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Original Research

Charting Uncharted Waters: AI-Driven Feedback and Writing Accuracy of Intermediate Iranian EFL Learners

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Abstract

This study explored the impact of AI-driven feedback on the writing accuracy of Iranian intermediate EFL learners using a quasi-experimental design. Through convenience sampling, 100 participants (male and female, aged 18-25) from two language institutes in Tehran were divided into four groups: two experimental groups that received direct and indirect feedback from AI ChatGPT, and two control groups that received the same feedback types from their teacher. Participants completed 250-350-word argumentative essays under timed conditions during a 14-week intervention (pre-test, 10 weekly assignments, post-test). Results, analyzed via descriptive statistics and one-way ANOVA, showed significant improvements in writing accuracy across all groups. The AI direct feedback group achieved the highest improvement, with a mean difference of 7.34 ($p < 0.05$). Writing accuracy was assessed using an analytical rubric that focused on nine error types: subject-verb agreement, article usage, verb form, pronoun usage, word choice, spelling, capitalization, punctuation, and sentence clarity/completeness. Post hoc comparisons revealed that AI direct feedback significantly outperformed both AI indirect feedback and traditional teacher feedback, while teacher indirect feedback resulted in the least progress. Error-type analysis highlighted the superior effectiveness of AI feedback, particularly direct feedback, in reducing spelling and verb form errors. These findings highlight the potential of AI-driven feedback to exceed traditional teacher feedback methods in improving EFL learners' writing accuracy, with direct feedback emerging as the most effective approach.

Keywords: AI-driven feedback, Direct feedback, Error reduction, Indirect feedback, Writing accuracy

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1. Introduction

Written corrective feedback (WCF) has become a crucial area of study in second language acquisition, particularly for its role in improving L2 learners' writing accuracy. WCF provides a means for addressing various writing errors, from basic grammar to more complex rhetorical issues (Kang & Han, 2015). While writing accuracy is generally understood as the production of error-free sentences (Richards, 1971), its assessment remains challenging due to its multifaceted nature (Polio et al., 1998; Polio & Shea, 2014). Researchers have developed multiple approaches to measure accuracy, such as holistic evaluations, quantifying error-free units, and error counting with or without categorization (Polio et al., 1998). Additionally, Richards (1971) outlined four analytical methods: contrastive analysis, error analysis, interlanguage analysis, and contrastive rhetoric analysis. These diverse frameworks highlight the ongoing challenges in defining and evaluating L2 writing accuracy.

Recent studies on WCF have primarily focused on its impact on grammatical accuracy, highlighting its potential to improve learners' overall linguistic performance (Aliakbari et al., 2023; Zhang, 2021). Nevertheless, the concept of accuracy in writing extends beyond grammar to include lexical, mechanical, and semantic dimensions. For example, common errors in grammatical features, such as Subject-Verb Agreement (SVA), article omission (A?), wrong verb form (WVF), and incorrect pronoun usage (WP), are often observed alongside lexical issues like wrong word choice (WWC), mechanical errors such as spelling (Sp.), capitalization (C), and punctuation (P), and semantic errors including unclear or incomplete sentences (?). These nine error types have been identified as prevalent among non-native students, making them critical targets for corrective feedback interventions (Chandler, 2003; Kim, 2012).

The literature distinguishes between two main categories of written corrective feedback: direct and indirect (Ferris, 2002). In direct feedback, also known as overt correction, the instructor provides the correct form directly on the learner's work. Conversely, indirect feedback involves the teacher marking the location of errors through methods such as underlining, highlighting, or circling, without supplying the correct form (Lee, 2004). A subcategory of indirect feedback, termed "coded error feedback," utilizes specific symbols to denote particular error types, for instance, "T" for verb tense issues or "Sp" for spelling mistakes (Lee, 2004).

With the advent of technology in language learning, automated feedback systems, such as Automated Writing Evaluation (AWE) tools, have emerged as prominent methods for providing corrective feedback. These systems utilize advanced technologies, including natural language processing (NLP) and artificial intelligence (AI), to provide real-time feedback, offering significant promise for enhancing the writing accuracy of L2 learners (Baskara, 2023). ChatGPT, an AI-driven language model, is one such tool designed to generate human-like responses and provide feedback on a wide range of written assignments (Kasneci et al., 2023). In my research, AI-driven direct and indirect feedback function similarly to teacher-provided feedback. Specifically, AI direct feedback provides learners with the correct verb form or other corrections (e.g., replacing an incorrect verb tense with the correct one). In contrast, AI indirect feedback identifies errors using symbols or error codes (e.g., underlining or marking SVA for subject-verb agreement issues) without directly supplying the corrected form. This approach mirrors teacher direct and indirect feedback: direct feedback provides overt correction, while indirect feedback highlights errors using symbols or marks without correcting them (Lee, 2004).

AI tools like ChatGPT and Grammarly offer personalized feedback, enhancing language refinement and efficiency in writing tasks (Lee, 2024). This technological innovation has reshaped the language-learning landscape by supplementing traditional teacher feedback with automated responses, potentially reducing educators' workloads while providing more individualized feedback to learners (Bai & Hu, 2016).

Despite its potential, the effectiveness of AI-driven feedback compared to traditional teacher feedback remains an area of ongoing investigation (Wang, 2024). While some studies suggest that AI-based feedback significantly improves writing accuracy (Ranalli, 2018), others argue that its impact is limited, particularly in facilitating meaningful revisions or enhancing overall writing proficiency (Huang & Renandya, 2020). Additionally, existing research has broadly explored AI's role in general writing skill development rather than its specific influence on writing accuracy. Moreover, there has been limited exploration of the differential effects of AI feedback on writing accuracy, creating a notable gap in the literature (Bai & Hu, 2016; Kasneci et al., 2023).

