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Feedback Literacy and EFL Learner Engagement With ChatGPT Feedback: Predicting Feedback Uptake and Perceived Usefulness

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***Abstract*—The proliferation of generative AI tools such as ChatGPT has transformed feedback provision in EFL writing, offering scalable and immediate support to learners. However, learner engagement with AI-generated feedback remains highly variable, raising questions about the internal mechanisms that shape feedback uptake. This study investigates how feedback literacy predicts both the behavioral adoption and perceived usefulness of ChatGPT-generated feedback among EFL learners, while also examining whether perceived ease of use mediates this relationship. Data were collected from 51 Chinese university students through questionnaires and revision-based tasks across three ChatGPT-supported writing assignments. Results from linear regression and bootstrapped mediation analyses revealed that feedback literacy significantly predicted both successful feedback uptake (R^2 = .56) and perceived usefulness (R^2 = .42). Moreover, perceived ease of use partially mediated this relationship, suggesting a layered cognitive-affective mechanism underlying learners' engagement with algorithmic feedback. These findings extend feedback literacy theory beyond interpersonal contexts to AI-mediated, non-dialogic writing environments. They also refine the Technology Acceptance Model by highlighting learner competence as a critical determinant of usability and value perceptions. Pedagogically, the study underscores the need to cultivate feedback literacy as a prerequisite for meaningful engagement with AI tools in writing instruction.**

***Index Terms*—feedback literacy, feedback uptake, perceived usefulness, ChatGPT-generated feedback, EFL writing**

I. Introduction

The emergence of generative artificial intelligence (AI) tools such as ChatGPT has transformed the landscape of feedback provision in second language (L2) writing (Hidayatullah, 2024; Polakova & Ivenz, 2024). Once hampered by time constraints and the dependence on teacher availability (Ginsburg & Stroud, 2023), feedback is now instant, massively efficient, and grammatically refined. In theory, these tools democratize access to high-quality language support by providing every learner with comparable system-generated suggestions, independent of instructional settings. As such, educators have welcomed ChatGPT to supplement traditional teacher input in writing classrooms and support learners more equitably (Khan et al., 2025).

However, the promise of democratized feedback is met with an emerging paradox: despite uniform access to ChatGPT, students exhibit widely divergent responses to the feedback they receive, which point to significant variation in how students engage with ChatGPT-generated feedback. One particularly salient dimension of this variation lies in feedback uptake—that is, the extent to which students accept, apply, or disregard the feedback provided (Zou et al., 2025). For instance, while some students demonstrate a deep, critical approach to revising their work based on feedback, others make minimal or no changes at all (Zhan & Yan, 2025). This divergence is also observed in the way students filter and apply suggestions: some strategically integrate ChatGPT feedback to enhance content and coherence, while others focus only on surface-level corrections or neglect the feedback entirely. Further research shows that although ChatGPT feedback increases the number of revisions, the quality of those revisions—measured by their depth and accuracy—can differ greatly between students (Zou et al., 2025). These findings suggest that the effectiveness of ChatGPT-generated feedback is not solely determined by the system itself but is heavily influenced by the learner's internal capacity to process and act upon it. This discrepancy calls for a shift in analytical focus: from the technological affordances of ChatGPT (Hidayatullah, 2024) to the learner-internal mechanisms that mediate feedback engagement. Understanding why some learners successfully incorporate ChatGPT-generated suggestions while others struggle to interpret or apply them requires closer examination of individual learner characteristics.

A promising conceptual lens to understand this learner variability is feedback literacy—defined as the capacity to interpret, emotionally manage, and act on feedback (Dawson et al., 2024). Research in L2 writing has shown that higher feedback literacy is associated with better uptake and more effective revision practices in response to teacher or peer feedback (Carless & Young, 2024). However, most of these studies are situated in feedback environments involving human-mediated dialogue, where learners benefit from socially contingent cues that help negotiate meaning. In contrast, ChatGPT-generated feedback originates from an algorithmic system devoid of human emotional nuance, potentially challenging learners' ability to interpret and act on suggestions—especially when their feedback literacy is still developing. This difference in feedback ecology imposes new interpretive and regulatory demands on learners since they are responsible for filtering and adapting AI feedback (Woo et al., 2024). In this sense, feedback literacy may no longer be a supplementary skill, but a prerequisite condition for productive engagement with AI-generated feedback.

Beyond cognitive ability, learners' subjective perceptions of ChatGPT-generated feedback tools also emerge as a significant factor in this context. The Technology Acceptance Model (TAM) identifies two key constructs—perceived ease of use (EOU) and perceived usefulness (PU)—as predictors of technology uptake (Davis, 1989a). In educational settings, these constructs have been widely used to assess learner attitudes toward learning management systems, intelligent tutors, and AI-based platforms (Tick, 2019a), and have often been conceptualized as stable judgments linked to system characteristics. However, emerging perspectives suggest that learners' cognitive engagement may also influence how these perceptions are formed, as students who are more mentally invested in learning tasks are more likely to perceive technological tools as useful for achieving their goals (Ma et al., 2024; Sheikh, 2024). These insights point to the need for a more integrated understanding of how internal learner capacities give rise to perceived usefulness, and ultimately influence engagement with ChatGPT-generated feedback.

Building on these insights, the present study selectively draws on Perceived Ease of Use (EOU) and Perceived Usefulness (PU) instead of adopting the full TAM framework, and centers on how feedback literacy functions as a foundational capacity that not only shapes learners' behavioral uptake of ChatGPT-generated feedback but also modulates their subjective perceptions of its usefulness. By analyzing the interplay between feedback literacy and feedback uptake, perceived ease of use, and perceived usefulness, this research seeks to unpack the learner-internal mechanisms, and illuminate how individual differences in feedback literacy determine whether algorithmic feedback translates into meaningful revision behavior.

