



Evaluating the impact of AI-assisted versus traditional feedback on EFL learners' writing self-efficacy

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Abstract

Background: In English as a Foreign Language (EFL) contexts, writing self-efficacy a learner's belief in their capability to produce specific writing tasks is a critical predictor of writing performance and engagement. With the rapid integration of Artificial Intelligence (AI) in education, AI-assisted feedback tools are increasingly competing with traditional teacher feedback.

Objective: This study aims to evaluate and compare the effects of AI-assisted feedback and traditional teacher feedback on the writing self-efficacy of undergraduate EFL learners.

Method: This study uses a simulated dataset created for academic training purposes. A quantitative, quasi-experimental research design was employed with a sample of 120 undergraduate EFL students divided into two groups: an experimental group (n=60) receiving AI-assisted feedback via an advanced grammar and style checker, and a control group (n=60) receiving traditional handwritten teacher feedback over a 10-week period. The Writing Self-Efficacy Scale was administered pre- and post-intervention. Data were analyzed using SPSS v27.

Key Results: Both groups demonstrated significant improvements in writing self-efficacy from pre-test to post-test ($p < 0.05$). However, the independent samples t-test revealed that the AI-assisted feedback group exhibited significantly higher gains in the "linguistic conventions" subscale, whereas the traditional feedback group showed marginally higher gains in the "ideation and organization" subscale.

Conclusion: AI-assisted feedback serves as a highly effective supplementary tool for enhancing EFL learners' confidence in grammatical accuracy, though traditional teacher feedback remains vital for higher-order cognitive writing skills.

Keywords: AI-assisted feedback, EFL writing, self-efficacy, automated writing evaluation, formative assessment, writing proficiency

Introduction

Writing in a second language (L2) is universally recognized as a highly complex cognitive endeavor that demands the orchestration of multiple linguistic, cognitive, and socio-cultural competencies^[1]. Unlike speaking, writing requires deliberate attention to syntax, vocabulary selection, cohesion, and genre-specific conventions, often under the pressure of time and assessment^[2]. Consequently, many English as a Foreign Language (EFL) learners experience significant anxiety and low motivation when confronted with L2 writing tasks. Within this context, the psychological construct of self-efficacy, conceptualized by Bandura^[3] as an individual's belief in their capacity to execute behaviors necessary to produce specific performance attainments, has emerged as a pivotal affective variable in L2 writing research. Writing self-efficacy influences the effort learners expend, their persistence in the face of challenges, and ultimately, their writing performance^[4].

Historically, the primary pedagogical intervention designed to improve both writing competence and confidence in EFL contexts has been Written Corrective Feedback (WCF). Traditional WCF, typically delivered by instructors in the form of handwritten marginal comments, endnotes, and error corrections, has been extensively researched^[5]. While studies confirm that teacher feedback provides necessary individualized scaffolding, it is inherently limited by teachers' workload, time constraints, and subjective variability^[6]. These limitations often result in delayed

feedback, which diminishes its potential impact on a learner's immediate self-efficacy, as the affective state of the learner at the time of writing may have passed^[7].

To address these logistical challenges, the field of Applied Linguistics has witnessed a paradigm shift toward the integration of Automated Writing Evaluation (AWE) and, more recently, AI-assisted feedback tools^[8]. Modern AI writing assistants, powered by sophisticated Natural Language Processing (NLP) algorithms, can generate instantaneous, granular feedback on spelling, grammar, punctuation, and stylistic mechanics^[9]. Despite the growing adoption of these technologies in L2 classrooms, the literature reveals a stark research gap regarding their psychological impact on learners. While much of the existing research focuses on the efficacy of AI tools in improving immediate linguistic accuracy or revision behaviors^[10], there is a paucity of empirical data comparing how AI-assisted feedback versus traditional human feedback influences the underlying writing self-efficacy of EFL learners^[11].

Therefore, this study aims to bridge this gap by investigating the comparative impact of AI-assisted feedback and traditional teacher feedback on EFL learners' writing self-efficacy. Specifically, the study is guided by three research objectives: ^[1] to measure the baseline writing self-efficacy of EFL learners prior to any intervention; ^[2] to determine the effect of a 10-week AI-assisted feedback intervention on writing self-efficacy compared to a

traditional feedback control group; and ^[3] to investigate whether the impact of the feedback type varies across different subscales of writing self-efficacy, namely ideation, self-regulation, and linguistic conventions. By addressing these objectives, this research seeks to provide evidence-based insights for educators and policymakers navigating the integration of AI in language education.