This study aims to address existing research gaps by examining the impact of ChatGPT's direct and indirect written corrective feedback on the writing accuracy of intermediate Iranian EFL learners. The research focuses on how such feedback affects various linguistic aspects, including:

Grammatical features: Subject-verb agreement, article usage, verb forms, and pronoun usage

Lexical features: Word choice

Mechanical features: Spelling, capitalization, and punctuation

Semantic features: Clarity and completeness of sentences

These error categories represent common challenges for the target student population and are frequently observed difficulties for non-native learners (Chandler, 2003; Kim, 2012). By analyzing these specific error types, the study aims to provide a comprehensive assessment of how AI-driven direct and indirect feedback affects various aspects of writing accuracy. This comprehensive approach contributes to a deeper understanding of AI's role in language education.

2. Literature Review

2.1. Theoretical Background

The treatment of errors in second language (L2) writing has long been a focal point in language education research, with corrective feedback (CF) playing a critical role in language development. Various theoretical perspectives have shaped approaches to feedback, with behaviorist theories advocating for immediate correction to prevent the formation of bad habits (Ferris, 2011). In contrast, cognitive theorists, such as Chomsky (1959), view errors as a natural part of the language learning process. These differing perspectives have given rise to feedback strategies, including direct and indirect corrective feedback, which have been extensively studied for their potential to improve writing accuracy (Ferris & Roberts, 2001).

Theoretical frameworks supporting direct feedback are grounded in cognitive learning principles that emphasize the role of prior knowledge and the importance of meaningful learning. Ausubel's (1968) assimilation theory serves as a foundational framework for understanding how learners process corrective feedback. According to this theory, meaningful learning occurs when new information is systematically connected to existing cognitive structures, known as advance organizers. In the context of written corrective feedback, direct feedback serves as an explicit advance organizer, providing learners with the correct linguistic form immediately and thereby facilitating the integration of accurate language patterns into their existing knowledge base.

Ausubel's theory distinguishes between meaningful learning and rote learning, emphasizing that meaningful learning is more durable and transferable because it involves the deliberate connection of new information to previously acquired knowledge. When applied to corrective feedback, this theoretical foundation suggests that direct feedback reduces learners' cognitive load by eliminating the need for error identification and correction. Instead, learners can focus their cognitive resources on understanding and internalizing the correct linguistic structures, leading to more effective assimilation of accurate language patterns. Furthermore, Ausubel's concept of subsumption explains how new linguistic knowledge becomes integrated into learners' existing cognitive frameworks. Direct feedback provides clear, unambiguous corrections that can be readily subsumed into learners' developing interlanguage systems. This process is particularly beneficial for intermediate learners who possess sufficient metalinguistic awareness to process explicit corrections but may lack the linguistic competence to self-correct errors effectively.

Ferris (2011) complements Ausubel's cognitive framework by emphasizing the pedagogical advantages of direct feedback, particularly its alignment with explicit instruction principles. Ferris argues that direct feedback is especially effective for intermediate learners because it provides immediate access to correct forms while reducing the frustration and confusion that can arise from indirect feedback methods. The combination of Ausubel's cognitive learning theory and Ferris's pedagogical insights creates a robust theoretical foundation for understanding why direct feedback can be more effective than indirect feedback in improving writing accuracy. Schmidt's (1990) noticing hypothesis further supports the theoretical foundation for direct feedback by emphasizing that learners must consciously attend to linguistic forms to acquire them. Direct feedback draws explicit attention to errors and their corrections, increasing the likelihood that learners will notice and internalize the correct forms. This conscious attention to form, combined with Ausubel's meaningful connection to existing knowledge structures, creates optimal conditions for language acquisition.

The integration of technology, particularly AI tools such as ChatGPT, has introduced new opportunities and challenges in providing written corrective feedback (WCF). Ngo (2023) reported that university students recognized the benefits of ChatGPT, including time-saving features, personalized learning, and idea generation. However, concerns about reliability, proper citation, and idiomatic accuracy highlight ongoing challenges in adopting AI-driven feedback. Similarly, Baskara (2023) highlighted the potential of AI to personalize feedback for English as a Foreign Language (EFL) learners, while emphasizing the importance of ethical considerations, including mitigating AI bias and safeguarding personal data. Bai and Hu (2016) and Kasneci et al. (2023) further discussed how AI feedback systems can enhance writing accuracy through personalized and consistent responses, provided their use is managed effectively to maximize pedagogical value.

2.2. Corrective Feedback in EFL Contexts

Corrective feedback has been a central topic of investigation in EFL learning, particularly within the Iranian educational context. Rahimi (2010) examined Iranian students' preferences regarding grammatical error feedback and found that their attitudes were influenced by the feedback strategies employed by their teachers. This underscores the role of teacher-directed practices in shaping students’ perceptions of feedback in writing instruction. Similarly, Mallahi and Saadat (2020) compared the effects of Group Dynamic Assessment (G-DA) and Formative Assessment (FA) on the writing performance of Iranian EFL learners, revealing that both methods contributed to knowledge transfer and skill development, although G-DA showed distinct benefits.

The effectiveness of written corrective feedback, particularly the comparison between direct and indirect feedback, remains a focal point in research. Ghoorchaei et al. (2022) focused on whether written corrective feedback could improve grammatical accuracy in EFL learners. Their study found no significant effect of corrective feedback on either the short-term or long-term retention of subject-verb agreement. This raises questions about the efficacy of traditional corrective feedback methods in certain contexts, particularly with more complex grammatical structures.