To address these aims, the study is guided by the following research questions:

1. To what extent does students' feedback literacy predict their uptake of ChatGPT-generated feedback in EFL writing?
2. How is students' feedback literacy associated with their perceived usefulness of ChatGPT-generated feedback?
3. To what extent does perceived ease of use mediate the relationship between students' feedback literacy and their perceived usefulness of ChatGPT-generated feedback?

II. Literature Review

Feedback literacy refers to the essential capabilities that students need to effectively engage with feedback throughout the learning process. It encompasses the ability to understand, interpret, and apply feedback, positioning it as an active process that directly contributes to improved learning outcomes (Carless & Boud, 2018; Molloy et al., 2020). Recent studies have explored student feedback literacy in L2 writing contexts, revealing its multifaceted nature and developmental trajectory. Research indicates that feedback literacy encompasses cognitive and socio-affective dimensions, including subject knowledge, linguistic competence, and attitudes towards feedback (Li & Han, 2022). Developing discipline-specific feedback literacies within curricula can enhance students' future work capacities (Winstone et al., 2022a). For health professional students, early development of feedback literacy is essential for lifelong learning and critical thinking (O'Connor & McCurtin, 2021). Systematic approaches integrating preparatory activities, multi-source feedback, and reflective practices can enhance students' feedback literacy over time (Zhang & Mao, 2023).

The measurement of feedback literacy has evolved over time. Early tools, such as the Student Assessment-Based Feedback Literacy (SAFL) scale (Liao, 2021) and the Peer Feedback Literacy Scale (PFLS) (Dong et al., 2023), focused mainly on measuring students' beliefs and attitudes towards feedback, providing insight into how students perceive feedback. However, over time, there has been a shift toward more comprehensive tools that assess not just beliefs but also students' active engagement with feedback. For example, the Feedback Literacy Behaviour Scale (Dawson et al., 2024) measures how students actively apply feedback to improve their learning, marking a crucial development in how feedback literacy is assessed. This shift provides a more complete and practical understanding of feedback literacy, which is essential for improving feedback practices and designing interventions to help students engage with feedback more effectively.

The extent to which students incorporate and apply received feedback into their revisions can be assessed through the concept of feedback uptake (Wu & Schunn, 2020). Feedback uptake refers to the process of how effectively students integrate feedback into their written work. Research on students' uptake of feedback has highlighted its crucial role in the feedback process, particularly in how students incorporate and utilize the feedback they receive in their revisions. It is a complex process, influenced by various theories of second language acquisition, such as Noticing Hypothesis (Schmidt, 1995), which posits that learners must consciously attend to linguistic features in feedback for them to be available for acquisition. Furthermore, feedback uptake has been recognized as a multidimensional construct involving cognitive, behavioral, and affective components (Zhang & Hyland, 2018). Studies have emphasized that uptake is not merely a matter of correcting surface errors but involves learners' active engagement in interpreting and transforming feedback into meaningful revisions. For instance, Liu and Storch (2023) highlighted that while students often accept feedback suggestions, the depth of engagement varies widely, influenced by individual and contextual factors.

With the increasing use of ChatGPT in education, ChatGPT-generated feedback, often recognized for its efficiency and timeliness (Dai et al., 2023), has become an important source of feedback for learners. Students with higher levels of feedback literacy are better equipped to understand and interpret AI-generated feedback, thereby facilitating its effective integration into their learning. According to Carless and Boud (2018), feedback literacy encompasses the abilities to appreciate feedback, make informed judgments, manage emotional reactions, and take appropriate action. From this perspective, it is plausible that students with stronger feedback literacy may demonstrate higher levels of feedback uptake. This view aligns with cognitive theories of learning, which suggest that learners' ability to process and apply information is critical to how they interpret and evaluate external inputs, including feedback (Sweller, 1988). However, empirical research specifically examining the relationship between feedback literacy and the uptake of ChatGPT-generated feedback remains limited.

Perceived Ease of Use (EOU) and Perceived Usefulness (PU) are two critical components in Technology Acceptance Model (TAM), which has long been a foundational framework in understanding the factors that influence users' acceptance of technology (Davis, 1989b). Specifically, EOU refers to the extent to which a learner believes that using a technology will be free from effort, while PU pertains to the degree to which a learner believes the technology will enhance their performance (Davis, 1989a). While these variables have been well-studied in the context of technology acceptance, research has rarely explored how learner-related factors such as feedback literacy (FL) may influence them in AI-assisted writing contexts. Feedback literacy—defined as a learner's ability to understand, process, and apply feedback—has been linked to more effective engagement with both human and AI-generated feedback (Carless & Boud, 2018). Emerging perspectives suggest that students with stronger feedback literacy are more capable of interpreting automated feedback, which may shape their perceptions of usefulness and ease of use (Winstone et al., 2022b). This aligns with cognitive learning theories, which emphasize that learners' ability to process information mediates their evaluation of instructional tools (Tang & Zhao, 2024).

Feedback uptake reflects learners' behavioral engagement, whereas PU and EOU pertain to their cognitive-affective evaluations of the tool. These distinct yet interrelated constructs may all be influenced by differences in feedback literacy. However, few studies have systematically examined how feedback literacy predicts both students' actual uptake of feedback and their perceptions of usefulness and ease of use in ChatGPT-supported learning environments. This gap calls for an integrative approach that connects internal learner capacities with both revision behaviors and technology perceptions in AI-enhanced writing contexts.

