Journal of English Language Teaching and Learning

University of Tabriz

Volume 17, Issue 35, 2025

Effects of AI-Driven Written Direct and Indirect Feedback on Iranian Intermediate EFL Learners' Writing Complexity*

Mohsen Banisharif-Dehkordi

Department of English, ShK.C., Islamic Azad University, Shahrekord, Iran. E-mail: mohsen.banisharif@iau.ac.ir

Parisa Riahipour (Corresponding Author)

Department of English, ShK.C., Islamic Azad University, Shahrekord, Iran. E-mail: priahipour@iau.ac.ir

Fariba Rahimi-Esfahani

Department of English, ShK.C., Islamic Azad University, Shahrekord, Iran. E-mail: fariba.rahimi@iau.ac.ir

ARTICLE INFO:

Received date:
2025.02.25
Accepted date:
2025.04.30

Print ISSN: 2251-7995
Online ISSN: 2676-6876

Keywords:

AI-Driven Feedback, Writing Complexity, Direct Feedback, Indirect Feedback, Syntactic Measures.

Abstract

This study examined the impact of AI-driven feedback on the writing complexity 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 receiving direct and indirect feedback from AI ChatGPT, and two control groups receiving the same feedback types from their teacher. Participants completed a pre-test, ten writing tasks over 14 weeks, and a post-test. Results, analyzed via descriptive statistics and one-way ANOVA, indicated notable improvements in writing complexity across all groups. The AI direct feedback group showed the highest improvement, with a mean difference of 5.24 ($p < 0.05$), followed by the teacher direct feedback group, which also demonstrated significant gains. The AI indirect feedback group exhibited moderate progress, while the teacher indirect feedback group showed the least improvement. Analysis of syntactic measures revealed that AI feedback, particularly direct feedback, effectively enhanced sentence structures and encouraged the use of more sophisticated vocabulary. These findings highlight AI-driven feedback's potential to enhance EFL learners' writing complexity, with direct feedback yielding the greatest benefits.

Citation: Banisharif-Dehkordi, M; Riahipour, P. & Rahimi-Esfahani, F. (2025). Effects of AI-Driven Written Direct and Indirect Feedback on Iranian Intermediate EFL Learners' Writing Complexity. *Journal of English Language Teaching and Learning*, 17 (35), 39-60. DOI:10.22034/elt.2025.66090.2760

* Derived from the PhD dissertation of Mohsen Banisharif-Dehkordi, entitled "Effects of AI-Driven Written Direct and Indirect Feedback on Iranian Intermediate EFL Learners' Writing Complexity, Accuracy, Fluency (CAF), and Willingness to Write," Supervisor: Parisa Riahipour, conducted at Islamic Azad University, Shahrekord Branch, Iran.

Introduction

The integration of artificial intelligence (AI) in education has revolutionized the methods of feedback delivery, particularly in enhancing writing skills for English as a Foreign Language (EFL) learners (Bagheri Nevisi & Arab, 2023; Thi & Nikolov, 2021). AI-driven systems, such as ChatGPT, have gained significant traction in language education by providing immediate, consistent, and scalable feedback that addresses challenges such as limited teacher resources and subjective assessments (Ranalli, 2018; Huang & Renandya, 2018). These systems have demonstrated their ability to complement traditional teacher feedback, effectively reducing workload while maintaining instructional quality (Dikli & Bleyle, 2014; Thi et al., 2022).

In EFL writing assessment, syntactic complexity is a crucial measure of language proficiency (Thi & Nikolov, 2023; Qassemzadeh & Gabinete, 2016). Defined as the sophistication and variety of syntactic structures, it serves as a key indicator of linguistic development and overall writing quality (Bagheri Nevisi & Arab, 2023; Zhang & Cheng, 2021). However, achieving improvements in syntactic complexity remains challenging. Feedback often prioritizes accuracy at the expense of complexity, which can lead to simpler sentence constructions (Hartshorn & Evans, 2015; Eckstein & Bell, 2021). Despite its significance, limited studies have focused solely on syntactic complexity and its response to different types of feedback (Van Beuningen et al., 2012; Fazilatfar et al., 2014).

Research has highlighted mixed effects of feedback on syntactic complexity. Direct written corrective feedback (WCF), which provides revised versions of students' texts, allows for immediate understanding and application of corrections (Hamano-bunce, 2022; Nicolas-Conesa et al., 2019). Conversely, indirect feedback, characterized by comments without providing corrections, encourages learners to self-correct and develop problem-solving skills (Shintani & Ellis, 2015; Thi & Nikolov, 2023). The effectiveness of these approaches varies depending on the feedback source; teacher feedback and AI-driven systems may yield different outcomes regarding writing development (Bagheri Nevisi & Arab, 2023; Huang & Renandya, 2018). A comparison of different types of feedback reveals notable distinctions in their impacts on writing. For instance, studies have shown that direct feedback, where fully revised texts are provided, can lead to more immediate improvements in writing accuracy and complexity (Hamano-Bunce, 2022). In contrast, indirect feedback, consisting solely of comments, may foster learner autonomy but could result in less immediate gains in complexity (Nicolas-Conesa et al., 2019). Despite the recognition that both forms of feedback can influence writing outcomes differently, there is a lack of comparative research specifically examining their effects on syntactic complexity. Most existing literature has predominantly focused on accuracy rather than fluency or complexity. AI-driven feedback systems like ChatGPT have been increasingly adopted as tools to enhance syntactic complexity. These systems provide learners with consistent and immediate feedback that can mitigate some limitations associated with traditional teacher feedback (Azennoud, 2024; Thi et al., 2022). However, the impact of AI-driven feedback on syntactic complexity compared to teacher-provided feedback remains underexplored (Xu & Zhang, 2021; Zhang & Cheng, 2021). This gap in the literature underscores the need for further investigation into how AI and teacher feedback affect syntactic complexity in EFL contexts (Thi & Nikolov, 2023; Bagheri Nevisi & Arab, 2023).

This study aims to address this significant research gap by investigating the effects of direct and indirect feedback delivered by both AI (ChatGPT) and teachers on the syntactic complexity of Iranian intermediate EFL learners. By employing established measures of syntactic complexity such as mean length of T-units (MLT), clauses per T-unit (C/T), and dependent clauses per clause (DC/C) this research seeks to assess improvements in writing quality (Fazila far et al., 2014; Van Beuningen et al., 2012). The distinction made between direct feedback entailing fully revised texts and indirect feedback consisting solely of comments without corrections will allow for a nuanced analysis of their respective impacts on syntactic complexity.