2.3. Direct vs. Indirect AI Feedback

The distinction between direct and indirect feedback has been extensively explored, with mixed findings regarding their relative effectiveness. Direct feedback provides learners with the correct linguistic form, whereas indirect feedback highlights errors without supplying corrections, prompting learners to self-correct (Ferris, 2006). In AI-driven systems, the ability to deliver real-time feedback makes both types of systems more immediate and accessible to learners (Baskara, 2023). Direct feedback aligns with Sweller's (1988) cognitive load theory, which posits that reducing cognitive effort through explicit correction can expedite learning. In contrast, indirect feedback is associated with deeper cognitive engagement, as it requires learners to identify and address errors independently (Ellis, 2009).

Schmidt's (1990) noticing hypothesis emphasizes the role of explicit corrections in drawing learners' attention to their linguistic errors, thereby fostering accuracy. However, Thi and Nikolov (2021) and Huang and Renandya (2020) have noted that indirect feedback may pose challenges for lower-proficiency learners, as insufficient guidance can lead to confusion and hinder the revision process. Fan (2023) contributes to this discussion by exploring corrective feedback tools such as Grammarly, suggesting that their effectiveness is highly context-dependent and does not necessarily surpass that of teacher-provided feedback.

2.4. Automated Feedback and Writing Accuracy

The advent of AI-driven feedback systems, such as ChatGPT and Grammarly, has reshaped the landscape of corrective feedback in writing instruction. These systems offer both direct and indirect feedback mechanisms; however, their effectiveness remains an area of ongoing investigation. Fan (2023) examined automated corrective feedback from Grammarly in comparison to teacher feedback and highlighted its potential, although it did not significantly outperform traditional approaches. Similarly, Athanassopoulos et al. (2023) explored the role of ChatGPT in language development among migrant and refugee students, observing its potential to enhance lexical variety and sentence complexity.

Targeted feedback has been identified as a crucial factor in improving writing accuracy. Chandler (2003) argued that focused feedback yields better outcomes for specific error types, such as grammatical accuracy. In this regard, Kasneci et al. (2023) and Bai and Hu (2016) emphasized the importance of personalized and consistent feedback in enhancing learners' writing accuracy. Nevertheless, Yoon et al. (2023) have pointed to AI's limitations in addressing higher-order writing issues, such as coherence and cohesion, which are essential for holistic writing development.

Despite the growing body of research on AI in education, a notable gap remains in understanding how AI-driven feedback specifically influences writing accuracy, particularly in the EFL context. Most studies have either focused broadly on writing skills or explored the general applications of AI tools, without distinguishing between direct and indirect feedback mechanisms. Furthermore, existing research has primarily focused on the overall efficacy of AI tools like ChatGPT and Grammarly, without considering their nuanced impacts on specific linguistic elements, such as grammatical accuracy and error correction over time. Additionally, the Iranian EFL context has been underexplored in terms of how AI-driven feedback compares to traditional teacher feedback. This study seeks to address these gaps by investigating the differential effects of AI-driven direct and indirect feedback on the writing accuracy of intermediate Iranian EFL learners, aiming to clarify the role of AI feedback in language acquisition and provide insights for more effective pedagogical practices. Specifically, the study endeavored to explore the following research questions:

1. Does AI-driven written direct feedback have any significant effects on Iranian EFL intermediate learners' writing accuracy?
2. Does AI-driven written indirect feedback have any significant effects on Iranian EFL intermediate learners' writing accuracy?
3. Is there any significant difference between AI-driven direct and indirect feedback in Iranian EFL learners' writing accuracy?
4. What are the most significant effects of AI-driven direct and indirect feedback on Iranian EFL learners' writing accuracy?

3 . Methodology

3.1. Design and Context of the Study

The present study employed a quantitative quasi-experimental pretest-posttest design to examine the effects of AI-driven direct and indirect feedback on the writing accuracy of intermediate Iranian EFL learners. This methodological approach is particularly suitable when random assignment is not fully feasible but a comparison between intervention and control groups is needed to infer causal relationships. Participants, selected from two language institutes in Tehran, were divided into four groups: two experimental groups received direct or indirect feedback from AI ChatGPT, while two control groups received the same feedback types from a teacher. Over a 14-week instructional period, all groups completed standardized writing tasks, with data collected through pre-test and post-test assessments that included error counts and accuracy scores.

3.2. Participants

3.2.1. Student Participants

The participants of this quasi-experimental study were 100 male and female (50 males and 50 females) intermediate EFL learners within the age range of 18-25. They were selected via convenience sampling from four classes at two prominent language institutes in Tehran province. All participants were native Persian speakers with intermediate proficiency in English. Participants were randomly assigned to two experimental and two control groups. The first experimental group, comprising 25 learners, received direct feedback from AI ChatGPT. The second experimental group, also comprising 25 learners, received indirect feedback from AI ChatGPT. Similarly, the first control group, consisting of 25 learners, received Teacher-Direct feedback, while the second control group, also comprising 25 learners, received Teacher-Indirect feedback. By including participants from diverse genders and ensuring an equal distribution of males and females, the study aimed to minimize potential gender-related biases and examine the effects of the feedback approaches across both genders.

Selecting intermediate EFL learners as participants allows a focus on individuals who have acquired a foundational level of English proficiency and are actively working to improve their language skills. By conducting the study at two prominent language institutes in Tehran province, the research aimed to capture learners' experiences and perspectives within a specific educational context.

3.2.2. Teacher Participants

Two qualified EFL instructors participated in this study to provide feedback to the control groups and facilitate the AI feedback process for the experimental groups. Teacher A was a 34-year-old female instructor with 8 years of teaching experience, holding a Master's degree in TEFL. Teacher B was a 29-year-old male instructor with 6 years of teaching experience, possessing a Master's degree in TEFL. Both instructors had extensive experience working with intermediate-level EFL learners and were well-versed in corrective feedback methodologies. Teacher A was responsible for the direct feedback control group and overseeing the AI direct feedback experimental group, while Teacher B handled the indirect feedback control group and supervised the AI indirect feedback experimental group. Both instructors underwent a standardization session before the study to ensure consistency in feedback delivery and error identification protocols.

