US-China Education Review A, October 2026, Vol. 16, No. 10, 699-708
doi: 10.17265/2161-623X/2026.10.003

Cognitive, Behavioural, and Affective Engagement With DeepSeek-generated Feedback: A Study of Chinese EFL Learners

LIU Yuwei, HUANG Jingwen, ZENG Xiaofeng, LIN Yumin, LIU Binlu, CHEN Jitong
Zhaoqing University, Zhaoqing, China

This study examined cognitive, behavioural, and affective engagement with DeepSeek-generated feedback among six Chinese university EFL learners at different proficiency levels across two argumentative writing-revision tasks. Data included learners' first and second drafts, DeepSeek feedback points and interaction records, screen recordings, post-task verbal reports, semi-structured interviews, and a supplementary questionnaire. Qualitative content analysis was supplemented by descriptive statistics on feedback uptake and self-reported revision strategies. The findings revealed variation in learners' understanding, evaluation and emotional responses to DeepSeek's feedback. Cognitively, learners understood most of the feedback points but applied different criteria when deciding whether to adopt feedback or not. Behaviourally, 251 of 272 feedback points were incorporated into revised drafts (92.3%), with much feedback partially adopted or adapted. Learners also reported using dictionaries, follow-up inquiries with DeepSeek, online searching, and proofreading. Affectively, participants generally reported positive attitudes and confidence, although confusion or irritation arose when feedback was unclear or considered inappropriate. Engagement appeared to vary with learners' self-perceived linguistic competence, their writing goals, previous task experiences, and perceptions of feedback quality. The findings suggest that teachers should help learners assess whether AI suggestions match their intended meaning, verify uncertain feedback, and adapt suggestions to learners' writing goals and linguistic abilities during L2 writing revision.

Keywords: learner engagement, DeepSeek-generated feedback, L2 writing and revision, generative artificial intelligence, different English proficiency levels

Introduction

Feedback plays an important role in L2 writing development by helping learners identify problems and improve their writing. With the recent development of generative artificial intelligence (GenAI), learners can

Acknowledgements: This study was supported by: (1) (Zhaoqing University) 2025 Provincial Undergraduate Innovation and Entrepreneurship Training Program (Project No. S202510580039) (Title: Local Adaptation and Optimization of AI Feedback Mechanisms in College English Writing Instruction: The Case of DeepSeek); (2) 2025 "Artificial Intelligence+" Course Development Project of Zhaoqing University (Title: Advanced English); (3) 2026 Zhaoqing Municipal Philosophy and Social Sciences Planning Project (Project No. 26GJ-33) (Title: Translation and Dissemination of Deqing's Red Cultural Resources from the Perspective of Cultural Confidence: A Case Study of the Red Heritage Site at Binshan Middle School).

LIU Yuwei (corresponding author), Ph.D., Associate Professor, School of Foreign Studies, Zhaoqing University, Zhaoqing, China.
HUANG Jingwen, School of Foreign Studies, Zhaoqing University, Zhaoqing, China.
ZENG Xiaofeng, School of Foreign Studies, Zhaoqing University, Zhaoqing, China.
LIN Yumin, LIU Binlu, and CHEN Jitong (co-fourth authors), School of Foreign Studies, Zhaoqing University, Zhaoqing, China.

now obtain immediate and interactive feedback on multiple aspects of writing. However, receiving feedback does not necessarily lead to effective revision or learning (Han & Hyland, 2015). Learners still need to notice and understand the feedback, evaluate its usefulness and appropriateness, and decide how to act upon it. Learner engagement is therefore crucial to understanding how feedback is processed and used and is commonly examined through cognitive, affective, and behavioural dimensions (Ellis, 2010).