This study makes three distinct contributions to the field of EFL writing instruction. First, it is among the first to systematically compare both direct and indirect feedback from AI and teacher sources with a specific focus on syntactic complexity, an area that has received considerably less attention than accuracy in previous research (Azennoud, 2024; Hamano-Bunce, 2022; Nicolas-Conesa et al., 2019; Ranalli, 2018; Thi & Nikolov, 2023). Second, by employing a four-group quasi-experimental design, this study isolates the effects of feedback source and type, offering a more rigorous and nuanced analysis than the two-group comparisons prevalent in existing literature (Thi & Nikolov, 2023; Dikli & Bleyle, 2014; Xu & Zhang, 2021). Third, the findings provide practical insights for EFL educators by clarifying which feedback modalities, AI-driven or teacher-provided, direct or indirect, most effectively foster syntactic development, thereby informing evidence-based integration of AI tools into language instruction Collectively, these contributions advance our understanding of how feedback type and source interact to shape the development of complex written language in EFL contexts. By directly addressing a critical gap in the literature, this research not only adds to the growing body of work on AI-assisted feedback and its role in enhancing syntactic complexity, but also highlights the potential for AI technologies to complement traditional pedagogical approaches.

1. Literature Review

1.2. Theoretical Background

This study is grounded in central theories of Second Language Acquisition (SLA), particularly Schmidt's (1990) noticing hypothesis, which posits that learners must consciously attend to linguistic features in order to internalize corrections and advance their language proficiency. Cognitive perspectives further reinforce this view, highlighting that repeated, meaningful feedback enables learners to reorganize their internal language systems and develop more complex syntactic structures (Van Beuningen et al., 2012). Within this framework, written corrective feedback (WCF)-whether provided as direct revisions or as indirect prompts-serves as a catalyst for the noticing process, encouraging learners to experiment with and adopt more sophisticated forms of expression (Hamano-Bunce, 2022; Nicolas-Conesa et al., 2019). The emergence of AI-driven feedback tools, such as ChatGPT, builds on these theoretical foundations by delivering immediate, individualized feedback that aligns with Krashen's comprehensible input hypothesis, thus supporting learners in processing advanced syntactic patterns while reducing cognitive load (Bai & Hu, 2016). Empirical research indicates that direct feedback, especially when generated by AI, leads to more rapid gains in syntactic complexity by providing clear, actionable models for learners to emulate, while indirect feedback, though slower to yield results, fosters learner autonomy and metalinguistic awareness (Hartshorn & Evans, 2015; Shintani & Ellis, 2015). At the same time, the integration of AI in feedback processes raises important ethical considerations, such as algorithmic bias and data privacy, underscoring the necessity of balancing technological tools with traditional teacher guidance (Baskara, 2023; Huang & Renandya, 2018). By weaving together these theoretical and empirical insights, this study's framework underscores how technology-enhanced feedback can scaffold EFL learners' writing development, while also highlighting the enduring value of teacher-student interaction in fostering linguistic growth (Bagheri Nevisi & Arab, 2023; Thi & Nikolov, 2023).

1.2. Written Corrective Feedback

Providing written corrective feedback (WCF) has become an indispensable strategy in second language acquisition for improving students' writing proficiency. Research consistently validates the role of WCF in promoting greater accuracy, highlighting its integral function in supporting learners' writing development (Thi & Nikolov, 2023). WCF involves varied responses to student output, encompassing both grammatical error corrections and written comments on content or rhetorical structure. Nevertheless, much of the existing work has given more attention to the overall impact and advantages of WCF than to written commentary (Pearson, 2022). Empirical findings indicate that feedback is vital for strengthening students' grammatical precision, with several studies documenting positive results from the use of WCF (Bonilla Lopez et al., 2018; Zhang, 2021). Even though some discussion persists about how effective WCF truly is (Truscott, 1996, 2007), writing instructors continue to consider it beneficial for enhancing writing quality. This view is partly sustained by students' openness to receiving instructor feedback and their favorable perceptions of such feedback (Lee, 2008; McMartin-Miller, 2014).

Recent work has explored the relative effectiveness of feedback delivered by teachers versus automated programs, revealing notable distinctions in areas such as focus, strategy, and overall precision (Dikli & Bleyle, 2014; Niu et al., 2021; Thi & Nikolov, 2021). Because both teacher-provided and automated feedback have strengths and weaknesses, current recommendations often propose that automated methods serve as a supplementary resource rather than a replacement for traditional instructor feedback (Dikli & Bleyle, 2014; O'Neill & Russell, 2019; Thi & Nikolov, 2021). Although most WCF studies have concentrated on accuracy gains, there is a growing concern that increasing accuracy might unwittingly limit syntactic complexity. Indeed, researchers have argued that worries about making errors may compel students to restrict the range of structures they use (Truscott, 1996, 2007), while others caution that aiming primarily for accuracy might compromise either fluency or complexity (Polio, 2012a).

To confront these issues, Polio (2012b) urged researchers to broaden WCF inquiries by examining how feedback shapes other facets of language growth, such as complexity and fluency. In line with this perspective, a more comprehensive investigation of WCF's influence has recently taken hold, yielding mixed findings when it comes to syntactic complexity. Van Beuningen et al. (2012) reported that WCF did not lead students to oversimplify, whereas

Hartshorn and Evans (2015) noted negative consequences for syntactic complexity. Other researchers discovered positive outcomes for complexity under certain conditions; unfocused WCF, for instance, was associated with elevated complexity (Fazilatfar et al., 2014), and automated feedback prompted some improvement in complexity features (Li et al., 2020). However, several studies found little to no impact on complexity after receiving feedback (Eckstein & Bell, 2021; Xu & Zhang, 2021; Zhang & Cheng, 2021). These inconsistent results underscore the continued need to clarify how WCF interactions affect syntactic complexity in second language writing.