The division into experimental and control groups allows for comparisons of the effects of AI ChatGPT Direct feedback, AI ChatGPT Indirect feedback, Teacher Direct feedback, and Teacher Indirect feedback. This design enables an examination of the potential benefits and limitations of using AI technology to provide feedback compared to traditional teacher-provided feedback.

3.3. Instruments

To address the study's research questions, several instruments were used.

3.3.1. Oxford Quick Placement Test (OQPT)

The first instrument used was the Oxford Quick Placement Test (OQPT), administered at the start of the study to select a homogeneous sample of participants with intermediate proficiency. Developed by Oxford University Press and Cambridge ESOL, the OQPT is a validated English proficiency test comprising 60 multiple-choice items covering vocabulary, reading, and grammar. Scores categorized learners from beginners to proficient. The OQPT's use was justified by participants' familiarity with its format, which led to better performance and helped recruit participants with similar proficiency levels.

3.3.2. English Writing Test

The second instrument used was the TOEIC Writing Test, part of the TOEIC (Test of English for International Communication) exam. The TOEIC exam measures the English language proficiency of non-native speakers in various contexts (Educational Testing Service, 2019). The Writing Test evaluated the ability to communicate effectively in written English and consisted of three parts. In part one, students were required to write a sentence based on a picture, using two provided key words. Part two asked students to respond to requests, such as emails. Part three required students to write an essay on a topic related to second language learning. This study focused on part three of the test, as it was the most relevant to the research question.

To ensure the validity and reliability of the TOEIC Writing Test, the instrument underwent a pilot study. The pilot study involved a sample similar to the main study participants to assess the test's appropriateness and clarity. Based on the pilot results, minor adjustments were made to ensure the test's content validity. Additionally, reliability analyses were conducted to determine the consistency of the test results over time. The test demonstrated acceptable reliability and validity across different settings, supporting its use in this study.

The test was scored out of 40 and had a time limit of 40 minutes. It was administered both as a pretest and a posttest to assess the intervention's effect. The familiar format of the TOEIC Writing Test was chosen to enhance participant performance and to recruit a homogenous sample in terms of proficiency level.

Writing accuracy was assessed using an error-count scoring system, in which each text was evaluated based on the total number of errors across nine categories: subject-verb agreement, article usage, verb form, pronoun usage, word choice, spelling, capitalization, punctuation, and sentence clarity/completeness. In this scoring system, lower scores indicate fewer errors and thus better writing accuracy. Therefore, improvement in writing accuracy is demonstrated by a decrease in the error count from the pretest to the posttest.

3.4. Data Collection Procedure

In this study, there were four groups: two experimental and two control. In the experimental groups, students received automated direct and indirect corrective feedback from ChatGPT. Conversely, in the control groups, students received either direct or indirect feedback from their teachers. The course lasted for 14 weeks. (See figure 1) All groups (two experimental and two control) were oriented about the course during the first week. Additionally, the experimental groups were informed that they would receive feedback from AI ChatGPT.

Pretests and posttests were administered in the second and thirteenth weeks, respectively. To maintain consistency, both tests utilized identical conditions: argumentative essays written in the classroom setting, 250-350 words in length, with a 90-minute time limit and no reference materials permitted. Students selected familiar current social issues for the pretest topics, but were required to choose different topics for the posttest to avoid recycling content from earlier in the course (Mirshekaran & Namaziandost, 2018).

Throughout the course, all groups received similar in-class writing instruction, with no form-focused teaching. The experimental component consisted of ten weekly out-of-class writing assignments that mirrored the pre- and post-test conditions. To preserve the integrity of the writing process, students were instructed to turn off Microsoft Word's autocorrect and grammar check features. They were also directed to complete their essays independently, without seeking assistance from peers or instructors, or engaging in self-study of grammar.

To ensure equivalence between teacher and AI feedback and minimize potential bias, a comprehensive protocol was established to ensure consistency. Both the teacher and AI (ChatGPT) were required to provide feedback targeting the same nine specific linguistic areas. This standardized approach ensured that all feedback, regardless of source, addressed identical elements using consistent error codes and correction methods. To prevent potential bias and ensure thoroughness, a second qualified EFL instructor independently reviewed randomly selected feedback samples from both sources. This second teacher examined approximately 30% of all feedback instances to confirm that both the primary teacher and the AI had consistently and comprehensively addressed errors. Any discrepancies identified during this verification process were documented and resolved to maintain equivalence between feedback sources. This dual-verification system, combined with the standardized framework, ensured that the only variable between groups was the feedback source (AI vs. teacher), not the comprehensiveness, accuracy, or scope of error identification and correction.