Research on technology-mediated feedback has been more extensively developed in the context of automated writing evaluation (AWE). Existing studies show that AWE feedback is generally more effective at identifying surface-level linguistic problems than addressing content, organisation, or rhetorical concerns. Learners also differ in how they evaluate and use automated suggestions (Zhang & Hyland, 2018). By contrast, fewer studies have examined learner engagement with GenAI feedback. Existing evidence suggests that learners may find GenAI feedback comprehensible and useful while still investing considerable cognitive effort in evaluating and implementing it (Zhan & Yan, 2026). However, this limited evidence has yet to provide a comprehensive understanding of learners' cognitive, behavioural, and affective engagement with GenAI feedback. Therefore, the present study investigates how six Chinese university EFL learners at different proficiency levels engage cognitively, behaviourally, and affectively with DeepSeek-generated feedback across two argumentative writing-revision tasks.

Literature Review

Learner Engagement With Feedback in L2 Writing

Feedback plays a central role in L2 writing instruction, but learners do not always revise effectively or learn from the feedback they receive (Ellis, 2010). Increasing attention has therefore been directed from the characteristics and quantity of feedback to how learners engage with and respond to feedback. Ellis (2010) conceptualised learner engagement with feedback as a multidimensional construct involving cognitive, behavioural, and affective dimensions. This perspective was subsequently developed in L2 writing research where engagement has been used to explain why learners receiving similar feedback may respond to and benefit from feedback in different ways.

Han and Hyland (2015) provided an influential account of this multidimensional perspective by examining four Chinese EFL university learners' cognitive, affective, and behavioural engagements with written corrective feedback. Their findings showed considerable variations both within and across the three dimensions, with engagement influenced by learners' beliefs, goals, previous feedback experiences, and individual characteristics. Subsequent studies have consistently demonstrated similar complexity. Zheng and Yu (2018), for example, found that low-proficiency learners generally responded positively to teacher written corrective feedback, yet limited understanding of indirect feedback constrained their cognitive and behavioural engagement, and their revisions did not all improve linguistic accuracy. Zhang and Hyland (2018) examined teacher and automated feedback over a 16-week semester, and showed that differences in engagement helped explain how learners used these feedback sources and the differences in their writing development.

Collectively, this body of research has suggested that feedback engagement is multidimensional, individualised, and dynamic (Xu et al., 2025). Cognitive, affective, and behavioural responses may reinforce one another, but they may also diverge. Positive attitudes do not necessarily indicate critical processing, higher uptake does not always represent meaningful management, and doubt or rejection may sometimes reflect careful evaluation rather than disengagement (Ma et al., 2026; Jiang & Yu, 2020). Learner engagement is therefore better

understood as a configuration of interrelated responses shaped by learner characteristics, feedback characteristics, and the context in which feedback is used. Research has extended this three-dimensional perspective to AI-generated feedback.

Student Engagement With AWE Feedback and AI-generated Feedback

Before the emergence of GenAI, research on automated writing evaluation (AWE) systems had already examined feedback quality, learners' perceptions and use of feedback, and effects on writing development. Shi and Aryadoust's (2024) systematic review of 83 SSCI-indexed studies identified writing system quality, learner-related experiences and writing outcomes as major areas of research on AWE feedback. AWE feedback was found to be more effective in identifying surface-level linguistic problems than addressing content, organisation, and rhetorical effectiveness (Li et al., 2015; Zhang & Hyland, 2018). Yet, AWE systems may generate inaccurate or decontextualised feedback, which can negatively affect learners' perceptions of credibility and usefulness (Bai & Hu, 2017). Zhang and Hyland (2018) found that teacher feedback covered a broader range of error categories, whereas the AWE system failed to identify some article and preposition errors. More importantly, the two learners in their study differed in the depth with which they processed and acted on the two feedback sources.