1.3.AI-Driven Feedback

AI-driven feedback has transformed language education, offering immediate, consistent, and scalable support for student writing, addressing limitations of teacher resources and assessment subjectivity (Thi & Nikolov, 2021). AI systems analyze writing using NLP and machine learning, identifying errors and evaluating style (Ranalli, 2018). Studies suggest AI feedback can improve writing (Azennoud, 2024; Bai & Hu, 2016), though some debate its effectiveness (Stevenson & Phakiti, 2014; Huang & Renandya, 2018). Key advantages include consistent and timely feedback at scale, reducing teacher burden (El Ebyary & Windeatt, 2010; Ranalli, 2018). Research explores AI's impact on syntactic complexity, with mixed results (Xu & Zhang, 2021; Azennoud, 2024). AI can provide targeted support for specific learning needs (Thi & Nikolov, 2021; O'Neill & Russell, 2019), but should complement, not replace, teacher feedback (Dikli & Bleyle, 2014; Thi & Nikolov, 2023). As AI evolves, tailoring feedback and analyzing complex writing aspects will become increasingly significant (Bagheri Nevisi & Arab, 2023; Zhang & Cheng, 2021). While promising, AI's effectiveness varies, requiring continued research for optimal integration (Niu et al., 2021).

1.4. Direct and Indirect Feedback

Researchers have long examined how written corrective feedback (WCF) influences second language (L2) writing, focusing largely on direct (explicit correction) versus indirect (indicating errors without supplying corrections) approaches (Shintani & Ellis, 2015). Direct feedback is often linked with quick improvements in accuracy by providing unambiguous corrections (Hamano-Bunce, 2022), which can help lower-proficiency learners who struggle to self-correct (Nicolas-Conesa et al., 2019). This method has also shown lasting gains in grammatical accuracy (Van Beuningen et al., 2012). However, some evidence suggests direct feedback can prompt learners to simplify sentence structures, potentially reducing syntactic complexity (Hartshorn & Evans, 2015). Indirect feedback, meanwhile, encourages students to identify and correct errors themselves, which can foster deeper learning and self-editing skills (Fazilatfar et al., 2014). By requiring active involvement, indirect feedback may support long-term retention and promote more complex language use (Eckstein & Bell, 2021). Impact can vary by error type, proficiency level, and learner preference (Frear & Chiu, 2015; Lee, 2008). Some learners benefit from explicit corrections, while others thrive with more autonomy (McMartin-Miller, 2014).

Recent research has explored blending direct and indirect feedback, suggesting a balanced, mixed approach can improve both accuracy and complexity (Bonilla Lopez et al., 2018; Zhang, 2021). At the same time, advances in AI-driven feedback offer immediate, consistent comments at scale. Automated tools may boost writing quality and reduce teachers' workload (Dikli & Bleyle, 2014; Thi et al., 2022), though their impact on syntactic complexity is still under investigation (Xu & Zhang, 2021; Zhang & Cheng, 2021). Overall, while direct and indirect feedback both contribute to writing development, their relative effectiveness in fostering syntactic complexity appears to depend on learners' proficiency, the nature of the errors, and individual preferences. As AI increasingly mediates feedback in L2 contexts, future research will need to clarify how best to combine automated and teacher-delivered strategies to optimize both accuracy and complexity in learner writing.

1.5. Feedback on Complexity

The impact of feedback on syntactic complexity in second language (L2) writing has been extensively researched, yielding diverse outcomes. Syntactic complexity, a key indicator of linguistic development and writing quality, is typically assessed through metrics such as mean length of T-unit (MLT) and clauses per T-unit (C/T) (Bagheri Nevisi & Arab, 2023; Zhang & Cheng, 2021). Studies have investigated the effects of various feedback types on syntactic complexity, with mixed results.

Eckstein et al. (2020) found that timely feedback supported syntactic complexity development in international graduate students. However, Eckstein and Bell (2021) reported that students receiving dynamic written corrective feedback (WCF) showed significantly less syntactic complexity over time. The effectiveness of dynamic WCF has been questioned by some researchers. Evans et al. (2011) observed a negligible effect of dynamic WCF on syntactic complexity, while Hartshorn et al. (2010) reported a slight unfavorable effect. Conversely, some studies have reported positive effects of feedback on syntactic complexity. Fazilatfar et al. (2014) found that unfocused WCF led to gains in syntactic complexity among advanced English learners. Van Beuningen et al. (2012) also observed a positive effect of comprehensive error correction on students' structural complexity.

The source of feedback may influence its impact. Azennoud (2024) found that automated writing evaluation (AWE) feedback led to development in some aspects of syntactic complexity. However, Xu and Zhang (2021) reported that syntactic complexity remained unchanged with AWE feedback. Teacher-provided feedback has also shown varied effects. Zhang and Cheng (2021) found that comprehensive WCF showed no effects on syntactic complexity, and Hartshorn and Evans (2015) similarly reported no meaningful difference between control and treatment groups. The inconsistent findings suggest that the relationship between feedback and syntactic complexity is complex and may be influenced by various factors, including feedback type, source, specific measures used, and learners' proficiency levels (Thi & Nikolov, 2023). Future research could benefit from more standardized measures and longer-term studies to better understand the developmental trajectories of L2 writers in response to different feedback types. Additionally, investigating the impact of AI-driven feedback systems compared to traditional teacher feedback remains an important area for further exploration (Huang & Renandya, 2018; Ranalli, 2018).

Related Studies

Table 1. *Effects of Feedback Type* on Syntactic *Complexity*

Authors	**Participants & Context**	**Feedback Source**	**Complexity Measure(s)**	**Key Findings**	**Type of feedback (just comments or giving revised texts to students)**	**What parameter did the teacher give feedback on**
Azennoud (2024)	Moroccan EFL learners; university level	AI tools (ChatGPT, Grammarly)	T-unit length, subordination ratio	AI tools improved writing accuracy and complexity	Comments and revised texts; feedback provided iteratively	Accuracy, word order, coherence
Hamano-Bunce (2022)	High school students; Japan	Teacher	Number of subordinate clauses per clause, T-unit length	Direct feedback improved syntactic complexity in revisions and new texts	Written corrective feedback with annotated comments	Syntactic complexity, grammatical accuracy
Nicolas-Conesa et al. (2019)	Undergraduate students; Spain	Teacher	Subordination ratio, mean clause length	Direct feedback improved accuracy, while indirect feedback promoted complexity over time	Direct and indirect comment; feedback on drafts	Accuracy, syntactic complexity
Ranalli (2018)	Graduate EFL learners; mixed contexts	Automated tools	Error correction rates, subordination ratios	Automated feedback reduced error rates but had limited impact on writing complexity.	Comments provided through automated platforms	Grammar, vocabulary