III. Research Methodology

To address the research questions, this study adopted a quantitative explanatory design integrating behavioral validation, following principles outlined by Creswell and Creswell (2017). This design is particularly advantageous for revealing both the underlying relationships among latent variables and the real-world enactment of learning behaviors.

A. *Participant*

This study involved 51 second-year undergraduate students majoring in non-English disciplines at a comprehensive university in southern China. A random sampling strategy was employed, as it is widely used in educational research to ensure that every individual in the target population has an equal chance of being selected, thereby enhancing the generalizability of findings and reducing selection bias (Creswell, 2015). This approach was appropriate given the study's aim to examine learner behavior within a naturally occurring instructional context.

Of the participants, 47.10% were male (n = 24) and 52.90% were female (n = 27). The average age was 18.33 years (SD = 0.48) (see Table 1). A majority of students (78%) had passed the College English Test Band 4 (CET-4), indicating an intermediate proficiency in English (approximately B1–B2 level on the CEFR scale). Approximately 70% of the students reported prior experience using ChatGPT.

The study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki and received departmental-level ethical approval. All participants provided informed consent prior to participation.

Table 1
Demographic Characteristics of Participants (N = 51)

Variable	Category	Frequency	Percentage (%)
Gender	Male	24	47.10%
	Female	27	52.90%
Age	M = 18.33	SD = 0.48	–

B. *Instruments*

(a). *Feedback Literacy Questionnaire*

To examine students' behavioral engagement with feedback, this study employed the Feedback Literacy Behaviour Scale (FLBS) developed by Dawson et al. (2024). Unlike earlier instruments focusing primarily on beliefs or dispositions, the FLBS was designed to capture enacted feedback behaviors in authentic learning environments, making it suitable for studies exploring feedback uptake in task performance.

The scale comprises five dimensions: Seek Feedback (SF) refers to students' proactive efforts to obtain feedback from instructors, peers, or exemplars; Make Sense of Feedback (MS) involves interpreting and evaluating the relevance of received comments; Use Feedback (UF) denotes applying feedback to revise or improve academic work; Provide Feedback (PF) relates to giving feedback to peers, enhancing reciprocal learning; and Manage Affect (MA) reflects the regulation of emotional responses when receiving critical or challenging feedback. The scale contains 24 items, with five for each dimension except MS, which includes four.

Responses were collected using a six-point Likert scale (1 = never, 6 = always), a format designed to minimize central tendency bias. The original study reported acceptable psychometric properties, with Cronbach's α values ranging from .64 to .81 across the five subscales. Model fit indices from confirmatory factor analysis ($\chi^2/df = 1.896$, GFI = 0.901, CFI = 0.911, RMSEA = 0.051), as well as supporting Rasch analyses and test–retest reliability ($r = .56$–$.71$), further affirmed the scale's internal consistency and construct validity (Dawson et al., 2024).

(b). ChatGPT Perceptions Questionnaire

Students' perceptions of ChatGPT were assessed using adapted items based on the Technology Acceptance Model (TAM), specifically drawing from a validated instrument developed by Kim and Moon (2025a). Originally designed to explore learners' acceptance of ChatGPT in general academic contexts, the instrument was tailored in this study to capture students' evaluations of perceived usefulness and ease of use in vocabulary-based multimodal assignments.

Perceived Usefulness (PU) reflects the degree to which students feel that ChatGPT enhance the effectiveness and outcomes of their vocabulary learning tasks. In contrast, Perceived Ease of Use (EOU) captures the perceived effortlessness of using such tools during the assignment process. To better align with the study context, minor wording adjustments were made—such as replacing "learning" with "completing writing assignments." A representative PU item is "Using ChatGPT helped me complete my writing assignment more effectively," while a typical EOU item is "It was easy to use ChatGPT to support my writing learning".

Items were rated on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Psychometric validation of the original scale indicated strong reliability and convergent validity, with composite reliability values of 0.861 for PU and 0.855 for EOU, and AVE values of 0.607 and 0.596, respectively. Confirmatory factor analysis also yielded an excellent model fit ($\chi^2/df = 1.752$, RMSEA = 0.040, CFI = 0.971, TLI = 0.967, GFI = 0.915) (Kim & Moon, 2025b).

(c). Feedback Uptake From Writing Tasks

To assess students' behavioral uptake of feedback in English writing, this study analyzed their revisions across three ChatGPT-supported writing tasks. A total of 153 compositions (three per student, N = 51) were collected. The use of three tasks, rather than a single composition, was intended to provide a more reliable and representative measure of feedback uptake, minimizing task-specific variation and allowing for averaging across multiple instances. After each initial draft, students received feedback exclusively generated by ChatGPT, and they subsequently revised their work based on the suggestions provided. The writing prompts were selected from the course textbook and were appropriate to their intermediate level of English proficiency (CET-4 or equivalent).

Following the framework proposed by Ellis (2010) and applied in recent L2 feedback research (Zou et al., 2025), each feedback response was segmented into independent feedback units. Only actionable feedback—i.e., suggestions that were both sufficiently clear and required the student to perform a concrete revision—was included in the analysis. Each feedback unit was categorized into one of three uptake types: successful uptake (accurate and appropriate revision), unsuccessful uptake (revision attempted but incorrectly executed), or not attempted (no revision was made). Examples of each category are presented in Table 2.