Compared with traditional AWE systems, GenAI tools are believed to generate more extended natural-language explanations and provide feedback on multiple aspects of writing, including content, organisation, vocabulary, grammar, and style. They can also respond to follow-up prompts, creating a more interactive form of feedback. Thus, recent studies have shifted their attention to AI-generated feedback and explored it in terms of quality and characteristics, learner perceptions, and writing improvement and feedback uptake. Comparative studies suggest that GenAI and human feedback differ in both focus and form. Lin and Crosthwaite (2024) found that teacher feedback addressed both local and global issues through a combination of direct and indirect feedback, whereas ChatGPT offered more metalinguistic explanations and reformulations. Similarly, Steiss et al. (2024) compared the quality of human and ChatGPT-generated feedback on student writing and found that although ChatGPT was capable of producing useful feedback, differences remained between AI-generated and human feedback in terms of feedback quality and instructional value. Guo and Wang (2023) found that ChatGPT addressed content, organisation, and language relatively comprehensively, but its feedback did not always demonstrate sufficient contextual or pedagogical sensitivity.

Studies of revision outcomes have generally reported improvements in areas such as grammar, lexis, coherence, and organisation, although the effectiveness of GenAI feedback varies by feedback focus and is not consistently superior to human feedback (Crosthwaite & Sun, 2026). Students also tended to value the accessibility and usefulness of GenAI feedback, while some students expressed concerns about accuracy, relevance, excessive feedback, and overreliance (Zou et al., 2026). Overall, these studies demonstrate the potential of GenAI as a feedback source, but evidence concerning feedback quality, writing outcomes, or learner perceptions alone provides only a partial account of how such feedback contributes to revision and writing improvement.

Only a small number of studies have begun to examine learner engagement with GenAI feedback, focusing on how learners actually understand, evaluate, and respond to AI-generated suggestions during revision. Zhan and Yan (2026) found that students used more cognitive than metacognitive strategies and sometimes demonstrated relatively superficial behavioural engagement. Ma et al. (2026) reported that learners sometimes consulted additional resources when they were uncertain about AI-generated suggestions. Their findings also

highlighted the interconnections among cognitive, affective, and behavioural engagement.

Research Gaps and the Current Study

Overall, despite the rapid growth of research on AI feedback, relatively few studies have examined learner engagement as a multidimensional construct involving cognitive, affective, and behavioural dimensions (Zhan & Yan, 2026). Additionally, many studies have examined engagement within a single writing task, so less is known about whether engagement changes across repeated writing-revision cycles.

Moreover, although substantial individual variation has been reported in prior studies (Shi & Aryadoust, 2024; Zhang & Hyland, 2018), engagement among learners at different proficiency levels remains insufficiently understood in the context of GenAI feedback. To address these gaps, the current study investigates how six Chinese EFL learners with different proficiency levels cognitively, behaviourally, and affectively engage with DeepSeek's feedback across two argumentative writing-revision tasks. Drawing on the multidimensional perspective on learner engagement with feedback (Fredricks et al., 2004) (see Table 1), the study aims to address the following questions:

(1) How do students at different proficiency levels cognitively engage with DeepSeek-generated feedback?

(2) How do these learners respond behaviourally to DeepSeek's feedback?

(3) What emotional and attitudinal responses do these learners demonstrate towards DeepSeek's feedback?

Table 1

Conceptual Framework of Student Engagement With DeepSeek-generated Feedback

Engagement	Dimensions
Cognitive	Noticing and understanding feedback
	Cognitive operations
	Metacognitive operations
Behavioural	Revision operations
	Revision strategies
Affective	Emotional responses
	Attitudinal responses

Methodology

Participants and Data Sources

Six Chinese university EFL learners with different English proficiency levels participated in the study. Their proficiency levels were determined based on three criteria: their English scores of the National College Entrance Examination, their prior English writing performance, and recommendations from their English teachers (see Table 2 for details).