Thi & Nikolov (2023)	EFL learners in Asian contexts	Teacher and AI tools combined	Syntactic complexity and lexical measures	Combined feedback improved both syntactic complexity and lexical measures more effectively than isolated sources.	Combined feedback (teacher revisions + AI comments)	Vocabulary diversity, syntactic structures
Dikli & Bleyle (2014)	Mixed EFL contexts	Automated feedback (general)	Error correction rates	Automated feedback reduced error rates but showed limited improvement in complexity	General comments via automated essay scoring systems	Grammar accuracy, sentence-level structure
Abdi Tabari & Wang (2022)	L2 learners; task readiness effects	Teacher feedback	Lexical diversity, syntactic complexity	Task readiness increased lexical diversity; teacher feedback improved complexity.	Written comments on drafts; feedback on revised versions	Vocabulary diversity, sentence complexity
Barrot & Gabinete (2021)	ESL and EFL learners	Instructor feedback	Complexity, Accuracy, Fluency (CAF measures: T-units, clauses per sentence	Instructor feedback significantly improved CAF measures	Written feedback with annotations on student texts	Complexity, accuracy, fluency

Benson & DeKeyser (2018)	ESL learners; university students	Written corrective feedback (WCF)	Verb tense accuracy, syntactic complexity (e.g., T-unit measures)	Corrective feedback improved verb accuracy but had moderate impact on syntactic measures	Comments on drafts; corrections provided on written texts	Verb tense, sentence structure
Bonilla Lopez et al. (2018)	Advanced EFL learners	Comprehensive teacher feedback	Syntactic complexity (mean clause length), writing structure	Comprehensive feedback improved overall structure and syntactic complexity	Comprehensive comments on structure; revised drafts used	Syntactic structures, text organization

Based on table 1, existing research has explored various aspects of feedback in second language writing, yet critical gaps remain. First, while studies like Hamano-Bunce (2022) and Nicolas-Conesa et al. (2019) highlight the benefits of teacher feedback on complexity, and Azennoud (2024) demonstrates AI's potential, direct comparisons between AI and teacher feedback, especially across direct (providing revised texts) and indirect (providing comments without corrected forms) approaches are underexamined. Second, despite findings from Thi and Nikolov (2023) on combined feedback efficacy, and Ranalli (2018) or Dikli & Bleyle (2014) on automated tools, the differential impacts of AI versus teacher-delivered feedback on syntactic complexity remain lacking. Third, although previous studies (e.g., Barrot & Gabinete, 2021; Bonilla Lopez et al., 2018) have explored ways to enhance linguistic complexity, the majority have focused primarily on accuracy, often at the expense of fluency or syntactic development. As a result, the nuanced relationship between different types and sources of feedback remains insufficiently understood.

Building on these identified gaps, there is a clear need for empirical research that directly contrasts the effects of AI-generated and teacher-provided feedback-both direct and indirect-on syntactic complexity in second language writing. Addressing this need, the present study systematically investigates how different feedback modalities influence the development of syntactic complexity among EFL learners. In doing so, it seeks to move beyond the predominant focus on accuracy and provide a more nuanced understanding of how feedback source and type shape linguistic development in writing. This study addresses these gaps by systematically comparing AI and teacher feedback (direct/indirect) on syntactic complexity, offering insights into optimal strategies for EFL writing instruction.

To systematically address these underexplored dynamics and operationalize the study's objectives, three targeted research questions guide this investigation:

Does AI-driven written direct feedback have any significant effect on Iranian EFL intermediate learners' writing complexity?

Does AI-driven written indirect feedback have any significant effect on Iranian EFL intermediate learners' writing complexity?

How do direct and indirect feedback from AI (ChatGPT) and teachers differentially affect the syntactic complexity of Iranian intermediate EFL learners' writing?

2. Methodology

2.1. 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 based on convenience sampling from four different classes at 2 prominent language institutes in Tehran province. All participants were native speakers of Persian studying at an intermediate level of English proficiency. Before the study, students confirmed their willingness to participate voluntarily. They were informed about the research objectives and the data that would be collected. Moreover, they were told their anonymity would be maintained.

2.2. Materials and Instruments

To address the research questions of this study, several instruments were utilized.

2.2.1 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 homogenous sample of intermediate proficiency level participants. Developed by Oxford University Press and Cambridge ESOL, the OQPT is a validated English proficiency test consisting of 60 multiple-choice items, focusing on vocabulary, reading, and grammar. Scores categorized learners from beginners to proficient. The OQPT's use was justified due to participants' familiarity with its format, leading to better performance, and aiding in recruiting participants with similar proficiency levels.

2.2.2. English Writing Test

The second instrument was the TOEIC Writing Test, which measures non-native English speakers' written communication skills (Educational Testing Service, 2019). It consists of three parts—writing sentences from pictures, responding to requests (such as emails), and writing an essay on a given topic. For this study, only the essay section was used, as it aligned most closely with our research objectives. To confirm the test's clarity and suitability, we conducted a pilot study with a sample similar to our main participants, making minor revisions for better content validity. Reliability analyses also showed acceptable consistency over time. The 40-minute test was scored out of 40, functioning as both a pretest and posttest to gauge the intervention's effects. We chose this familiar format to help students perform more comfortably and to ensure a uniform proficiency level across participants.

2.2.3. Syntactic Complexity Measures

To assess the impact of direct and indirect feedback from both AI (ChatGPT) and teachers on the syntactic complexity of Iranian intermediate EFL learners' writing, this study utilized the

L2 Syntactic Complexity Analyzer (L2SCA) developed by Lu (2010). This automated text analysis tool was employed to examine three critical measures of syntactic complexity:

Mean length of T-unit (MLT)
Clauses per T-unit (C/T)
Dependent clauses per clause (DC/C)

The selection of these specific metrics was informed by their established reliability and frequent use in evaluating syntactic complexity in second language writing. A comprehensive analysis of 21 studies on college-level L2 writing by Ortega (2003) identified these measures, along with mean length of sentence (MLS), as the most commonly used and effective indicators of syntactic complexity1. This choice is further supported by research from Van Beuningen et al. (2012) and Fazilatfar et al. (2014), which highlighted the efficacy of these measures in gauging improvements in writing quality.

The chosen metrics provide insights into distinct aspects of syntactic complexity:

Length of production: MLT
Amount of subordination: C/T and DC/C

The automated approach using L2SCA was selected for its accessibility, efficiency, and reliability. Previous studies have reported high accuracy and reliability for this tool in structural unit identification, with scores ranging from 0.830 to 1.000 when compared to hand-coding (Lu, 2010; Polio & Yoon, 2018).

2.3. Data Collection Procedure

This study employed a rigorous experimental design comprising four distinct groups: two experimental groups and two control groups. The composition of these groups was as follows:

1. Experimental Group 1 (AI Direct Feedback): Participants in this group received comprehensive, revised drafts generated by ChatGPT, with a specific focus on enhancing syntactic complexity.