TABLE 2
ILLUSTRATIVE EXAMPLES OF FEEDBACK UPTAKE

Uptake Type	Feedback Example	Student Revision (Excerpt)	Uptake Classification
Successful uptake	"Clarify your topic sentence to better reflect the paragraph."	"Online learning offers both flexibility and interaction."	Accurate and appropriate
Unsuccessful uptake	"Use a more academic synonym instead of 'a lot'."	"There is lots of evidence showing..."	Attempted but incorrect
Not attempted	"Avoid using second-person pronouns in academic writing."	"You can learn more by practicing regularly."	No revision made

Four expert coders with backgrounds in language education and assessment conducted the coding independently, using a shared coding scheme developed through team consensus. Prior to the formal analysis, they participated in a calibration session using sample texts to align their understanding of the coding procedures. The inter-rater reliability, calculated using Fleiss' Kappa, was 0.71, indicating substantial agreement among the coders (Landis & Koch, 1977). Any discrepancies were subsequently resolved through discussion and consensus. Based on the coded data, the proportion of each uptake category was calculated to serve as behavioral indicators for further analysis.

C. Data Collection

Data collection was conducted over a six-week period during the 2024 fall semester (Weeks 5–10). At the outset of the study, two questionnaires were administered concurrently: one assessed students' feedback literacy (FL), and the other measured perceived usefulness (PU) and perceived ease of use (EOU) of ChatGPT-generated feedback. Both questionnaires were distributed via Wenjuanxing, the largest online survey platform in China, which allows for efficient and secure data collection.

Following the survey stage, students engaged in three ChatGPT-supported writing tasks at two-week intervals. Each writing cycle included the submission of an initial draft, receipt of automated feedback from ChatGPT, and subsequent revision. All students were enrolled in two parallel classes taught by the same instructor, using the same course textbook and syllabus.

To standardize the feedback process, all students used a teacher-provided ChatGPT prompt and engaged in a single round of feedback interaction for each task, minimizing variability in the type and quantity of feedback received, ensuring greater comparability across participants. The exact prompt was:

"Please act as an English writing tutor. Read the following paragraph and provide clear, concise feedback on grammar, word choice, coherence, and sentence structure. Do not rewrite the text. Use numbered points to suggest improvements".

While data were originally collected from 53 students enrolled in a compulsory English writing course, two participants were excluded due to incomplete writing data. The final dataset consisted of 51 students with complete responses to both questionnaires and all three writing tasks. All compositions were independently completed in class under teacher supervision to ensure authenticity and to prevent external assistance.

D. Data Analysis

The study employed a combination of descriptive, correlational, and inferential statistical techniques to analyze both questionnaire responses and writing task outcomes. All quantitative analyses were conducted using SPSS 26, with mediation modeling performed through the PROCESS macro (Model 4). Visualizations such as scatterplots and bar charts were generated using SPSS's built-in charting functions. The dataset included self-reported variables (e.g., feedback literacy, perceived usefulness, ease of use) and behavioral indicators (e.g., uptake rate) coded from students' AI-prompted revisions. Statistical significance was determined at the $p < .05$ level.

Prior to inferential analysis, Pearson correlation coefficients were computed to assess the associations among key variables. Feedback literacy (FL) showed a strong positive correlation with perceived usefulness (PU; $r = .82$), and moderate-to-strong correlations with perceived ease of use (EOU; $r = .63$) and successful uptake rate ($r = .69$). These associations provided empirical support for the subsequent regression and mediation analyses.

Before testing, assumption checks were carried out. Key continuous variables (i.e., FL, PU, EOU) were found to follow approximately normal distributions, as confirmed by Shapiro–Wilk tests ($p > .05$) and visual inspection of Q–Q plots and histograms. The variable successful uptake rate showed a mild deviation from normality ($p = .009$; kurtosis = –1.26), but was considered acceptable for regression analysis given the robustness of linear models in samples exceeding 30, particularly when residuals are normally distributed (Lumley et al., 2002; Ghasemi & Zahediasl, 2012). Model residuals were visually assessed and found to approximate normality. In addition, variance inflation factors (VIFs) for feedback literacy and perceived ease of use were both below 2.0, indicating no serious multicollinearity issues.

Simple linear regressions were conducted to address RQ1 and RQ2. For RQ1, it examined if FL predicted students' uptake of ChatGPT-generated feedback. For RQ2, it explored if FL predicted perceived usefulness of ChatGPT feedback, with additional analyses for each FL subscale. Finally, a bootstrapped mediation analysis (5,000 resamples) was carried out to answer RQ3, testing whether EOU mediated the relationship between FL and PU by estimating three paths, with significance determined by a 95% bias-corrected bootstrap confidence interval excluding zero.

IV. FINDINGS

A. Feedback Literacy as a Predictor of Uptake Behavior (RQ1)

To examine how students' feedback literacy influences their incorporation of ChatGPT-generated feedback, we analyzed students' revision outcomes in relation to their feedback literacy scores. Feedback literacy was measured by a five-dimensional questionnaire, and uptake behavior was calculated based on the proportion of actionable feedback successfully implemented in students' revised texts.

Students demonstrated moderately high levels of feedback literacy. As shown in Table 3, the overall feedback literacy score was moderately high ($M = 3.89$, $SD = 0.45$), indicating a generally positive level of engagement with feedback practices. Among the subscales, students reported the highest score in using feedback (UF; $M = 4.18$, $SD = 0.94$), followed by making sense of feedback (MS; $M = 3.97$, $SD = 0.80$) and managing affect (MA; $M = 3.97$, $SD = 1.06$). Providing feedback (PF) and seeking feedback (SF) received relatively lower mean scores of 3.75 ($SD = 0.97$) and 3.58 ($SD = 0.93$), respectively. The distribution across the five subscales suggests a relatively balanced perception of feedback competence among participants.