Table 2

Student Profile

Participant (Pseudonym)	Proficiency level	Writing scores	College Entrance Exam
Alice	High	90	125
Betty	High	91	125
Kim	Intermediate	85	114
Yuri	Intermediate	87	112
Grace	Low	79	103
Harry	Low	78	102

DeepSeek was used as the source of writing feedback because it can provide immediate, multi-dimensional feedback, including evaluations of essay organisation and logical reasoning. The study included two argumentative writing tasks of comparable difficulty. Data sources included students' first draft and revised drafts, their prompts and complete DeepSeek feedback records, screen recordings of the revision process, two immediate post-task verbal reports, one semi-structured interview, and a questionnaire adapted from Zou et al. (2026). The screen recordings were used to cross-check how participants interacted with DeepSeek. The verbal reports and interviews were used to explore how learners understood individual feedback points, why they adopted, adapted, or rejected particular suggestions, how they felt about the feedback, and what they did when they experienced uncertainty. The questionnaire was used as supplementary descriptive evidence of participants' affective and cognitive engagement. It also included questions asking participants to report the revision strategies they used and how frequently they used them in each writing task.

Data Collection and Analysis

Each participant completed two writing-revision cycles following the same procedure: Draft 1 → AI feedback → student revision → Draft 2 → verbal report. Participants first completed a first draft, obtained DeepSeek-generated writing feedback, and revised their texts based on the feedback to produce a second draft. A post-task verbal report was conducted after each revision task to explore how participants engaged with DeepSeek's feedback. A semi-structured interview was conducted with each participant to explore their prior feedback experience and overall experiences of engaging with DeepSeek feedback.

The textual revision data were analysed by matching each DeepSeek feedback point with the corresponding changes in the revised drafts. In the study, learners' responses to DeepSeek's feedback were classified into four categories: direct adoption, partial adoption, adoption after adaptation, and rejection. The frequencies and proportions of each response category were calculated to describe feedback uptake across the two tasks.

The qualitative data were analysed using content analysis (Drisko & Maschi, 2016). The verbal reports, interview transcripts, and screen recordings were repeatedly examined to identify recurring patterns in how participants engaged with DeepSeek-generated feedback. Codes emerging from the data were then organised and interpreted in relation to the three dimensions of learner engagement adopted in the study. Evidence from different data sources was compared to identify recurring, convergent, and divergent patterns.

The questionnaire provided supplementary descriptive evidence of participants' cognitive and affective engagement. Participants' self-reported revision strategies and their frequencies were also summarised descriptively. Screen recordings and verbal reports were used to provide additional evidence of how learners interacted with DeepSeek and approached revision.

Results and Discussion

Cognitive Engagement

The collected data indicated generally active but uneven cognitive engagement. Regarding noticing and understanding feedback, participants reported that they could sometimes understand the composition problems identified by DeepSeek ($M = 3.7$, $SD = 0.5$) and revised their writing accordingly ($M = 3.8$, $SD = 0.8$). Moreover, the verbal reports showed that comprehension varied with feedback type. Concrete comments on vocabulary and grammar were usually easier to understand, whereas feedback concerning logic, organisation, or unfamiliar expressions sometimes caused difficulty.

Metacognitive operations were reflected in how learners monitored and organised the revision process. Participants reported consulting feedback repeatedly (M = 3.8, SD = 1.0), whereas the perceived mental effort required was moderate (M = 3.2, SD = 0.8). Students also tended to address surface-level problems before deeper issues of meaning and coherence (M = 4.3, SD = 0.5).

The greatest variation appeared in cognitive operations. “Complete acceptance of DeepSeek suggestions” received the lowest rating (M = 2.5, SD = 1.1), whereas “evaluating suggestions before adoption” received the highest rating (M = 4.5, SD = 0.6). Among the high-proficiency learners, Alice often relied on her own linguistic judgment, while Betty paid greater attention to whether suggested expressions were realistically producible. Among the intermediate students, Kim rejected suggestions he considered unreasonable, whereas Yuri more often sought verification. Grace, a low proficiency learner, evaluated suggestions primarily according to whether she herself could produce them. Harry, however, relied more on DeepSeek in areas where he perceived himself as weaker, particularly organisation and structure.