2. Experimental Group 2 (AI Indirect Feedback): This cohort was provided with ChatGPT-generated comments or coded indications of syntactic issues, without explicit corrections or revised text.

3. Control Group 1 (Teacher Direct Feedback): Participants in this group obtained fully revised texts directly from the instructor.

4. Control Group 2 (Teacher Indirect Feedback): This cohort received instructor-provided comments identifying syntactic errors, necessitating students to engage in self-revision.

The investigation was conducted over a 14-week course (see Figure 1 for a visual representation). The initial week was dedicated to familiarizing participants with the study's protocols and, for those in the experimental groups, introducing the use of ChatGPT for feedback purposes. In the second week, all participants completed a writing pretest, which involved composing an argumentative essay of 250–350 words within a 90-minute timeframe, without access to reference materials. The subsequent ten weeks (Weeks 3–12) constituted the treatment phase, during which each student produced a weekly out-of-class argumentative essay under conditions mirroring those of the pretest. Throughout this period, students adhered to their assigned feedback condition:

Experimental Group 1 (AI Direct Feedback on Syntactic Complexity): Participants submitted their typed essays to the instructor, who then input the text into the ChatGPT (O1 version) platform, requesting feedback based on predetermined criteria. The AI-generated feedback was subsequently shared with the students, who were tasked with revising and resubmitting their work. This iterative process was repeated for ten essays over the course of ten weeks.

Experimental Group 2 (AI Indirect Feedback on Syntactic Complexity): Students submitted their typed essays to the instructor, who utilized the ChatGPT platform to obtain feedback focused on syntactic complexity. The AI-driven comments were then conveyed to the students, who were required to revise their texts accordingly. The instructor subsequently verified the final version using ChatGPT and addressed any remaining errors or feedback points.

Control Group 1 (Teacher Direct Feedback on Syntactic Complexity): This group followed a process similar to Experimental Group 1, with the crucial distinction that the instructor personally provided feedback by revising the text based on syntactic complexity criteria, without the use of ChatGPT.

Control Group 2 (Teacher Indirect Feedback on Syntactic Complexity): Mirroring the process of Experimental Group 2, this cohort received instructor-generated comments on syntactic errors, without the involvement of ChatGPT.

To maintain experimental integrity, participants were instructed to disable autocorrect and grammar-checking features in their word processors, refrain from seeking peer or instructor assistance, and abstain from independent grammar study. To mitigate potential confounds related to topic familiarity and content reuse, students selected distinct current social issues for the pretest and posttest (Mirshekaran & Namaziandost, 2018). The posttest was administered in the 13th week under conditions identical to those of the pretest. Both the weekly tasks and the pre-/posttests emphasized feedback on syntactic complexity, adhering to criteria adapted from Thi and Nikolov (2023). These criteria encompassed: (1) task fulfillment, (2) organizational coherence, (3) grammatical range and accuracy (including structural complexity), and (4) lexical range and accuracy. This meticulously designed four-group study, grounded in distinct feedback modes (direct vs. indirect) and sources (ChatGPT vs. teacher), aimed to systematically examine the impact of these approaches on the writing complexity of intermediate learners. Furthermore, the research considered potential gender-related effects by ensuring an equitable distribution of male and female participants. Through this structured methodology, the investigation sought to yield valuable insights pertinent to optimizing feedback strategies for EFL writing instruction in comparable educational contexts.