TABLE 3
DESCRIPTIVE STATISTICS FOR FEEDBACK LITERACY AND ITS DIMENSIONS

Variable	Mean	Std. Dev.	Min	Max
Feedback Literacy (Total)	3.89	0.45	2.9	5
Seek Feedback information (SF)	3.58	0.93	1.8	5.7
Make sense of information (MS)	3.97	0.8	1.6	5.4
Use feedback information (UF)	4.18	0.94	2.3	6
Provide feedback information (PF)	3.75	0.97	1.9	6
Manage affect (MA)	3.97	1.06	1.9	6

Note. All variables were measured on a 6-point Likert scale. Total feedback literacy score was computed as the average of four subscales.

In terms of uptake behavior, the average number of actionable feedback units received per student was 8.2, with a range of 6 to 10. Students implemented an average of 61% of the actionable feedback provided by ChatGPT ($M = 0.61$, $SD = 0.19$), as summarized in Table 4. The remaining feedback was either unsuccessfully applied ($M = 0.19$) or not attempted ($M = 0.20$). These results suggest variability in students' feedback engagement patterns, with most students demonstrating partial but not complete uptake of the feedback provided.

TABLE 4
DESCRIPTIVE STATISTICS FOR UPTAKE BEHAVIOR VARIABLES

Variable	Mean	Std. Dev.	Min	Max
Actionable Feedback Count	8.2	1.34	6	10
Successful Uptake Rate	0.61	0.19	0.29	0.89
Unsuccessful Uptake Rate	0.19	0.09	0	0.38
Not Attempted Rate	0.2	0.13	0	0.44

Note. Successful uptake rate refers to the proportion of actionable feedback items successfully implemented by students across three writing tasks. Rates do not sum exactly to 1 due to rounding.

Table 5 presents the results of a simple linear regression analysis examining whether students' feedback literacy predicted their uptake of ChatGPT-generated feedback. The model was significant, $F(1, 49) = 61.78$, $p < .001$, and accounted for approximately 56% of the variance in uptake behavior ($R^2 = .558$; Adjusted $R^2 = .549$), indicating substantial explanatory power. Feedback literacy significantly predicted successful uptake ($B = 2.86$, $SE = 0.36$, $\beta = 0.75$, $t = 7.86$, $p < .001$), suggesting that higher levels of feedback literacy were associated with greater incorporation of ChatGPT-generated suggestions during revision. The strength of this relationship is further reflected in the high standardized coefficient and Pearson correlation ($r = .75$), which indicate a strong and consistent association across the sample. These findings confirm the central role of feedback literacy in shaping how students engage with ChatGPT-based feedback in writing tasks.

TABLE 5
LINEAR REGRESSION PREDICTING SUCCESSFUL UPTAKE RATE FROM FEEDBACK LITERACY (N = 51)

Predictor	B (Unstd.)	SE	β (Std.)	t	p	R²	Adj. R²	r (Pearson)
Intercept	-6.15	1.42	—	-4.32	< .001	—	—	—
Feedback literacy (total)	2.86	0.36	0.75	7.86	< .001	0.56	0.55	0.75

Note. Unstandardized coefficients (B), standard errors (SE), standardized coefficients (β), t values, and significance levels are reported. $R^2 = .558$; Adjusted $R^2 = .549$. Pearson r is derived from bivariate correlation. Intercept is reported for model completeness and not interpreted substantively.

To visually illustrate this relationship, Figure 1 plots the regression line between feedback literacy and successful uptake. The scatterplot shows a clear upward trend, indicating that students with higher levels of feedback literacy tended to achieve greater success in applying ChatGPT-generated suggestions. The strength and clarity of this pattern reinforce the interpretation that feedback literacy contributes meaningfully to students' ability to act on ChatGPT-based feedback. Together, these results provide empirical support for a positive relationship between students' perceived feedback competence and their revision outcomes in an ChatGPT-supported writing context.

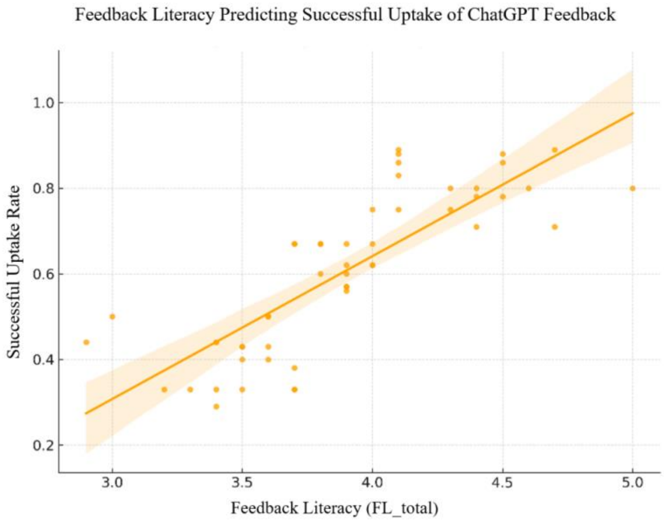

Figure 1. Scatterplot With Regression Line: FL Predicting Successful Uptake

B. Feedback Literacy and Perceived Usefulness of ChatGPT Feedback (RQ2)

To further understand how students perceive AI-generated feedback, this section explores the relationship between feedback literacy and students' perceived usefulness (PU) of ChatGPT suggestions. As shown in the table 6, students' perceived usefulness of ChatGPT-generated feedback (PU) was moderate overall ($M = 3.01$, $SD = 0.81$), with scores ranging from 1.00 to 5.00 on a 5-point Likert scale. This range indicates that while students generally found ChatGPT feedback helpful and relevant to their writing tasks, some variation existed in how consistently this usefulness was experienced.