No consistent proficiency-related pattern in cognitive engagement was evident across the six participants. Previous studies have shown that lower proficiency may constrain learners’ interpretation and use of feedback (Zheng & Yu, 2018). However, Cheng and Liu (2022) found that proficiency interacts with feedback focus in shaping engagement. The present cases, however, showed variations within the same level. Alice and Betty, both high proficiency learners, relied on different criteria when judging AI suggestions. Betty and Grace, despite belonging to different proficiency groups, both considered whether the suggested language was within their productive abilities. Proficiency therefore appears to be only one of the individual factors shaping AI feedback engagement (Han & Hyland, 2015). Self-perceived competence also appeared to influence how learners make revision decisions (Tsao, 2021).

Table 3

Descriptive Statistics for Cognitive Engagement Questionnaire Items

Sub-categories	Item	M	SD
Noticing and Understanding	Q1: After reading the feedback from DeepSeek, I was able to clearly understand the composition problems pointed out in it.	3.7	0.5
	Q2: After reading the feedback, I can easily revise my composition according to the prompts.	3.8	0.8
Meta-cognitive Operations	Q3: When revising the composition, I need to repeatedly review the feedback given by DeepSeek.	3.8	1.0
	Q4: Understanding and handling this feedback requires me to invest a great deal of mental effort.	3.2	0.8
	Q5: When making revisions, I will prioritize correcting superficial grammatical errors and then deal with deeper issues such as semantics and coherence.	4.3	0.5
Cognitive Operations	Q6: During the revision process, I will completely follow the suggestions of DeepSeek to modify the composition.	2.5	1.1
	Q7: After receiving the feedback, I will first critically review the AI suggestions and then compare them with my own composition to determine whether to adopt them.	4.5	0.6

The cross-task comparison showed that cognitive engagement changed for some learners. Betty, for example, became more selective in Task 2, increasingly choosing suggestions that she considered compatible with her own ability and writing needs. This suggested that both prior task experience and self-perceived confidence can become influencing factors of student engagement. Kim developed a clearer focus in Task 2, concentrating more specifically on word choice and precision after AI identified these as common problems in his writing. These changing trajectories suggest that engagement may be influenced by both learner-related factors and feedback-related factors. Specifically, potential factors identified in the study were proficiency levels, writing confidence,

feedback type, and learners' writing intentions. This interpretation is consistent with research viewing feedback engagement as dynamic (Han & Hyland, 2015) and context sensitive (Ma et al., 2026).

Behavioural Engagement

Behavioural engagement was examined through learners' revision operations and the observable strategies they employed during revision. Across the two tasks, 272 DeepSeek feedback points were identified, of which 251 were adopted into learners' revised texts. This resulted in an overall uptake rate of 92.3% (as shown in Table 4). Among the 251 adopted feedback points, "adoption after adaptation" was the most frequent response (107 cases, 42.6%), followed by "direct adoption" (101 cases, 40.3%) and "partial adoption" (43 cases, 17.1%). "Partial adoption" and "adoption after adaptation" together accounted for 59.7% of total uptake. This indicates that although learners responded behaviourally to most of the feedback, a substantial portion of suggestions were modified or selectively incorporated rather than reproduced directly.

The cross-task comparison showed a more selective pattern of behavioural response in Task 2. The uptake rate decreased from 97.4% in Task 1 to 88.5% in Task 2, while the rejection rate increased from 2.6% to 11.5%. Among adopted feedback, direct adoption decreased from 47.3% to 34.5%, whereas partial and adaptive adoption together increased from 52.7% to 65.5%. Therefore, in general, learners were less likely to accept the feedback directly and more likely to modify or selectively incorporate suggestions in the second task. However, individual differences still existed. Betty, for example, reported that whereas she had adopted most of the AI revisions in Task 1, she became more selective in Task 2. She reflected that adopting some suggestions in Task 1 had contributed little to her learning because the AI-generated language was not always at a level she could independently reproduce.