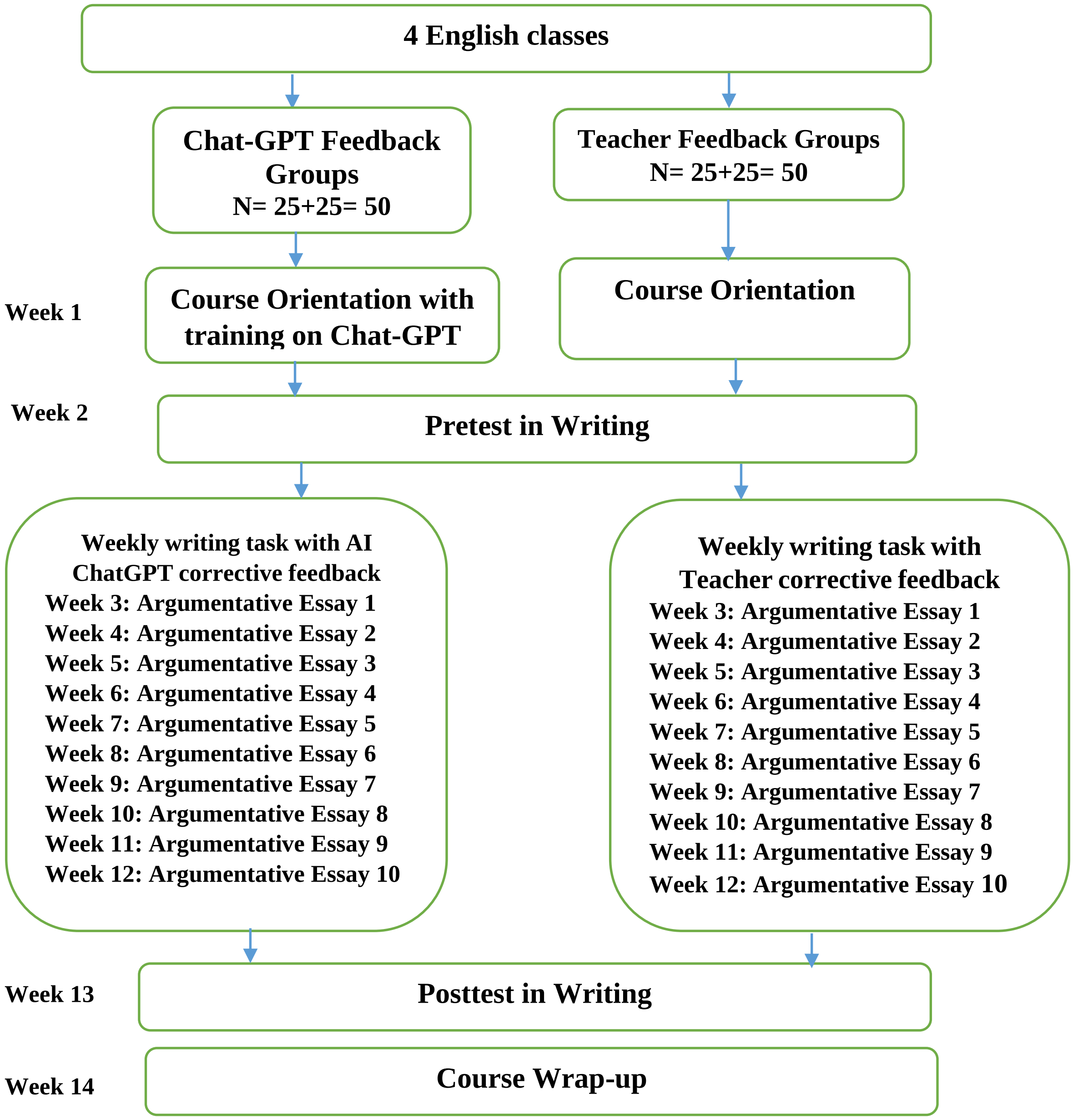

Figure1

Empirical procedure

3.4.1. Experimental group 1 (AI Direct feedback on accuracy)

As part of the weekly writing task, the students handed in their typed writing to the teacher. The teacher then submitted the writing to the ChatGPT platform and requested feedback based on a specific prompt. After receiving the feedback, the teacher shared it with the students, who were asked to revise and resubmit their texts. This process was repeated for 10 essays over a period of 10 weeks.

Prompt 1= Direct feedback

"Provide direct explanatory corrective feedback on bolded mistakes by placing the corrections in parentheses in front of the mistakes. Ensure the text's accuracy based on the following criteria: 1- subject- verb Agreement (like he has) 2- Article Missing (a, an, the) 3- Wrong Verb Form 4- Wrong Pronoun 5- Wrong Word Choice 6- Spelling 7- Capitalization 8- Punctuation 9- Unclear/Incomplete-Meaning Sentence

3.4.1.1. Examples of AI-generated direct feedback provided to students:

Example 1 - Subject-Verb Agreement Error:

- Student's original text: "The students *was* studying hard for their exams."
- AI direct feedback: "The students (were) studying hard for their exams." [SVA - subject-verb agreement error corrected]

Example 2 - Article Usage Error:

- Student's original text: "I went to *university* yesterday to meet my professor."
- AI direct feedback: "I went to (the) university yesterday to meet my professor." [A? - missing article corrected]

Example 3 - Wrong Verb Form:

- Student's original text: "She has *went* to the library."
- AI direct feedback: "She has (gone) to the library." [WVF - wrong verb form corrected]

3.4.2. Experimental group 2 (AI Indirect feedback on accuracy)

Every week, the students typed their writing and submitted it to the teacher. The teacher used the ChatGPT platform to obtain feedback on the writing based on prompt 2. The teacher then provided the AI-generated, indirect-coded feedback to the students, who were asked to revise their texts and return them. The teacher then checked the final version with ChatGPT and corrected any remaining errors or feedback. This cycle continued for ten weeks, resulting in a
total of ten essays.

Prompt 2: Indirect feedback

“Provide indirect coded feedback on bolded mistakes regarding text accuracy by placing the corrections in parentheses in front of the mistakes. Mention the feedback with the codes as provided below, in parentheses, in front of every mistake in the text.” [Subject-Verb Agreement (SVA), Article Missing (A?), Wrong Verb Form (WVF); Wrong Pronoun (WP) Wrong Word Choice (WWC) 6- Spelling (Sp.) 7- Capitalization (C) 8- Punctuation (P) 9- Unclear/Incomplete-Meaning Sentence (?)]

3.4.2.1. Examples of AI-generated indirect feedback provided to students:

Example 1 - Subject-Verb Agreement Error:

- Student's original text: "The students was studying hard for their exams."
- AI indirect feedback: "The students was **(SVA)** studying hard for their exams."