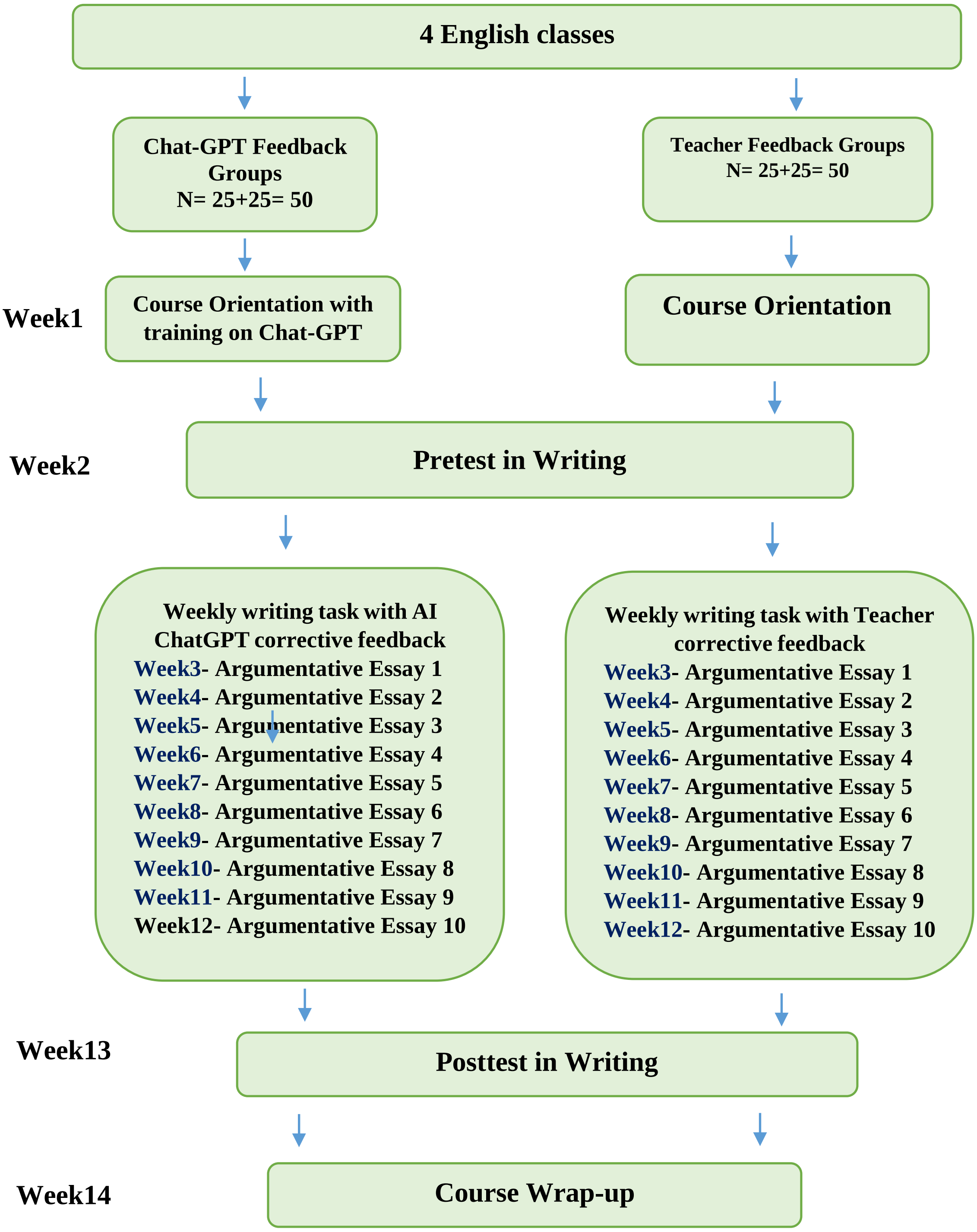

Figure 1. *Empirical procedure*

3. Results

3.1. The Results of the Pretest

To address the research questions and establish a baseline and ensure comparability among the groups at the start of the study, descriptive statistics were calculated and a homogeneity test was conducted. Table 1 presents these initial results:

Table 2. *Descriptive Statistics and Homogeneity Test Results*

Group	N	Mean	Std. Deviation	Std. Error	Skewness	Kurtosis
AI Direct	25	14.32	2.18	0.44	-0.16	-1.22
Teacher Direct	25	14.25	2.2	0.44	-0.12	-1.34
AI Indirect	25	14.18	2.25	0.45	0.18	-1.34
Teacher Indirect	25	14.29	2.22	0.44	-0.43	-1.17

Levene's Test for Equality of Variances: F = 0.185, p = 0.906

This table presents the initial descriptive statistics for the four feedback groups. The means across groups are very similar, ranging from 14.18 to 14.32, indicating comparable baseline levels of syntactic complexity. The standard deviations are also similar (2.18 to 2.25), suggesting consistent variability within groups. The non-significant Levene's test result (F = 0.185, p = 0.906) confirms homogeneity of variances, establishing that the groups were statistically equivalent at the start of the study. This homogeneity is crucial for validating subsequent comparisons between groups.

Following the intervention, paired samples t-tests were performed to assess the changes in syntactic complexity measures from pre-test to post-test for each group. Table 2 displays these comparative results:

3.2. The Participants' Performance on the Posttest

After the intervention, the posttest results were analyzed. Table 2 shows the posttest scores:

Table 3. *Paired Samples t-Test Results for Pre-test and Post-test Comparisons*

Group	Measure	Mean Difference	T	df	p-value
AI Direct	MLT	5.24	8.12	24	0.001
	C/T	0.36	5.78	24	0.001
	DC/C	0.14	6.23	24	0.001
Teacher Direct	MLT	4.47	6.92	24	0.002
	C/T	0.32	5.12	24	0.001
	DC/C	0.12	5.45	24	0.001
AI Indirect	MLT	3.17	4.85	24	0.062
	C/T	0.23	3.65	24	0.072
	DC/C	0.09	3.98	24	0.081
Teacher Indirect	MLT	2.13	3.21	24	0.078
	C/T	0.15	2.34	24	0.091
	DC/C	0.06	2.67	24	0.089

This table reveals the changes in syntactic complexity measures (MLT, C/T, DC/C) from pre-test to post-test for each group:

AI Direct Feedback showed the largest improvements:

MLT increased by 5.24 ($t = 8.12$, $p = 0.001$)
C/T increased by 0.36 ($t = 5.78$, $p = 0.001$)
DC/C increased by 0.14 ($t = 6.23$, $p = 0.001$)

Teacher Direct Feedback also showed significant improvements:

MLT increased by 4.47 ($t = 6.92$, $p = 0.002$)
C/T increased by 0.32 ($t = 5.12$, $p = 0.001$)
DC/C increased by 0.12 ($t = 5.45$, $p = 0.001$)

AI Indirect and Teacher Indirect Feedback groups showed smaller, non-significant improvements ($p > 0.05$).

These results suggest that direct feedback methods, especially AI-driven, were more effective in enhancing syntactic complexity.

To further investigate the differences observed in the paired samples t-tests, a one-way ANOVA was conducted to compare the performance of all groups in the posttest. Table 3 presents the ANOVA results:

Table 4. *One-Way ANOVA for Comparing the Performance of Groups (posttest)*

Measure	Source	Sum of Squares	Df	Mean Square	F	p-value
MLT	Between Groups	142.36	3	47.45	12.34	0.001
	Within Groups	368.52	96	3.84		
C/T	Between Groups	0.89	3	0.3	3.75	0.013
	Within Groups	7.68	96	0.08		
DC/C	Between Groups	0.15	3	0.05	4.55	0.005
	Within Groups	1.06	96	0.01		

The ANOVA results indicate significant differences between groups in post-test scores for all three complexity measures:

MLT: $F(3, 96) = 12.34$, $p = 0.001$
C/T: $F(3, 96) = 3.75$, $p = 0.013$
DC/C: $F(3, 96) = 4.55$, $p = 0.005$

These results suggest that the type of feedback received had a substantial impact on the development of syntactic complexity.

Post Hoc Analysis (Tukey HSD)

Given the significant differences found in the ANOVA, a post hoc analysis using Tukey's HSD test was performed to identify specific differences between groups. Table 4 shows the detailed comparisons of syntactic complexity measures between groups:

Table 5. *Post Hoc Comparisons of Syntactic Complexity Measures Between Groups*

Measure	(I) Group	(J) Group	Mean Difference (I-J)	Std. Error	p-value
MLT	AI Direct	Teacher Direct	0.77	0.55	0.041
		AI Indirect	2.07	0.55	0.001
		Teacher Indirect	3.11	0.55	0.001
C/T	AI Direct	Teacher Direct	0.04	0.08	0.618
		AI Indirect	0.13	0.08	0.041
		Teacher Indirect	0.21	0.08	0.005
DC/C	AI Direct	Teacher Direct	0.02	0.03	0.509
		AI Indirect	0.05	0.03	0.038
		Teacher Indirect	0.08	0.03	0.004

The post hoc analysis provides detailed comparisons between groups. For MLT, the AI Direct group showed significantly higher improvement compared to all other groups ($p < 0.05$). For C/T and DC/C, AI Direct feedback was significantly more effective than AI Indirect and Teacher Indirect feedback ($p < 0.05$), but not significantly different from Teacher Direct feedback. This detailed comparison reinforces the superiority of AI Direct feedback in enhancing syntactic complexity, while also highlighting the effectiveness of Teacher Direct feedback.