Table 4

Uptake of DeepSeek-generated Feedback Across Two Writing Tasks

Revision response	Task 1	Task 2	Total	Percentage of total uptake
Direct adoption	53	48	101	40.3%
Partial adoption	13	30	43	17.1%
Adoption after adaptation	46	61	107	42.6%
Rejection	3	18	21	—
Total uptake	112	139	251	100%
Total feedback	115	157	272	—
Uptake rate	97.4%	88.5%	92.3%	—
Rejection rate	2.6%	11.5%	7.7%	—

Revision strategies provided further evidence of how learners responded to DeepSeek feedback. As shown in Table 5, participants reported a total of 151 instances of strategy use across the two writing tasks. Dictionary consultation was the most frequent strategy (N = 50, 33.1%), followed by further inquiry with DeepSeek (N = 46, 30.5%), proofreading (N = 28, 18.5%), and online searching (N = 27, 17.9%). More importantly, "dictionary consultation" and "follow-up inquiry" together accounted for 63.6% of all self-reported strategy instances, indicating that clarification and verification were important aspects of learners' revision behaviour. Qualitative data helped explain the functions of these strategies. When Yuri was uncertain about the feedback, she reported either continuing to question DeepSeek or consulting an online dictionary. Kim described seeking evidence from multiple online sources when he doubted a suggestion. Alice reported cross-checking questionable feedback with another AI tool. These behaviours showed that revision strategies were not simply additional editing actions, but

also served as mechanisms through which learners managed uncertainty and evaluated whether AI feedback was sufficiently understandable, accurate and appropriate to act upon.

Table 5

Revision Strategies Across the Two Writing Tasks

Revision strategy	Task 1	Task 2	Total	%
Using dictionaries	30	20	50	33.1%
Inquiring DeepSeek	23	23	46	30.5%
Online searching	13	14	27	17.9%
Proofreading	14	14	28	18.5%
Total	80	71	151	100%

Affective Engagement

The current data showed generally positive but differentiated affective engagement across the two sub-dimensions: emotional responses and attitudinal responses.

Regarding emotional responses, participants reported moderate confidence and inspiration during AI-supported revision (M = 3.3, SD = 0.8), while "enjoyment of AI-supported revision" (M = 3.8, SD = 1.2) and "happiness in response to positive feedback" (M = 3.8, SD = 0.8) received relatively high ratings. "Frustration in response to negative feedback" was rated comparatively low (M = 2.3, SD = 0.8) (as shown in Table 6). The qualitative data revealed specific emotional responses, including confidence, satisfaction, contentment, confusion and irritation. Five of the six learners reported increased confidence in their revised writing at least once across the two tasks. Alice was the exception, explaining that she had already been confident in her original draft. Satisfaction was explicitly evident in Betty, Kim and Grace, who described their experience as "quite good" or the feedback as "meeting their expectations". Confusion occurred across all six cases, typically when learners encountered unfamiliar vocabulary, abstract concepts or suggestions that conflicted with their own interpretation. Negative emotions were less frequent, but Alice displayed clear irritation when she believed some suggestions had misinterpreted the task requirement and reported that she "immediately want to ignore them".

For attitudinal responses, participants showed relatively strong "interest in" DeepSeek's feedback (M = 3.7, SD = 0.5), willingness to "continue to use" (M = 4.2, SD = 0.8) and overall satisfaction (M = 4.2, SD = 0.8). Yet, the qualitative data showed clear differences in trust. Betty described herself as "always trusting" DeepSeek. Grace explained that DeepSeek appeared "more professional", which made her "trust it more". Harry showed the opposite pattern and reported lower trust in Task 2 after believing that DeepSeek identified fewer problems than before.