Literature review

1. Theoretical framework: Social cognitive theory and self-efficacy

The theoretical foundation of this study is rooted in Albert Bandura's Social Cognitive Theory (SCT), which posits a dynamic triadic interaction between personal factors, behavior, and the environment ^[12]. Central to SCT is the construct of self-efficacy. Bandura identified four primary sources of information that shape self-efficacy beliefs: enactive mastery experiences, vicarious experiences, verbal persuasion, and physiological and affective states ^[13]. In the context of L2 writing, enactive mastery experiences are arguably the most powerful; when students successfully revise and improve a text based on feedback, their belief in their writing capabilities increases. Verbal persuasion, manifested through teacher comments or automated praise/corrections, also plays a critical role. However, the mechanism by which verbal persuasion is delivered—whether through human empathy or algorithmic precision—may alter its efficacy, forming the core theoretical tension investigated in this study.

2. Writing self-efficacy in EFL contexts

Writing self-efficacy is not a unidimensional construct; rather, it encompasses a learner's confidence in various components of the writing process. Researchers have operationalized L2 writing self-efficacy to include confidence in writing conventions (grammar, spelling, punctuation), ideation (generating and organizing ideas), and self-regulation (managing time, overcoming writer's block) ^[14]. Studies consistently demonstrate a strong positive correlation between L2 writing self-efficacy and actual writing performance ^[15]. Lower self-efficacy often leads to writing avoidance behaviors, whereas higher self-efficacy correlates with greater cognitive engagement and the willingness to undertake complex writing tasks ^[16]. Consequently, assessing how different pedagogical tools impact these distinct subscales of self-efficacy is essential for holistic L2 writing instruction.

3. Traditional teacher feedback versus AI-assisted feedback

The debate surrounding the efficacy of WCF has dominated L2 writing literature for decades. Proponents of traditional teacher feedback argue that human instructors possess the pragmatic and socio-linguistic competence necessary to evaluate higher-order concerns, such as argumentation, tone, and audience awareness, which machines cannot fully comprehend ^[17]. Furthermore, human feedback carries an affective weight; students often perceive teacher comments as personally tailored, which can enhance motivation through the source credibility of the feedback provider ^[18]. Conversely, AI-assisted feedback, particularly modern AWE systems, excels in lower-order concerns. These tools provide immediate, unlimited, and objective corrections, primarily targeting linguistic conventions ^[19]. Recent

advancements in AI have enabled these tools to move beyond simple rule-based error detection to utilizing machine learning for stylistic suggestions and clarity improvements ^[20]. From an SCT perspective, AI tools uniquely influence self-efficacy through immediate enactive mastery experiences; a student can correct a grammatical error and instantly see the "green light" from the software, potentially providing a rapid boost to their confidence in linguistic conventions ^[21].

4. Research gap

While comparative studies between AWE and teacher feedback exist, they predominantly utilize quantitative measures of text improvement (e.g., error reduction rates) or qualitative analyses of student revision behaviors ^[22]. The affective domain, specifically writing self-efficacy, remains under-examined. Moreover, when self-efficacy is measured, studies rarely disaggregate the results by the subscales of writing (ideation vs. conventions) ^[23]. Given that AI and human teachers possess fundamentally different strengths, it is highly plausible that their impact on self-efficacy is not uniform across all writing sub-skills. This study addresses this specific lacuna by providing a disaggregated analysis of writing self-efficacy under two distinct feedback conditions.

Methodology

1. Research design

This study employed a quantitative, quasi-experimental research design with a pre-test and post-test control group structure ^[24]. This design was selected to measure the causal impact of the independent variable (type of feedback: AI-assisted vs. traditional) on the dependent variable (writing self-efficacy scores) over a specified time frame.

2. Data source statement

This study uses a simulated dataset created for academic training purposes. The data, including demographic variables and survey responses, were algorithmically generated to reflect statistically plausible distributions based on established parameters in applied linguistics research. No real human subjects were involved in this dataset.

3. Population and sample size

The target population for this simulated study was undergraduate EFL learners enrolled in first-year academic writing courses. Using GPower 3.1 to calculate the required sample size for a medium effect size (Cohen's $d = 0.50$), an alpha of 0.05, and a power of 0.80, a minimum sample of 128 was recommended. To account for potential data attrition, the simulated sample size was set at $N = 120$. The participants were randomly assigned to two groups: the Experimental Group (AI-assisted feedback, $n = 60$) and the Control Group (Traditional teacher feedback, $n = 60$).

4. Sampling method

A stratified random sampling method was simulated to ensure gender balance and a homogenous distribution of language proficiency levels (intermediate to upper-intermediate) across both groups, as confirmed by a simulated placement test score equivalence ($p > 0.05$).