Overall, these results suggest that AI-driven direct feedback is the most effective method for improving syntactic complexity in EFL learners' writing, followed closely by teacher-provided direct feedback. Indirect feedback methods, while still beneficial, appear to be less impactful in enhancing syntactic complexity measures, with AI indirect feedback showing slightly better results than teacher indirect feedback.

Discussion

This study investigated the effects of AI-driven and teacher-provided feedback on the syntactic complexity of Iranian intermediate EFL learners' writing. Specifically, it examined direct feedback, which involved providing fully revised texts, and indirect feedback, which consisted of comments only. Writing complexity was measured with mean length of T-units (MLT), clauses per T-unit (C/T), and dependent clauses per clause (DC/C). Overall, the findings revealed that direct feedback—especially when delivered by AI—led to the most substantial gains in syntactic complexity, while indirect feedback produced comparatively modest results. These observations add to the existing literature highlighting the prominent role of explicit guidance in fostering more sophisticated syntactic structures (Hamano-Bunce, 2022; Nicolas-Conesa et al., 2019).

Regarding the first research question, namely whether AI-driven written direct feedback significantly affects intermediate learners' writing complexity, the results indicated pronounced improvements in measures such as MLT, C/T, and DC/C. Scholars who underscore the advantages of direct feedback, including Hartshorn and Evans (2015), maintain that fully revised texts reduce the cognitive load on learners and help them emulate advanced grammatical structures. In the present study, the AI direct feedback group recorded the largest gains, echoing findings by Azennoud (2024) and Bai and Hu (2016), who both reported that AI-generated corrections afford consistency, immediacy, and ample opportunities for noticing more complex patterns. Although Truscott (1996, 2007) has contended that frequent correction might prompt learners to avoid risk-taking in language use, the observed leaps in complexity here counter such concerns, suggesting that explicitly revised AI feedback, by alleviating self-correction pressures, frees learners to incorporate more sophisticated syntactic forms. The justification for this outcome lies in the immediacy and clarity of AI-driven revisions, which allow learners to observe and replicate complex exemplars without being overwhelmed by their own linguistic uncertainties.

Regarding the second research question, which explored whether AI-driven written indirect feedback can significantly enhance learners' syntactic complexity, the data showed modest but generally non-significant gains in C/T, DC/C, and MLT. Several researchers (e.g., Shintani & Ellis, 2015; Xu & Zhang, 2021) concur that indirect feedback encourages self-editing and deeper metalinguistic processes but may not foster immediate improvements for learners still developing confidence in syntactic experimentation. This limitation aligns with observations reported by Hartshorn and Evans (2015), who noted that learners often remain cautious about intricate grammatical constructions if the feedback does not explicitly model them. In partial contrast, others (e.g., Fazilatfar et al., 2014) have documented that indirect methods can yield positive outcomes in lexical or broader structural development, yet such effects tend to require more time and higher degrees of learner autonomy. The justification for the limited gains in indirect feedback conditions thus stems from the inherent complexity of making nuanced syntactic revisions without a concrete corrected model, especially for intermediate learners whose knowledge gaps may impede optimal uptake.

Regarding the third research question, focusing on how direct and indirect feedback from AI (ChatGPT) and teachers differentially affect learners' syntactic complexity, the analyses indicated a robust impact of direct feedback from both AI and teachers but more pronounced gains when AI provided fully revised texts. The current results are consistent with studies by Thi and Nikolov (2023) and Van Beuningen et al. (2012), which underscore how comprehensive, explicit corrections can spark measurable syntactic developments in the short term. Conversely, teacher indirect feedback resembled AI indirect feedback in producing smaller improvements, mirroring what Xu and Zhang (2021) saw when comparing automated feedback and traditional approaches. The heightened efficacy of AI direct feedback may reflect the technology's capacity to supply extensive, consistent corrections without straining human resources (Dikli & Bleyle, 2014; Ranalli, 2018). By contrast, teacher feedback, while valuable for rhetorical guidance and nuanced commentary, can be subject to time constraints, personal judgment variability, and a narrower scope of systematic revision (Huang & Renandya, 2018; Nicolas-Conesa et al., 2019). The justification here lies in AI's potential to combine speed, accuracy, and consistent modeling of advanced language forms, thereby allowing learners to notice and appropriate complex syntactic structures more efficiently than indirect commentary or limited teacher interventions can sometimes accomplish.

In sum, this study advances our understanding of how feedback types, particularly direct versus indirect, provided by either AI or teachers, distinctly shape syntactic complexity in EFL writing. AI- driven direct feedback triggered conspicuously greater gains, aligning with research that advocates explicit correction for immediate structural transformation (Hamano-Bunce, 2022; Bai & Hu, 2016). Teacher direct feedback also contributed meaningfully, showing that human expertise remains essential for facilitating accuracy and development (Hartshorn & Evans, 2015). Though indirect feedback showed less dramatic effects on complexity, it may still build learners' autonomy and long-term problem-solving skills (Shintani & Ellis, 2015). Taken together, these findings affirm that, when aiming for improved syntactic complexity, explicit guidance coupled with technology's immediacy can efficiently scaffold the sophisticated structures learners need for more advanced writing.

Conclusion

The present study aimed to investigate the effects of AI-driven and teacher-provided feedback on the syntactic complexity of Iranian intermediate EFL learners' writing, focusing on direct feedback (fully revised texts) and indirect feedback (comments only). The findings revealed significant advancements in syntactic complexity, particularly among learners who received direct feedback. The AI-driven direct feedback group showed the highest gains, followed by the teacher direct feedback group. Indirect feedback approaches, whether AI-driven or teacher-provided, yielded smaller, non-significant improvements in syntactic complexity. These results highlight the transformative potential of AI-driven tools in fostering linguistic development, particularly in enhancing sentence-level complexity and encouraging the use of more sophisticated syntactic structures.

Like any research, this study has its own limitations, and it's important to take them into account. Because the researcher was also an English teacher at the participating institutes, and due to both ethical considerations and institutional policies, it was not possible to randomly assign students to different groups or to reorganize existing classes. In addition, privacy concerns and the institutes' rules regarding class composition further restricted the use of random sampling, making convenience sampling the only practical option. While this approach allowed for efficient data collection, it limits the generalizability of the findings, even though efforts were made to include only students with similar proficiency levels and to omit those who were not homogeneous. The intervention lasted 14 weeks, which was chosen to fit within the institutes' 16-week course structure; while this was a practical and necessary decision, it may not have been long enough to capture the long-term effects of feedback on writing complexity. The quasi-experimental design, lacking full randomization, introduces potential bias and should be considered when interpreting the results. Finally, the focus on specific syntactic complexity measures (MLT, C/T, DC/C) means that other important aspects of writing, such as lexical diversity and fluency, were not addressed. Future research should aim for longer study durations, more representative sampling, and a broader range of writing measures to provide a more comprehensive understanding of feedback's impact.