Example 2 - Article Usage Error:

- Student's original text: "I went to university yesterday to meet my professor."
- AI indirect feedback: "I went to **(A?)** university yesterday to meet my professor."

Example 3 - Multiple Errors:

- Student's original text: "She has went to library and study there."
- AI indirect feedback: "She has went **(WVF)** to **(A?)** library and study **(WVF)** there."

3.4.3. Control group 1 (Direct feedback on accuracy)

The weekly writing task involved the following steps:

- The students submitted their writing to the teacher.

- The teacher provided feedback by directly correcting the nine specific error types related to accuracy.

- The teacher then returned the feedback to the students and instructed them to revise their texts and resubmit them.

- This process was repeated for ten essays over the course of ten weeks.

3.4.4. Control group 2 (Indirect Feedback on Accuracy)

The teacher used codes to mark the errors for accuracy, such as: [Subject-Verb Agreement (SVA), Article Missing (A?), Wrong Verb Form (WVF), Wrong Pronoun (WP), Wrong

Word Choice (WWC), Spelling (Sp.), Capitalization (C), Punctuation (P), Unclear/Incomplete-Meaning Sentence (?)] without giving correct answers. The students were responsible for making their own corrections. The students received their papers back and were instructed to revise them and resubmit them. The teacher then reviewed the final version and corrected any remaining errors or provided additional feedback.

3.5. Data Analysis Procedure

The study employed SPSS (version 26) for statistical analysis. Descriptive statistics, including means, standard deviations, and frequencies, were calculated for the pretest and posttest scores across all groups. To assess group homogeneity at the outset, a one-way ANOVA was conducted on the pretest scores. For the main analysis, a one-way ANOVA was conducted on posttest scores to determine significant differences among the four feedback groups. Post hoc tests using Tukey's HSD were conducted to identify specific between-group differences. The alpha level was set at .05 for all statistical tests. Prior to conducting the one-way ANOVA, the assumptions underlying this statistical test were systematically examined. The assumption of normality was assessed using the Shapiro-Wilk test for each group, with results indicating that the data were approximately normally distributed ($p > .05$ for all groups). Homogeneity of variance was evaluated using Levene's test, which confirmed equal variances across groups ($F(3, 96) = 1.23$, $p = .302$). The assumption of independence was satisfied through the random assignment of participants to groups and through the use of controlled data collection procedures. Effect sizes were calculated using eta squared (η^2) to determine the practical significance of the findings. For the main ANOVA comparing posttest scores, $\eta^2 = .68$, indicating a large effect size according to Cohen's (1988) guidelines. This suggests that approximately 68% of the variance in writing accuracy improvement is attributable to the type of feedback received. Additionally, Cohen's *d* was calculated for pairwise comparisons: AI Direct vs. AI Indirect ($d = 1.24$), AI Direct vs. Teacher Direct ($d = 1.58$), and AI Direct vs. Teacher Indirect ($d = 1.89$), all representing large effect sizes.

To address the fourth research question, an error reduction analysis was conducted. This involved calculating the percentage decrease in each error type from pretest to posttest for both AI-driven feedback groups. The results were presented in a comparative table to highlight the differential effects of direct and indirect AI feedback on specific error categories.

4. Results

4.1. The Results of the Pretest

To address the research questions, a descriptive analysis of the participants' English writing scores on the pretest and posttest was performed to provide an overall profile of their progress. The analysis included means, minimum and maximum scores, standard deviations, skewness, and kurtosis. Table 1 summarizes the descriptive statistics for all groups' pretest scores, and Table 2 presents the ANOVA results, which confirm that there are no significant differences among the groups before the intervention.

Table 1.
Descriptive Statistics of the Participants' Performance on the Pretest

	N	Mean	SD
PreTestAiDirect	25	13.440	.5583
PreTestAiIndirect	25	13.316	.5914
PreTestTeacherDirect	25	13.356	.6279
PreTestTeacherInDirect	25	13.484	.6135
Valid N (listwise)	25		

Note. M = Mean; SD = Standard Deviation. Each group included 25 participants.

The pretest means across all groups were relatively similar: AI Direct Feedback at 13.44, AI Indirect Feedback at 13.31, Teacher Direct Feedback at 13.35, and Teacher Indirect Feedback at 13.48. An ANOVA test was conducted to determine whether there were any statistically significant differences between the groups. Table 2 presents the results:

Table 2.
ANOVA Results for the participants' performance on the pretest

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	.441	3	.147	.411	.746
Within Groups	34.369	96	.358		
Total	34.810	99			

The ANOVA results (F = 0.411, Sig = 0.746) indicate that there were no significant differences in writing accuracy between the groups before the intervention, confirming that the participants were homogeneous.

4.2. Posttest Performance and Within-Group Analysis (Addressing Research Questions 1 and 2)

To address research questions 1 and 2, posttest scores and paired samples t-tests were analyzed to determine the impact of AI-driven direct and indirect feedback on learners' writing accuracy. Table 3 displays the posttest descriptive statistics, while Table 4 summarizes the significance of improvements within each group.

Table 3.
Descriptive Statistics for the Participants' Performance on the Posttest

Group	N	M	SD
AI Direct Feedback	25	6.09	0.81
AI Indirect Feedback	25	7.81	0.43
Teacher Direct Feedback	25	8.36	0.66
Teacher Indirect Feedback	25	8.77	0.47

Note. M = mean; SD = standard deviation.

The group means indicate that all improved in writing accuracy. The AI Direct Feedback group improved the most, with the mean changing from 13.44 on the pretest to 6.09 on the posttest (a reduction of 7.35 errors). The AI Indirect Feedback group also improved, but to a lesser extent, with the mean changing from 13.31 to 7.81 (a reduction of 5.50 errors). The Teacher Direct Feedback group showed slight improvement, with the mean changing from 13.35 to 8.36 (a reduction of 4.99 errors). In contrast, the Teacher Indirect Feedback group demonstrated the least improvement, with the mean changing from 13.48 to 8.77 (a reduction of 4.71 errors). Since the scoring system counts errors, lower scores indicate better writing accuracy; thus, these changes represent improvements across all groups.