A simple linear regression analysis was conducted to examine whether students' feedback literacy predicted their perceived usefulness (PU) of ChatGPT-generated feedback. As shown in Table 6, the model was statistically significant, $F(1, 49) = 40.05$, $p < .001$, accounting for approximately 45% of the variance in PU ($R^2 = .450$; Adjusted $R^2 = .439$). Feedback literacy emerged as a significant positive predictor ($B = 1.21$, $SE = 0.19$, $\beta = 0.67$, $t = 6.33$, $p < .001$), suggesting that students with higher levels of feedback literacy tended to view AI-generated feedback as more beneficial for improving their writing. The strong standardized coefficient and correlation ($r = .67$) further indicate a robust association between students' feedback competence and their subjective evaluation of ChatGPT's usefulness.

TABLE 6
LINEAR REGRESSION PREDICTING PERCEIVED USEFULNESS FROM FEEDBACK LITERACY (TOTAL) (N = 51)

Predictor	B (Unstd.)	SE	β (Std.)	t	p	R^2	Adj. R^2	r (Pearson)
Intercept	-1.66	0.75	—	-2.23	0.03	—	—	—
Feedback literacy (total)	1.21	0.19	0.67	6.33	< .001	0.45	0.44	0.67

Note. Unstandardized coefficients (B), standard errors (SE), standardized coefficients (β), t values, and significance levels are reported. $R^2 = .450$; Adjusted $R^2 = .439$. Pearson r is derived from bivariate correlation. Intercept is reported for model completeness and not interpreted substantively.

Figure 2 provides a visual representation of the linear relationship between students' feedback literacy and their perceived usefulness of ChatGPT-generated feedback. The scatterplot, along with the fitted regression line and 95% confidence interval, illustrates a clear positive trend. Students with higher feedback literacy levels tended to perceive the AI-generated feedback as more useful.

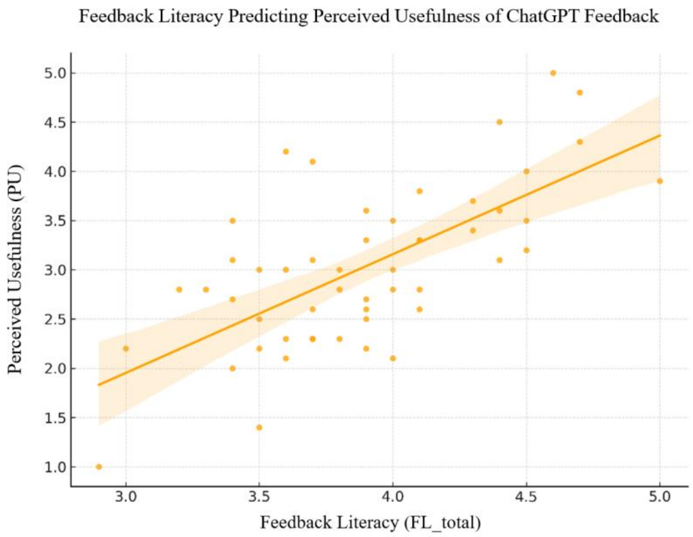

Figure 2. Scatterplot With Regression Line: Feedback Literacy Predicting Perceived Usefulness

To examine how different subdimensions of feedback literacy contribute to students' perceived usefulness (PU) of ChatGPT-generated feedback, a multiple regression analysis was conducted. This method was used to identify the unique effects of each dimension while controlling for the influence of the others. Five subdimensions—Seeking Feedback (SF), Making Sense of Feedback (MS), Using Feedback (UF), Providing Feedback (PF), and Managing Affect (MA)—were entered simultaneously as predictors. As summarized in Table 7, the overall model was statistically significant, $F(5, 45) = 108.86$, $p < .001$, and explained 92.4% of the variance in PU ($R^2 = .924$; Adjusted $R^2 = .915$). Among the five predictors, using feedback ($\beta = 0.76$, $p < .001$) and making sense of feedback ($\beta = 0.58$, $p < .001$) emerged as strong and significant contributors. The remaining three subdimensions—seeking feedback, providing feedback, and managing affect—did not significantly contribute to the model. These findings suggest that students who are more capable of interpreting and applying feedback are more likely to perceive AI-generated feedback as useful in supporting their writing development.

TABLE 7
MULTIPLE REGRESSION PREDICTING PERCEIVED USEFULNESS OF CHATGPT FROM FEEDBACK LITERACY SUBDIMENSIONS (N = 51)

Predictor	B (Unstd.)	SE	β (Std.)	t	p
Intercept	-2.07	0.29	—	-7.14	< .001
Seeking Feedback (SF)	0.04	0.04	0.05	1.09	0.281
Making Sense of Feedback (MS)	0.58	0.04	0.58	13.34	< .001
Using Feedback (UF)	0.65	0.04	0.76	18.24	< .001
Providing Feedback (PF)	-0.03	0.04	-0.03	-0.71	0.481
Managing Affect (MA)	0	0.03	0	-0.02	0.983

Note. B = unstandardized coefficient; β = standardized coefficient. The model was significant, $F(5, 45) = 108.86$, $p < .001$; $R^2 = .924$, Adjusted $R^2 = .915$.