These emotional episodes indicate that affective responses were closely tied to what learners believed the feedback meant for their own writing. Confidence tended to increase when feedback made improvement visible or brought the revised text closer to learners' expectations. In contrast, confusion emerged when feedback contained unfamiliar language, remained too abstract, or conflicted with learners' intended meanings. Irritation arose from perceived mismatch rather than from negative feedback itself. This finding is consistent with Mahfoodh's (2017) finding that emotional responses depend partly on how feedback is interpreted. The finding also agreed with Ranalli (2021), who highlighted that trust is central to learner engagement with feedback, and is shaped by perceived feedback reliability and usefulness. The present findings suggest that affective engagement can be influenced by the interaction of baseline confidence and trust, self-perceived competence, feedback quality and appropriateness, and accumulated feedback experience.

Table 6

Descriptive Statistics for Affective Engagement Questionnaire Items

Sub-categories	Item	M	SD
Emotional responses	Q8: After reading the feedback, I felt more confident and inspired during the process of revising my composition.	3.3	0.8
	Q9: In general, I really enjoyed this revision process based on AI feedback.	3.8	1.2
	Q10: The positive feedback given by DeepSeek makes me happy.	3.8	0.8
	Q11: The negative feedback given by DeepSeek makes me frustrated.	2.3	0.8
Attitudinal responses	Q12: I'm very interested in the feedback from DeepSeek.	3.7	0.5
	Q13: In my future writing practice, I look forward to continuing to use the DeepSeek feedback.	4.2	0.8
	Q14: Generally speaking, how satisfied am I with the entire feedback from DeepSeek.	4.2	0.8

Conclusion

This study investigated six Chinese university EFL learners' cognitive, behavioural, and affective engagement with DeepSeek-generated feedback across two argumentative writing tasks. The findings revealed that learner engagement was multidimensional and varied across individuals. Learners generally understood and responded positively to DeepSeek feedback, but differed in how they evaluated and used specific suggestions. Although most feedback points were adopted, learners frequently adapted suggestions or consulted additional resources in revision. Engagement also changed across the two tasks, with some students becoming more selective or changing their revision priorities. These differences appeared to be associated with learner-related factors, such as self-perceived linguistic competence, writing confidence, writing goals, and previous task experiences, as well as feedback-related factors, including feedback focus, perceived feedback accuracy and appropriateness.

The findings also highlighted the interrelationships among cognitive, behavioural, and affective engagement. Positive attitudes towards GenAI feedback did not consequently lead to uncritical acceptance, while confusion or disagreement sometimes resulted in further evaluation, verification, or selective incorporation (Han & Hyland, 2015; Ma et al., 2026).

Theoretically, these findings provide additional empirical support for the multidimensional perspective on learner engagement with feedback in a GenAI-supported writing context, highlighting the dynamic and context-sensitive relationships among cognitive, affective, and behavioural responses (Ellis, 2010; Han & Hyland, 2015). Practically, teachers should encourage learners to critically evaluate AI-generated suggestions, verify uncertain feedback, and adapt revisions to their writing needs and linguistic abilities, rather than accepting feedback uncritically (Ma et al., 2026).

Several limitations should be acknowledged. The study involved only six learners and one writing genre (i.e., argumentation), which limits the transferability of the findings. Furthermore, the short observation period does not allow conclusions about long-term changes in engagement or writing development. Future research could involve more participants, different writing genres, and a longer observation period to explore how engagement develops in different contexts.

References

Bai, L., & Hu, G. (2017). In the face of fallible AWE feedback: How do students respond? *Educational Psychology*, *37*(1), 67-81.

Cheng, X., & Liu, Y. (2022). Student engagement with teacher written feedback: Insights from low-proficiency and high-proficiency L2 learners. *System*, *109*, 102880. https://doi.org/10.1016/j.system.2022.102880

Crosthwaite, P., & Sun, S. (2026). Generative AI and L2 written feedback studies: A scoping review. *RELC Journal*, *57*(1), 207-219.