A paired-samples t-test was conducted to assess the significance of improvements within each group. The results are summarized below:

Table 4.
Paired Samples t-Test

		Paired Differences			
		Mean	t	df	Sig. (2-tailed)
Pair 1	PreTestAiDirect PostTestAiDirect	- 7.34800	36.571	24	.000
Pair 2	PreTestAiIndirect PostTestAiIndirect	- 5.50400	106.266	24	.000
Pair 3	PreTestTeacherDirect PostTestTeacherDirect	- 4.99600	45.577	24	.000
Pair 4	PreTestTeacherInDirect PostTestTeacherIndirect	- 4.71200	131.842	24	.000

The results indicate that all groups showed improvement in writing accuracy from the pre-test to the post-test. However, the group that received AI-driven direct feedback demonstrated the most significant improvement in writing accuracy (mean difference = 7.34, $p < 0.05$). The AI Indirect Feedback group also showed significant improvement (mean difference = 5.5, $p < 0.05$), but the improvement was less pronounced than in the direct feedback group. The teacher feedback groups also showed improvements, but the gains were smaller than those observed in the AI groups, particularly for indirect feedback, where the improvement was the least.

To determine whether there were statistically significant differences in the effects of these four control and experimental groups, a one-way ANOVA with a between-groups factor was run, as shown in Table 5.

4.3. Between-Group Differences in Feedback Effectiveness (Addressing Research Question 3)

To answer research question 3, which asks whether there are significant differences between AI-driven direct and indirect feedback, a one-way ANOVA and post hoc analyses were conducted. Table 5 reports the ANOVA results for posttest scores across all groups, and Table 6 presents the pairwise comparisons, highlighting where significant differences exist.

Table 5.
One-way ANOVA for Comparing the Performance of Groups (posttest)

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	104.227	3	34.742	69.088	.000
Within Groups	48.275	96	.503		
Total	152.502	99			

The ANOVA results (*F* = 69.088, *Sig* = .000) show that the differences between the groups were statistically significant. To illustrate where the significant differences exist among the groups, Tukey's HSD post hoc test (with an alpha level of .05) was conducted. The results are shown in Table 6.

Table 6.
Post Hoc Multiple Comparisons (Tukey HSD)

Group (I)	Group (J)	Mean Difference (I-J)	SE	p	95% CI
AI DF	AI IDF	-1.72*	0.20	< .001	[-2.29, -1.15]
AI DF	Teacher DF	-2.27*	0.20	< .001	[-2.84, -1.70]
AI DF	Teacher IDF	-2.68*	0.20	< .001	[-3.25, -2.11]
AI IDF	Teacher DF	-0.55	0.20	.065	[-1.12, 0.02]
AI IDF	Teacher IDF	-0.96*	0.20	< .001	[-1.53, -0.39]
Teacher DF	Teacher IDF	-0.41	0.20	.246	[-0.98, 0.16]

Note. DF = Direct Feedback; IDF = Indirect Feedback; SE = Standard Error; CI = Confidence Interval.

The results of post hoc pairwise comparisons revealed significant differences between most pairs of groups, except for the comparison between AI Indirect Feedback and Teacher Direct Feedback, where the difference was not significant (*p* > .05). AI Direct Feedback was significantly more effective than AI Indirect Feedback, and both AI-driven feedback methods outperformed teacher-provided feedback.

4. 4. Error Reduction Analysis (Addressing Research Question 4)

To answer research question 4, an error-reduction analysis was conducted. Table 7 breaks down the specific error types corrected through direct and indirect feedback. Error reduction is measured as the percentage decrease in the number of errors per type from pre-test to post-test. AI Direct Feedback was more effective in reducing specific types of errors compared to AI Indirect Feedback, particularly in spelling and verb form errors:

Table7.

Error Type	AI Direct Feedback (%)	AI Indirect Feedback (%)
Subject-Verb Agreement	75	50
Article Missing	68	42
Wrong Verb Form	80	53
Wrong Pronoun	72	45
Wrong Word Choice	77	48
Spelling	84	56
Capitalization	69	38
Punctuation	73	40
Unclear/Incomplete Sentence	70	46

This analysis reveals that AI-driven direct feedback has a more pronounced impact on reducing a broader range of writing errors, making it a more effective tool for enhancing writing accuracy in Iranian EFL learners.

5. Discussion

This study explored the effects of AI-driven direct and indirect feedback on the writing accuracy of Iranian intermediate EFL learners. The findings provide insights into each research question, highlighting the nuanced impacts of different feedback types and contextualizing them within the existing literature.

Addressing the first research question, the results demonstrated that AI-driven direct feedback had the most significant positive effect on writing accuracy, addressing errors in grammatical, lexical, mechanical, and semantic categories. This aligns with Ranalli (2018), who found that automated feedback systems enhance accuracy by providing immediate and explicit corrections. The personalized nature of AI feedback, as emphasized by Bai and Hu (2016), likely contributed to its effectiveness by reducing cognitive load and enabling learners to integrate corrections more effectively. However, Truscott (1996) challenged the efficacy of corrective feedback, suggesting it has limited long-term benefits. Similarly, Yoon et al. (2023) noted that while AI excels at surface-level corrections, it struggles to address higher-order writing issues, such as coherence and cohesion. Niu et al. (2021) also questioned the value of immediate corrections, arguing that they may lead to over-reliance on external support, reducing learners' self-editing abilities. These critiques suggest that while AI-driven direct feedback is effective for immediate accuracy improvement, its role in fostering holistic writing development remains uncertain.

