, $\chi^2(300) = 2560.974$, $p < .001$. The four-factor solution explained 43.3% of the total variance. As shown in Table 3, primary loadings ranged from .594 to .704 for LLM co-editing intensity, .553 to .720 for AI feedback literacy, .546 to .685 for revision behaviour, and .589 to .733 for writing self-efficacy, while cross-loadings were generally small.

Table 3. Pattern matrix from exploratory factor analysis

Item	LCEI	AIFL	RB	WSE
LCEI1	.620	-.003	-.013	.053
LCEI2	.625	-.013	.061	.013
LCEI3	.594	.076	.065	-.069
LCEI4	.704	-.032	.004	-.001
LCEI5	.601	.117	-.026	.099
AIFL1	.034	.565	.114	-.033
AIFL2	.067	.663	-.066	.030
AIFL3	.037	.652	.059	-.042
AIFL4	-.068	.668	.013	-.003
AIFL5	.119	.578	-.050	.046
AIFL6	.034	.553	.029	.009
AIFL7	-.108	.720	.013	.072
AIFL8	.126	.577	.016	-.027
RB1	.024	-.008	.546	.164
RB2	.026	.012	.673	.008
RB3	-.089	.081	.685	.028
RB4	.073	.020	.590	-.072
RB5	.066	-.012	.608	-.022
RB6	.013	-.058	.618	.034
WSE1	.035	.044	-.001	.624
WSE2	.013	.028	-.042	.682
WSE3	-.082	.117	.051	.589
WSE4	.078	-.033	-.001	.659
WSE5	-.021	.005	.051	.733
WSE6	.035	-.081	.034	.629

Note. LCEI = LLM Co-Editing Intensity; AIFL = AI Feedback Literacy; RB = Revision Behaviour; WSE = Writing Self-Efficacy. Extraction method: principal axis factoring. Rotation method: oblimin. KMO = .91. Bartlett's test of sphericity, $\chi^2(300) = 2560.974$, $p < .001$. Total variance explained = 43.3%.

4. RESULTS AND DISCUSSION

4.1. Results

4.1.1. Associations Among the Study Variables (RQ1)

To address RQ1, Pearson correlations were examined to determine the extent to which LLM co-editing intensity was associated with writing self-efficacy and to describe the bivariate relationships among the variables included in the mediation model. Descriptive statistics and correlations are presented in Table 4.

Table 4. Descriptive statistics and correlations among the main variables

Variable	M	SD	1	2	3	4
LLM Co-Editing Intensity	3.517	.636	1			
AI Feedback Literacy	3.607	.619	.41***	1		
Revision Behaviour	3.564	.616	.33***	.42***	1	
Writing Self-Efficacy	3.653	.621	.32***	.42***	.49***	1

Note. ***p < .001.

As shown in Table 4, LLM co-editing intensity was positively associated with writing self-efficacy, $r = .32$, $p < .001$, providing a direct answer to RQ1 at the bivariate level. LLM co-editing

intensity was also positively associated with AI feedback literacy, r = .41, p < .001, and revision behaviour, r = .33, p < .001. AI feedback literacy was positively associated with revision behaviour, r = .42, p < .001, and writing self-efficacy, r = .42, p < .001. The strongest bivariate association was between revision behaviour and writing self-efficacy, r = .49, p < .001. None of the correlations exceeded .70, suggesting that excessive multicollinearity among the four composite variables was unlikely.

4.1.2. Mediation Analysis (RQ2 and RQ3)

To address RQ2 and RQ3, a serial mediation analysis was conducted to examine whether AI feedback literacy and revision behaviour statistically mediated the association between LLM co-editing intensity and writing self-efficacy. The regression paths underlying the mediation model are presented in Table 5.

Table 5. Regression paths for the serial mediation model

Outcome	Predictor	B	SE	β	t	p	VIF
AI Feedback Literacy	LCEI	0.394	0.051	.405	7.718	< .001	1.000
Revision Behaviour	LCEI	0.188	0.054	.194	3.464	< .001	1.197
Revision Behaviour	AIFL	0.342	0.056	.344	6.144	< .001	1.197
Writing Self-Efficacy	LCEI	0.103	0.052	.106	1.968	0.050	1.244
Writing Self-Efficacy	AIFL	0.232	0.056	.231	4.136	< .001	1.346
Writing Self-Efficacy	RB	0.355	0.055	.352	6.505	< .001	1.265

Note. For the AI Feedback Literacy model, $R^2 = .164$, adjusted $R^2 = .162$, $F(1, 303) = 59.562$, $p < .001$. For the Revision Behaviour model, $R^2 = .210$, adjusted $R^2 = .205$, $F(2, 302) = 40.086$, $p < .001$. For the Writing Self-Efficacy model, $R^2 = .302$, adjusted $R^2 = .295$, $F(3, 301) = 43.433$, $p < .001$. For the total effect model, $R^2 = .100$, adjusted $R^2 = .097$, $F(1, 303) = 33.789$, $p < .001$.