C. *The Mediating Role of Perceived Ease of Use (RQ3)*

To investigate how students' feedback literacy (FL_total) influences their perception of the usefulness of ChatGPT-generated feedback, and whether this relationship is mediated by perceived ease of use (EOU), a mediation analysis was performed using PROCESS Macro (Model 4, 5000 bootstrap samples). Figure 3 visually depicts the hypothesized model and standardized regression coefficients for each path. The results indicated that FL had a significant positive effect on EOU ($\beta = .639$, $p < .001$), suggesting that students with stronger feedback literacy skills tend to find ChatGPT easier to use. In turn, EOU significantly predicted students' perceived usefulness of the feedback received ($\beta = .751$, $p < .001$), highlighting the importance of user experience in shaping learners' value judgments toward AI-generated feedback. Notably, the direct path from FL to PU remained statistically significant after accounting for EOU ($\beta = .191$, $p < .05$), though reduced in strength. This pattern of results supports a partial mediation, indicating that perceived ease of use serves as an intermediary mechanism through which feedback literacy exerts its effect on perceived usefulness, but does not fully account for it.

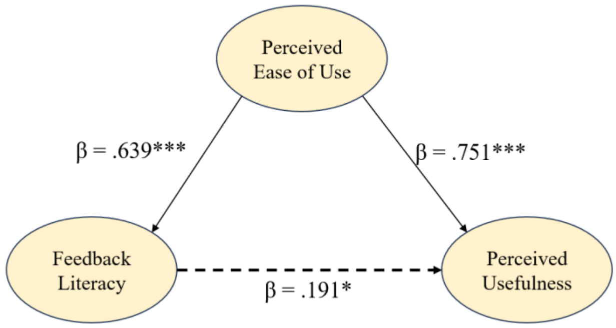

Figure 3. Mediation Model of the Effect of Feedback Literacy on Perceived Usefulness via Perceived Ease of Use
Note. Coefficients are standardized (β). *p < .05, ***p < .001.

Further support for the mediating role of EOU was provided by the bootstrapped indirect effect. The indirect path from FL to PU via EOU was statistically significant, with an unstandardized estimate of B = 0.861 (SE = 0.207) and a 95% bias-corrected confidence interval ranging from 0.476 to 1.292. Because the confidence interval does not include zero, the mediation effect can be considered statistically reliable. The total effect of FL on PU (without accounting for the mediator) was B = 1.205 ($p < .001$), and the drop in coefficient size from the total effect (B = 1.205) to the direct effect (B = 0.344) provides additional evidence of a partial mediation. The overall explanatory power of the model improved substantially from $R^2 = .450$ in the direct model to $R^2 = .783$ in the full mediation model. These findings suggest that students' ability to understand, evaluate, and use feedback meaningfully not only contributes directly to how helpful they perceive AI-generated feedback to be, but also does so indirectly by shaping their perception of how easy it is to engage with the tool. In this way, EOU functions as a cognitive-affective bridge between internal feedback capacities and external technological judgments. Detailed statistical results are presented in Table 8.

TABLE 8
REGRESSION RESULTS FOR MEDIATION MODEL (FL → EOU → PU)

Path	B	SE	t	p	95% CI (Bootstrapped)	β (Std.)	R^2
FL → EOU	1.062	0.183	5.809	<.001	[0.695, 1.430]	0.639	0.408
EOU → PU	0.811	0.094	8.598	<.001	[0.621, 1.001]	0.751	—
FL → PU (Direct)	0.344	0.157	2.192	0.033	[0.028, 0.659]	0.191	—
Indirect Effect (a × b)	0.861	0.207	—	—	[0.476, 1.292]	—	—
Model R^2 (FL → PU)	—	—	—	—	—	—	0.45
Model R^2 (FL, EOU → PU)	—	—	—	—	—	—	0.783

Note. PU = Perceived Usefulness; FL = Feedback Literacy; EOU = Perceived Ease of Use. Confidence intervals are based on 5000 bootstrap samples. Model R^2 values reflect explained variance in each dependent variable. Indirect effect is significant as CI does not include zero.

V. DISCUSSION

A. *Feedback Literacy as a Key Predictor of Feedback Uptake*

While prior research has emphasized the importance of feedback literacy in traditional interpersonal feedback settings (Han & Hyland, 2019; Winstone et al., 2017), the present findings highlight a redefinition of its role in AI-mediated contexts. Specifically, this study reveals that feedback literacy becomes more than a mediator of understanding; it operates as a cognitive infrastructure that enables students to transform structurally sparse and affectively neutral feedback into meaningful revisions. Given that ChatGPT feedback often lacks elaboration or contextual cues, it places greater inferential demands on learners—making internal schema activation more central to task completion. This aligns with Sweller's Cognitive Load Theory, which suggests that in minimally guided contexts, learners must bear increased cognitive load to construct meaning. This extends (Carless & Boud, 2018) conceptualization of feedback literacy by situating it in a non-dialogic ecosystem, where no interpersonal repair mechanisms or clarification loops are available.

In contrast to earlier studies where uptake was jointly shaped by peer dialogue, teacher modeling, or contextual cues (Evans, 2013), the learners in this study interacted with a static interface, receiving feedback devoid of rhetorical softening or audience awareness. As such, this study refines (Dawson et al., 2024) notion of feedback literacy as a situationally enacted resource by showing that its enactment becomes increasingly consequential when feedback lacks personalization, elaboration, or scaffolding.

B. *Cognitive and Affective Dimensions of Usefulness: Extending the Explanatory Scope of Feedback Literacy*

While TAM-based research has long established perceived usefulness as a key determinant of technology engagement (Davis, 1989b), few studies have probed the learner-internal mechanisms that shape this perception. The present findings fill this gap by demonstrating that students' ability to understand and emotionally process feedback is pivotal in whether they view it as instructionally valuable.