5. Data collection instrument

The primary instrument used was the L2 Writing Self-Efficacy Scale (WSES), adapted from established scales in

the literature ^[25]. The questionnaire consisted of 20 items measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The scale was divided into three subscales: Linguistic Conventions (8 items, e.g., "I am confident I can use correct grammar in my essays"), Ideation and Organization (7 items, e.g., "I am confident I can generate relevant ideas for a topic"), and Self-Regulation (5 items, e.g., "I am confident I can manage my time while writing"). The simulated Cronbach's alpha for the overall scale was 0.89, indicating excellent internal consistency.

6. Intervention procedure

The intervention spanned 10 weeks. Both groups were required to write one argumentative essay per week (300-350 words). The Control Group submitted their essays to a human instructor (simulated) and received handwritten, comprehensive feedback focusing on both higher-order (content, organization) and lower-order (grammar, mechanics) concerns within 7 days. The Experimental Group submitted their essays to a simulated advanced AI writing platform, receiving instant, algorithmic feedback focusing predominantly on grammar, syntax, vocabulary enhancement, and basic structural formatting. Students in

the AI group were required to review the AI suggestions and resubmit the essay.

7. Statistical analysis

Data were analyzed using SPSS version 27. Descriptive statistics (means, standard deviations) were calculated for demographic profiling. To test the assumptions of normality and homogeneity of variance, the Shapiro-Wilk test and Levene's test were utilized. Paired-samples t-tests were conducted to measure within-group growth (pre-test to post-test). Finally, an independent samples t-test was used to compare the post-test self-efficacy gains between the two groups. An alpha level of 0.05 was set for statistical significance ^[26].

Results and discussion

1. Descriptive statistics and demographics

Table 1 presents the demographic distribution of the simulated sample. The chi-square analysis confirmed no significant differences in gender ($\chi^2 = 0.13$, $p = 0.72$) or proficiency level ($\chi^2 = 0.15$, $p = 0.70$) between the AI-assisted group and the Traditional feedback group, ensuring baseline comparability.

Table 1: Demographic Characteristics of Participants (N = 120)

Characteristic	Categories	AI Group (n=60)	Traditional Group (n=60)	Total (n=120)
Gender	Male	28 (46.7%)	30 (50.0%)	58 (48.3%)
	Female	32 (53.3%)	30 (50.0%)	62 (51.7%)
Proficiency	Intermediate	25 (41.7%)	27 (45.0%)	52 (43.3%)
	Upper-Intermediate	35 (58.3%)	33 (55.0%)	68 (56.7%)

2. Within-group improvements in writing self-efficacy

To address the first and second research objectives, paired-samples t-tests were conducted to evaluate the pre-test to post-test changes within each group. As displayed in Table 2, both the AI-assisted group and the Traditional feedback group demonstrated statistically significant improvements in their overall writing self-efficacy scores.

The AI group's mean score increased from 3.12 (SD = 0.54) to 3.85 (SD = 0.48), $t^{59} = -9.42$, $p < 0.001$. Similarly, the Traditional group's mean score rose from 3.15 (SD = 0.51) to 3.72 (SD = 0.52), $t^{59} = -7.81$, $p < 0.001$. These results indicate that both pedagogical interventions successfully enhanced learners' writing confidence.

Table 2: Paired Samples t-Test for Overall Writing Self-Efficacy (Pre vs. Post)

Group	Time	Mean	SD	t-value	df	p-value
AI-Assisted	Pre-test	3.12	0.54	-9.42	59	< 0.001
	Post-test	3.85	0.48	—	—	—
Traditional	Pre-test	3.15	0.51	-7.81	59	< 0.001
	Post-test	3.72	0.52	—	—	—

Note: $p < 0.001$

3. Between-group differences and subscale analysis

To address the third research objective, an independent samples t-test was conducted on the post-test gain scores (Post-test minus Pre-test) between the two groups. While the

overall gain scores were not significantly different ($p = 0.12$), a divergent picture emerged when the data were disaggregated by the three subscales of writing self-efficacy, as shown in Table 3.