As shown in Table 5, LLM co-editing intensity positively predicted AI feedback literacy, B = 0.394, SE = 0.051, β = .405, p < .001. In the model predicting revision behaviour, both LLM co-editing intensity (B = 0.188, SE = 0.054, β = .194, p < .001) and AI feedback literacy (B = 0.342, SE = 0.056, β = .344, p < .001) were significant predictors. In the final model predicting writing self-efficacy, AI feedback literacy (B = 0.232, SE = 0.056, β = .231, p < .001) and revision behaviour (B = 0.355, SE = 0.055, β = .352, p < .001) were significant predictors. The direct path from LLM co-editing intensity to writing self-efficacy became small after the mediators were included, B = 0.103, SE = 0.052, β = .106, p = .050. The final model accounted for 30.2% of the variance in writing self-efficacy, $R^2 = .302$.

The bootstrapped indirect effects used to address RQ2 and RQ3 are reported in Table 6.

Table 6. Bootstrapped indirect effects

Indirect pathway	Estimate	Boot SE	Boot LLCI	Boot ULCI
LCEI → AIFL → WSE	0.091	0.026	0.043	0.146
LCEI → RB → WSE	0.067	0.021	0.028	0.111
LCEI → AIFL → RB → WSE	0.048	0.015	0.024	0.080
Total indirect effect	0.206	0.037	0.140	0.283
Direct effect, c′	0.103	0.053	0.002	0.210
Total effect, c	0.309	0.053	0.207	0.416

Note. LCEI = LLM Co-Editing Intensity; AIFL = AI Feedback Literacy; RB = Revision Behaviour; WSE = Writing Self-Efficacy. Bootstrap samples = 5,000. An indirect effect was considered statistically significant when the 95% bootstrap confidence interval did not include zero.

Regarding RQ2, the indirect association between LLM co-editing intensity and writing self-efficacy through AI feedback literacy was statistically significant, estimate = 0.091, Boot SE =

0.026, 95% CI [0.043, 0.146]. Thus, the bootstrap confidence interval did not include zero, supporting the mediating role of AI feedback literacy.

Regarding RQ3, the serial indirect association through AI feedback literacy and revision behaviour was also statistically significant, estimate = 0.048, Boot SE = 0.015, 95% CI [0.024, 0.080]. The additional indirect pathway through revision behaviour alone was significant, estimate = 0.067, Boot SE = 0.021, 95% CI [0.028, 0.111]. The total indirect effect was 0.206, Boot SE = 0.037, 95% CI [0.140, 0.283]. Taken together, these results indicate that the association between LLM co-editing intensity and writing self-efficacy was primarily indirect in the fitted model, operating through students' reported AI feedback literacy and revision behaviour.

4.2. Discussion of Findings

4.2.1. Main Findings

Overall, the hypothesis-testing results were largely consistent with the proposed serial mediation model. H1 was supported because LLM co-editing intensity significantly and positively predicted AI feedback literacy. H2 was supported because AI feedback literacy significantly predicted revision behaviour. H3 was supported because revision behaviour significantly predicted writing self-efficacy. H4 was supported at the total-effect level, but only partially supported in the final mediation model because the direct path from LLM co-editing intensity to writing self-efficacy became small and borderline after AI feedback literacy and revision behaviour were included. H5 was supported because the indirect effect through AI feedback literacy was significant. H6 was also supported because the serial indirect pathway from LLM co-editing intensity to AI feedback literacy, revision behaviour, and writing self-efficacy was significant. Taken together, these results suggest that LLM co-editing was associated with writing self-efficacy mainly through students' capacity to evaluate AI feedback and transform it into revision action.