Among the five dimensions of feedback literacy examined, only Using Feedback (UF) and Making Sense of Feedback (MS) emerged as significant predictors of PU. This finding both aligns with and extends the work of Winstone and Boud (2022b), who argued that feedback is only as useful as the learner's ability to make sense of it. However, while their argument was situated in human-mediated settings, the current study shows that this interpretive burden becomes even more consequential when feedback is generated by AI, which lacks elaboration, personalization, and contextual adaptation. In such decontextualized environments, the burden of meaning-making shifts decisively onto the learner, magnifying the role of individual agency and feedback literacy.

Notably, dimensions such as Seeking Feedback (SF) and Providing Feedback (PF), commonly emphasized in dialogic models of feedback engagement, were not significantly associated with PU in this study. This divergence may reflect a contextual shift in what literacy "counts": in ChatGPT-mediated environments, feedback is passively received and lacks opportunities for clarification or negotiation. Therefore, proactive seeking or evaluative comparison may play a diminished role. Rather than undermining these dimensions, the result highlights how feedback ecology alters the salience of learner competencies.

Taken together, these findings advance a more nuanced understanding of perceived usefulness in algorithmic feedback contexts. They suggest that the cognitive-affective substructure of feedback literacy—not motivational orientation or behavioral effort—best predicts whether students find AI feedback valuable. In this way, the current study challenges TAM's long-standing emphasis on perceived usefulness as a relatively stable, tool-based belief (Tick, 2019b), and instead repositions it as an outcome contingent on the learner's interpretive and regulatory capacities.

C. Perceived Ease of Use as a Cognitive Filter: Rethinking Mediation in TAM

The mediation analysis revealed that perceived ease of use (EOU) partially mediated the relationship between students' feedback literacy and their perceived usefulness (PU) of ChatGPT-generated feedback, with a significant indirect effect (B = 0.861, 95% CI [0.476, 1.292]). While this supports the canonical TAM pathway (Davis, 1989a), the findings also complicate its assumptions. Rather than reflecting interface simplicity, EOU appears to function as a cognitive filter—shaped by learners' ability to interpret and operationalize feedback.

The strong predictive link between feedback literacy and EOU ($\beta = .639$, $R^2 = .408$) suggests that ease is not tool-driven but learner-constructed. This supports critiques of TAM that highlight the role of cognitive fluency in shaping user experience (Plass & Kalyuga, 2019). In this study, all students interacted with the same AI system and prompts, yet those with higher feedback literacy reported greater ease—implying that usability perceptions are emergent from interpretive competence. Notably, the model's explanatory power improved from $R^2 = .450$ in the direct model to $R^2 = .783$ when EOU was included as a mediator, underscoring its key role in shaping perceived usefulness.

Crucially, even after accounting for EOU, feedback literacy remained a significant direct predictor of PU ($\beta = .191$), confirming a partial mediation. This dual pathway suggests that students' perceptions of usefulness are both enhanced by cognitive ease and directly shaped by their ability to extract relevance from feedback.

These findings challenge the idea that usability is a fixed property of the system. In contexts where ChatGPT-generated feedback is concise, impersonal, and lacking contextual cues, EOU depends on learners' ability to actively transform suggestions into action. Thus, improving user experience cannot rely on interface design alone; it requires building learners' feedback literacy.

D. Theoretical and Pedagogical Implications

This study reconceptualizes feedback literacy as a prerequisite for engaging with algorithmic feedback, rather than a supplementary skill relevant only to human-mediated settings. In doing so, it expands existing feedback literacy frameworks (Carless & Boud, 2018; Dawson et al., 2024) to encompass decontextualized, non-dialogic feedback environments where learners must compensate for the absence of interpersonal cues. The partial mediation model also revises assumptions within the Technology Acceptance Model (TAM), showing that perceived ease of use is not simply a function of system design but is significantly shaped by learner cognition.

Pedagogically, the findings emphasize the importance of embedding feedback literacy development into ChatGPT-supported writing instruction. This involves not only training students to interpret and act on feedback, but also fostering the cognitive fluency needed to navigate AI-generated suggestions. Practical strategies may include explicit modeling of feedback use, peer-based revision discussions, and scaffolded exercises that guide students through rewriting based on AI input.

VI. CONCLUSION

As generative AI tools like ChatGPT become increasingly integrated into writing instruction, they are often assumed to democratize access to high-quality feedback. Yet growing evidence suggests that access alone does not guarantee learning gains. Students vary widely in how they respond to and benefit from machine-generated suggestions, raising the question: What determines whether AI feedback is pedagogically effective?

This study addresses this challenge by examining the role of feedback literacy (FL) in shaping EFL students' engagement with ChatGPT-generated feedback. Based on data from 51 Chinese university students, the findings show that FL strongly predicts both students' uptake behavior and their perceived usefulness of feedback. Moreover, perceived ease of use (EOU) partially mediates this relationship, indicating that students' ability to apply feedback is closely tied to how cognitively accessible they find the tool (Lipnevich & Panadero, 2021). Together, these results suggest that the effectiveness of AI feedback is not merely a function of design or availability, but of learner readiness.

Theoretically, the study reframes feedback literacy as a cognitive infrastructure for navigating algorithmic, non-dialogic environments. It also challenges the technocentric assumptions in the Technology Acceptance Model (TAM) (Davis, 1989a), showing that PU and EOU are not system-fixed beliefs but learner-dependent outcomes. Pedagogically, the findings point to the need for explicit instruction in interpreting, regulating, and applying AI feedback. Instructors must equip students not only to receive feedback, but to render it usable. Ultimately, the educational value of AI tools like ChatGPT lies not in their presence, but in students' capacity to transform them into learning opportunities.

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