Drisko, J. W., & Maschi, T. (2016). *Content analysis.* Oxford University Press.

Ellis, R. (2010). Epilogue: A framework for investigating oral and written corrective feedback. *Studies in Second Language Acquisition*, *32*(2), 335-349.

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research*, *74*(1), 59-109.

Guo, K., & Wang, D. (2023). To resist it or to embrace it? Examining ChatGPT's potential to support teacher feedback in EFL writing. *Education and Information Technologies*, *29*(7), 8435-8463. https://doi.org/10.1007/S10639-023-12146-0

Han, Y., & Hyland, F. (2015). Exploring learner engagement with written corrective feedback in a Chinese tertiary EFL classroom. *Journal of Second Language Writing*, *30*, 31-44. https://doi.org/10.1016/j.jslw.2015.08.002

Jiang, L., & Yu, S. (2020). Appropriating automated feedback in L2 writing: Experiences of Chinese EFL student writers. *Computer Assisted Language Learning*, *35*(7), 1-25. https://doi.org/10.1080/09588221.2020.1799824

Li, J., Link, S., & Hegelheimer, V. (2015). Rethinking the role of automated writing evaluation (AWE) feedback in ESL writing instruction. *Journal of Second Language Writing*, *27*, 1-18. https://doi.org/10.1016/j.jslw.2014.10.004

Lin, S., & Crosthwaite, P. (2024). The grass is not always greener: Teacher vs. GPT-assisted written corrective feedback. *System*, *127*, 103529.

Ma, X., Zhang, C., & Lee, I. (2026). L2 learners' engagement with AI-generated feedback on writing. *Assessing Writing*, *68*, 101020.

Mahfoodh, O. H. A. (2017). "I feel disappointed": EFL university students' emotional responses towards teacher written feedback. *Assessing Writing*, *31*, 53-72. https://doi.org/10.1016/j.asw.2016.07.001

Ranalli, J. (2021). L2 student engagement with automated feedback on writing: Potential for learning and issues of trust. *Journal of Second Language Writing*, *52*, 100816. https://doi.org/10.1016/j.jslw.2021.100816

Shi, H., & Aryadoust, V. (2024). A systematic review of AI-based automated written feedback research. *ReCALL*, *36*(2), 187-209.

Steiss, J., Tate, T., Graham, S., Cruz, J., Hebert, M., Wang, J., ... & Olson, C. B. (2024). Comparing the quality of human and ChatGPT feedback of students' writing. *Learning and Instruction*, *91*, 101894.

Tsao, J. J. (2021). Effects of EFL learners' L2 writing self-efficacy on engagement with written corrective feedback. *Asia-Pacific Education Researcher*, *30*, 575-584.

Xu, S., Su, Y., & Liu, K. (2025). Investigating student engagement with AI-driven feedback in translation revision: A mixed-methods study. *Education and Information Technologies*, *30*, 16969-16995. https://doi.org/10.1007/s10639-025-13457-0

Zhan, Y., & Yan, Z. (2026). Students' engagement with ChatGPT feedback: Implications for student feedback literacy in the context of generative artificial intelligence. *Assessment & Evaluation in Higher Education*, *51*(5), 821-834.

Zhang, Z. V., & Hyland, K. (2018). Student engagement with teacher and automated feedback on L2 writing. *Assessing Writing*, *36*, 90-102.

Zheng, Y., & Yu, S. (2018). Student engagement with teacher written corrective feedback in EFL writing: A case study of Chinese lower-proficiency students. *Assessing Writing*, *37*, 13-24. https://doi.org/10.1016/j.asw.2018.03.001

Zou, S., Guo, K., Wang, J., & Liu, Y. (2026). Investigating students' uptake of teacher-and ChatGPT-generated feedback in EFL writing: A comparison study. *Computer Assisted Language Learning*, *39*(4), 1062-1091.