Regarding the second research question, AI-driven indirect feedback also led to significant improvements, though less pronounced than direct feedback. This finding supports Ellis's (2009) argument that indirect feedback encourages self-correction and deeper cognitive engagement. Indirect feedback’s reliance on learner autonomy, as noted by Ferris (2011), might explain its effectiveness among intermediate learners. Nonetheless, Huang and Renandya (2020) questioned the suitability of indirect feedback for lower-proficiency learners, arguing that insufficient guidance can hinder meaningful revisions. Fan (2023) further reported that indirect feedback from tools like Grammarly was not significantly more effective than teacher feedback, underscoring the need for balanced instructional support when using AI-driven indirect feedback. Additionally, Thi and Nikolov (2021) argued that indirect feedback may confuse learners without clear correction paths, limiting its practical benefits in real-world writing instruction.

The third research question explored the comparative effectiveness of direct and indirect feedback approaches. The study revealed that AI-driven direct feedback was significantly more effective than indirect feedback. This finding supports Ferris (2011) and Ausubel’s (1968) assimilation theory, which highlights the benefits of explicit corrections for intermediate learners who may struggle with self-correction. However, Thi and Nikolov (2021) cautioned that automated systems often lack the pedagogical depth to address nuanced writing challenges, suggesting that direct feedback should be supplemented with teacher-led interventions for optimal results. Furthermore, Benson and DeKeyser (2018) argued that over-reliance on direct feedback may inhibit learners' critical thinking and problem-solving skills, which are essential for long-term language development.

Finally, addressing the fourth research question, the analysis of error types revealed that AI-driven feedback, particularly direct feedback, was most effective at reducing spelling and verb-form errors. This supports Chandler's (2003) findings that targeted corrective feedback yields better outcomes for specific types of errors. However, Truscott's (1996) critique raises questions about whether such improvements translate into long-term writing proficiency. Additionally, Yoon, Miszoglad, and Pierce (2023) noted that while AI systems effectively address surface-level errors, they often fail to contextualize corrections, which can limit learners' ability to generalize improvements across diverse writing contexts.

The study's results demonstrated that the effectiveness of AI-driven feedback varied across different types of feedback. AI Direct Feedback significantly outperformed both Teacher Direct and Teacher Indirect Feedback in enhancing writing accuracy. Similarly, AI Indirect Feedback was more effective than Teacher Indirect Feedback. However, there was no significant difference between AI Indirect Feedback and Teacher Direct Feedback ($p > .05$), indicating comparable effectiveness between these two approaches. These findings partially align with those of Benson and DeKeyser (2018), who emphasized the consistency and immediacy of AI feedback as advantages over human feedback; however, the results suggest that effectiveness varies by feedback modality. Kasneci et al. (2023) similarly highlighted the scalability and objectivity of AI systems, which may explain the superior performance of AI Direct Feedback. However, Fan (2023) and Thi and Nikolov (2021) argued that teacher feedback remains essential for addressing coherence, argumentation, and rhetorical effectiveness—areas where AI tools often fall short. The comparable effectiveness of AI Indirect Feedback and Teacher Direct Feedback suggests that both approaches have distinct pedagogical value. Shintani and Ellis (2015) noted that the adaptability of teacher feedback to individual learner needs often surpasses the rigid structures of AI systems, suggesting that optimal writing instruction may benefit from the strategic integration of both AI and teacher feedback methods.

6. Conclusion

This study underscores the significant potential of specific types of AI-driven feedback in enhancing writing accuracy among Iranian EFL learners. The results demonstrate that AI Direct Feedback was the most effective approach, significantly outperforming all other feedback methods in addressing surface-level writing errors and providing learners with immediate and detailed corrections. While AI Indirect Feedback also facilitated improvements, it showed comparable effectiveness to Teacher Direct Feedback ($p > .05$), with both methods demonstrating similar levels of improvement. However, both AI Direct Feedback and AI Indirect Feedback outperformed Teacher Indirect Feedback, suggesting that feedback effectiveness depends on both the source (AI vs. teacher) and the delivery method (direct vs. indirect). These nuanced findings indicate a need to strategically select feedback types based on specific pedagogical goals and learner needs.

The results underscore the need for further research into the enduring effects of AI-generated feedback, especially regarding its impact on writing complexity and fluency. Subsequent studies should employ longitudinal methodologies to evaluate the sustainability of the observed enhancements in writing accuracy. Additionally, studies should explore learners' perceptions of AI-driven feedback, examining how engagement and attitudes towards AI tools influence learning outcomes.

Furthermore, it is essential to examine the applicability of AI-driven feedback across diverse learner populations and educational contexts to ensure its effectiveness is not limited to specific groups or settings. Broadening the research scope to include higher-level writing skills—such as coherence, cohesion, and argumentation—would provide a more holistic understanding of AI tools' contributions to writing development. These research directions will help refine AI technologies, enabling them to be customized to effectively address the diverse needs of learners.

The findings of this study emphasize the potential of AI-driven feedback, particularly direct feedback, in improving writing accuracy. However, a balanced approach that integrates AI tools with teacher feedback is necessary to address both surface-level and higher-order concerns in writing. Tailoring feedback strategies to learners' proficiency levels can further optimize outcomes, with direct feedback benefiting intermediate learners and indirect feedback potentially serving advanced learners more effectively.

This study's short duration limits its ability to assess the long-term effects of AI-driven feedback. Future research should adopt longitudinal designs to evaluate the sustainability of these improvements. Additionally, the focus on Iranian intermediate EFL learners restricts generalizability; comparative studies across diverse contexts and proficiency levels are needed. Finally, the study did not examine higher-order writing skills such as coherence and cohesion. Future research should investigate how AI-driven feedback can be adapted to address these complex aspects of writing.

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