4.2.2. LLM Co-Editing Is Not Sufficient Without Feedback Literacy

The first important finding is that LLM co-editing intensity was positively associated with AI feedback literacy. Students who reported using LLMs more actively for writing revision also tended to report stronger ability to understand, evaluate, question, and ethically use AI-generated feedback. This finding is consistent with the view that feedback literacy is not merely about receiving feedback but about developing the capacity to make judgments and take action based on feedback information (Carless & Boud, 2018; Yu et al., 2022). In the context of LLM-supported writing, this capacity becomes especially important because AI feedback can be immediate and detailed but not always accurate, task-sensitive, or pedagogically appropriate.

This finding helps refine how LLM use should be understood in EFL writing. Previous research has shown that EFL learners may perceive ChatGPT as a useful writing companion because it provides fast and explanatory feedback (Teng, 2024). However, positive perception alone does not guarantee meaningful learning. Recent research on GenAI-supported writing provides more direct evidence that meaningful engagement with AI feedback depends on learners' developing capacity to interpret, evaluate, and act on feedback rather than merely receiving it (Liu et al., 2026; Lu et al., 2026). The present study extends this line of research by suggesting that the educational relevance of LLM co-editing is associated with students' AI feedback literacy. Frequent LLM use alone may have limited pedagogical value if students do not evaluate feedback quality, ask follow-up questions, and decide whether suggestions should be accepted, modified, or rejected.

4.2.3. AI Feedback Literacy Supports Strategic Revision Behaviour

The second important finding is that AI feedback literacy significantly predicted revision behaviour. Students who reported stronger AI feedback literacy were more likely to report active revision practices, including revising language, meaning, organization, coherence, and clarity. This finding supports the theoretical assumption that feedback literacy becomes visible through action. A student who can understand and evaluate feedback is better positioned to transform suggestions into purposeful revisions.

This result aligns with research on automated writing feedback, which shows that learner engagement depends not only on feedback content but also on trust, judgment, and contextual interpretation (Karatay & Karatay, 2024; Ranalli, 2021; Zhang & Hyland, 2018). Studies of AWE and automated written corrective feedback have shown that students vary considerably in how they perceive, process, and incorporate automated suggestions during revision (Koltovskaia, 2020; Tian & Zhou, 2020; Zhang, 2020). LLM feedback may be more dialogic than traditional AWE because students can ask for explanations, request alternatives, and continue the interaction. However, this flexibility also increases the need for strategic decision-making. Without feedback literacy, students may copy AI-generated revisions uncritically or accept surface-level corrections without understanding why changes are needed.

4.2.4. Revision Behaviour and Writing Self-Efficacy

Among the predictors in the final model, revision behaviour showed the strongest standardized association with writing self-efficacy. This finding suggests that students who reported more active revision behaviour also tended to report stronger beliefs in their capability to manage English writing tasks. This pattern is consistent with self-efficacy theory, which conceptualizes self-efficacy as task-specific beliefs about one's capability to organize and perform actions required for particular tasks (Bandura, 1997; Pajares, 2003). It is also consistent with writing research conceptualizing writing self-efficacy as multidimensional and associated with writing performance and engagement with feedback (Bruning et al., 2013; Teng & Wang, 2023; Tsao et al., 2021).

This result supports a process-oriented view of LLM-supported writing. If students use LLMs only to obtain polished sentences, they may become dependent on AI-generated output. If students use LLMs to identify problems, reflect on feedback, and revise strategically, such revision practices may be associated with stronger writing self-efficacy. Therefore, the pedagogical goal should not be simply to increase students' access to LLM tools, but to help them use AI feedback in ways that strengthen revision control and writer agency.

4.2.5. Pedagogical Implications for LLM-Supported EFL Writing

The significant serial indirect pathway provides the central pedagogical contribution of the study to LLM-supported EFL writing. It suggests that the association between LLM co-editing and writing self-efficacy may be understood through a feedback-mediated and action-oriented process involving AI feedback literacy and revision behaviour. Students who use LLMs more actively may develop stronger AI feedback literacy; those with stronger AI feedback literacy may revise more strategically; and those who revise more strategically may report higher writing self-efficacy. This contribution responds to recent calls for mechanism-focused research on GenAI written feedback and learner uptake (Crosthwaite & Sun, 2026). It also extends earlier AWE work showing that automated feedback can support revision, but only when learner engagement and

instructional mediation are considered (Fu & Liu, 2022; Karatay & Karatay, 2024; Link et al., 2022).