Table 3: Independent Samples t-Test Comparing Post-Test Gain Scores by Subscale

Subscale	Group	Mean Gain	SD	t-value	df	p-value
Linguistic Conventions	AI-Assisted	1.02	0.31	4.56	118	< 0.001
	Traditional	0.72	0.35	—	—	—
Ideation & Organization	AI-Assisted	0.45	0.40	-2.15	118	0.034
	Traditional	0.62	0.38	—	—	—
Self-Regulation	AI-Assisted	0.55	0.42	0.89	118	0.375 (ns)
	Traditional	0.48	0.45	—	—	—

Note: $p < 0.05$, $p < 0.001$, ns = not significant

The data reveal a statistically significant difference in the "Linguistic Conventions" subscale, favoring the AI-assisted group ($p < 0.001$). Conversely, the "Ideation and Organization" subscale showed a statistically significant difference favoring the Traditional feedback group ($p = 0.034$). There was no significant difference in the "Self-Regulation" subscale ($p = 0.375$).

4. Discussion of Findings

The findings of this study yield critical insights into the intersection of technology and affective variables in L2 writing. The first major finding that both AI and traditional feedback significantly enhance overall writing self-efficacy aligns with Bandura's^[27] premise that enactive mastery experiences, regardless of the feedback source, build competence beliefs. As students engaged in the cyclical process of drafting, receiving feedback, and revising over 10 weeks, their overall confidence in writing improved.

However, the disaggregated subscale analysis provides a more nuanced narrative that addresses the central research gap. The significant superiority of AI-assisted feedback in boosting "Linguistic Conventions" self-efficacy can be explained through the lens of SCT's verbal persuasion and immediate enactive mastery^[28]. AI tools provide instantaneous, deterministic corrections. When a learner writes a sentence, immediately receives an algorithmic flag, corrects it, and sees the error disappear, the feedback loop is closed within seconds. This rapid cycle heavily reinforces the learner's belief in their ability to handle grammar and mechanics, reducing the affective filter associated with linguistic insecurity^[29].

Conversely, the superiority of traditional teacher feedback in enhancing "Ideation and Organization" self-efficacy underscores the irreplaceable value of human cognition in L2 pedagogy. While AI tools can identify structural anomalies (e.g., missing topic sentences), they lack the pragmatic and socio-cultural awareness required to evaluate the depth, originality, and nuanced logic of an argument^[30]. Teacher feedback often involves dialogic questioning, prompting the student to think deeper, which serves as a highly effective form of verbal persuasion for higher-order thinking skills^[31]. The human instructor's ability to say, "This is a fascinating point, can you connect it to your thesis?" provides an affective boost to ideation confidence that an algorithmic "clarity suggestion" cannot replicate^[32]. The lack of significant difference in the "Self-Regulation" subscale suggests that the medium of feedback (AI vs. Human) has little bearing on a student's confidence in managing time, overcoming anxiety, or initiating the writing process. Self-regulation is likely governed more by intrinsic motivation and broader classroom pedagogy than by the specific modality of formative feedback^[33].

Conclusion

1. Summary of findings

This study set out to evaluate the comparative impact of AI-assisted feedback and traditional teacher feedback on EFL learners' writing self-efficacy. Utilizing a simulated dataset for a 10-week quasi-experimental design, the research demonstrated that while both interventions significantly improve overall writing self-efficacy, their impacts are highly domain-specific. AI-assisted feedback is significantly more effective at bolstering learners' confidence in linguistic conventions (grammar, mechanics), whereas traditional

teacher feedback remains superior in fostering confidence in ideation and organization.

2. Implications

These findings carry substantial implications for ELT practitioners, curriculum designers, and policymakers. Rather than viewing AI as a threat or a wholesale replacement for human instructors, educators should adopt a hybrid approach. By offloading the labor-intensive correction of lower-order concerns to AI tools, teachers can dedicate more of their finite time and cognitive resources to providing targeted feedback on higher-order thinking, critical analysis, and creative ideation^[34]. For policymakers, this study supports the integration of AI-assisted writing tools into national EFL curricula, provided that teacher training programs simultaneously emphasize advanced feedback techniques for content development.

3. Limitations and future scope

As this study utilized a simulated dataset, the findings are intended for academic training and methodological modeling rather than direct empirical generalization to real-world populations. Furthermore, the study focused exclusively on argumentative essays; different genres (e.g., narrative, descriptive) might yield different interactions between feedback type and self-efficacy. Future research utilizing real-world data should employ mixed-methods designs to capture the qualitative nuances of how students subjectively experience AI versus human feedback. Additionally, longitudinal studies are needed to determine whether the self-efficacy gains induced by AI tools are sustainable over extended periods^[35].

Ethical statement

This research article has been generated for academic training and formatting practice purposes. The dataset used in the methodology and results sections is entirely simulated and does not represent any real human subjects. No actual experiments were conducted, and no personal data was collected. All references cited are real, verifiable academic sources used to contextualize the simulated study, adhering strictly to ethical guidelines against the fabrication of empirical data or identities.

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