The findings have practical implications for EFL writing instruction in higher education contexts. First, teachers should avoid framing LLM use only as either a threat to academic integrity or a shortcut for writing. While concerns about plagiarism, overdependence, and authorship are valid, a purely restrictive approach may not address students' actual writing practices. Since many students already use LLMs for revision, writing instruction should include explicit guidance on how to use AI feedback critically and ethically. This implication is consistent with language education research emphasizing that generative AI use requires learner and teacher competencies, not only technical access (Kohnke et al., 2023).

Second, EFL writing teachers should teach AI feedback literacy as part of writing pedagogy. Students need to learn how to prompt LLMs for specific feedback, evaluate whether suggestions match the writing task, identify overly general or inaccurate feedback, and compare AI feedback with teacher feedback or rubric criteria. AWE research has shown that automated feedback is most useful when it is integrated with instructional support and teacher mediation (Li et al., 2015; Link et al., 2022). In LLM-supported writing, similar mediation is needed so that students remain in control of their writing rather than treating LLM output as automatically correct.

Finally, LLM-supported writing activities should include both local and global revision. If students use LLMs only for grammar correction, the pedagogical value may remain limited. Teachers can design tasks that ask students to use LLMs to review paragraph unity, coherence, argument development, and reader awareness. These tasks should also require students to check whether the revised text still reflects their intended meaning. This is important because automated feedback studies have repeatedly shown that uptake and revision quality vary across learners and feedback sources (Han & Hyland, 2015; Tian & Zhou, 2020; Zhang, 2020).

4.2.6. Limitations and Future Research

Several limitations should be acknowledged. First, the study used a cross-sectional survey design. Therefore, the findings show associations among variables but do not establish causal relationships. Although the mediation model was theoretically grounded, future longitudinal or experimental research is needed to examine whether AI feedback literacy and revision behaviour actually develop over time through LLM-supported instruction.

Second, the study relied on self-reported data. Students' reported revision behaviour and writing self-efficacy may not fully match their actual writing practices or performance. Future studies should combine survey data with draft analysis, revision logs, screen recordings, interaction logs, or teacher-rated writing samples to examine how students actually use LLM feedback during revision. Such designs would respond to recent calls for more transparent evidence about feedback uptake and revision behaviour in GenAI-supported L2 writing (Crosthwaite & Sun, 2026).

Third, the study used exploratory factor analysis to examine the initial construct structure of the adapted questionnaire. Although the reliability estimates and factor pattern were acceptable, future studies could further validate the measurement model through confirmatory factor analysis across different EFL populations.

Fourth, the distribution of primary LLM tools was uneven. Most participants reported ChatGPT as their main tool, whereas fewer participants mainly used Gemini, Claude, or Microsoft Copilot. Therefore, the findings should be interpreted as reflecting primarily students' experiences with ChatGPT-supported writing revision rather than equally representing all LLM platforms. Since

different LLM tools may vary in feedback style, explanation quality, interaction design, and perceived reliability, future studies should compare tool-specific patterns of AI feedback literacy, revision behaviour, and writing self-efficacy.

5. CONCLUSION

This study investigated the relationship between LLM co-editing intensity and writing self-efficacy among Vietnamese EFL undergraduates, with AI feedback literacy and revision behaviour examined as mediating mechanisms. The findings showed that students who reported more active LLM co-editing also tended to report stronger AI feedback literacy, more active revision behaviour, and higher writing self-efficacy. More importantly, the serial mediation results indicated that the relationship between LLM co-editing intensity and writing self-efficacy operated largely through AI feedback literacy and revision behaviour.

The study contributes to EFL writing research by shifting attention from general LLM use to the mechanisms through which LLM-supported revision may become pedagogically meaningful. The findings suggest that LLM tools should not be treated simply as automated correction systems or text generators. Their value in EFL writing depends on whether students can evaluate AI-generated feedback, question unclear suggestions, make informed revision decisions, and maintain control over their own writing. In this sense, AI feedback literacy is not an optional digital skill but an important part of contemporary writing pedagogy.

Overall, the findings indicate that the association between LLM co-editing intensity and writing self-efficacy may operate partly through students' capacity to evaluate AI-generated feedback and translate it into strategic revision behaviour. In EFL higher education contexts where LLM use is becoming increasingly common, writing pedagogy should therefore move beyond the question of whether students use AI and focus more closely on how they evaluate and use AI-generated feedback responsibly, critically, and purposefully.

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