The findings of this study carry several pedagogical implications for second language writing instruction. AI-driven tools such as ChatGPT can serve as effective complements to traditional teacher feedback, particularly in contexts where resources are limited. These tools provide learners with immediate, tailored feedback that can enhance both their engagement and writing proficiency. Direct feedback, whether provided by AI or teachers, emerges as a clear strategy for fostering syntactic complexity, as it reduces the cognitive load on learners by providing fully revised texts. Meanwhile, indirect feedback, while less immediately impactful, can still be valuable in promoting learner autonomy and problem-solving skills, particularly when paired with adequate training in metalinguistic awareness.

Future research should address several important avenues. First, longitudinal studies are needed to examine the sustained impact of AI-driven and teacher feedback on syntactic complexity over time. Expanding the sample size and including learners from diverse proficiency levels and educational contexts could enhance the generalizability of findings. Additionally, future investigations could explore the integration of direct and indirect feedback approaches, as suggested by previous studies (Bonilla Lopez et al., 2018; Thi & Nikolov, 2023), to determine whether a hybrid model might optimize gains in both accuracy and complexity. Finally, the use of more comprehensive measures of writing development, including lexical sophistication, fluency, and cohesion, would provide a more nuanced understanding of how feedback influences overall writing quality.

In conclusion, this study underscores the efficacy of AI-driven feedback, particularly in its direct form, for enhancing the syntactic complexity of EFL learners' writing. By complementing traditional teacher feedback, AI tools offer scalable, consistent, and immediate support, addressing many challenges faced by educators in language classrooms. These findings emphasize the potential of leveraging AI technologies to improve writing instruction and highlight the importance of feedback type and source in promoting linguistic proficiency. As the integration of AI in education continues to expand, it is crucial to further explore its implications for second language acquisition and to develop evidence-based strategies for its effective use in language teaching and learning.

References

Abdi Tabari, M., & Wang, Y. (2022). Assessing linguistic complexity features in L2 writing: Understanding effects of topic familiarity and strategic planning within the realm of task readiness. *Assessing Writing*, 52, 100605. https://doi.org/10.1016/j.asw.2022.100605.

Azennoud, A. (2024). Enhancing Writing Accuracy and Complexity through AI-Assisted Tools among Moroccan EFL University Learners. *International Journal of Linguistics and Translation Studies*, 5(4), 211–226. https://doi.org/10.36892/ijlts.v5i4.529

Bagheri Nevisi, R., & Arab, N. (2023). Computer-generated vs. direct written corrective feedback and Iranian EFL students' syntactic accuracy and complexity. *Teaching English as a Second Language Quarterly*, 42(2), 111–148. https://doi.org/10.22099/tesl.2023.46955.3177

Bai, L., & Hu, G. (2016). In the face of fallible AWE feedback: How do students respond? *Educational Psychology*, 37*(*1), 67–81. https://doi.org/10.1080/01443410.2016.1223275.

Barrot, J., & Gabinete, M. K. (2021). Complexity, accuracy, and fluency in the argumentative writing of ESL and EFL learners. *International Review of Applied Linguistics in Language Teaching*, 59(2), 209–232. https://doi.org/10.1515/iral-2017-0012.

Baskara, F. R. (2023). Integrating ChatGPT into EFL writing instruction: Benefits and challenges. *International Journal of Education and Learning*, 5(1), 44-55. https://doi.org/10.31763/ijele.v5i1.858

Benson, S., & DeKeyser, R. (2018). Effects of written corrective feedback and language aptitude on verb tense accuracy. *Language Teaching Research*, 23(6), 702–726. https://doi.org/10.1177/1362168818770921.

Bonilla Lopez, M., Van Steendam, E., Speelman, D., & Buyse, K. (2018). The differential effects of comprehensive feedback forms in the second language writing class. *Language Learning*, 68(3), 813–850. https://doi.org/10.1111/lang.12295.

Dikli, S., & Bleyle, S. (2014). Automated essay scoring feedback for second language writers: How does it compare to instructor feedback? *Assessing Writing*, 22, 1–17. https://doi.org/10.1016/j.asw.2014.03.006.

Eckstein, G., & Bell, L. (2021). Dynamic written corrective feedback in first-year composition: Accuracy and lexical and syntactic complexity. *RELC Journal*. https://doi.org/10.1177/00336882211061624

Eckstein, G., Sims, M., & Rohm, L. (2020). Dynamic written corrective feedback among graduate students: The effects of feedback timing. *TESL Canada Journal*, 37(2), 78–102. https://doi.org/10.18806/tesl.v37i2.1339

El Ebyary, K., & Windeatt, S. (2010). The impact of computer-based feedback on students' written work. *International Journal of English Studies*, 10(2), 121–142. https://doi.org/10.6018/ijes/2010/2/119231.

Evans, N. W., Hartshorn, K. J., McCollum, R. M., & Wolfersberger, M. (2010). Contextualizing corrective feedback in second language writing pedagogy. *Language Teaching Research*, 14(4), 445-463. https://doi.org/10.1177/1362168810375367

Fazilatfar, A. M., Fallah, N., Hamavandi, M., & Rostamian, M. (2014). The effect of unfocused written corrective feedback on syntactic and lexical complexity of L2 writing. *Procedia-Social and Behavioral Sciences*, 98, 482–488. https://doi.org/ 10.1016/j.sbspro.2014.03.443

Frear, D., & Chiu, Y. H. (2015). The effect of focused and unfocused indirect written corrective feedback on EFL learners' accuracy in new pieces of writing. *System*, 53, 24–34. https://doi.org/10.1016/j.system.2015.06.006

Hamano-bunce, D. (2022). The effects of direct written corrective feedback and comparator texts on the complexity and accuracy of revisions and new pieces of writing. Language Teaching Research. https://doi.org/10.1177/1362168822 1127643

Hartshorn, K. J., & Evans, N. W. (2015). The effects of dynamic written corrective feedback: A 30-week study. *Journal of Response to Writing*, 1(2), 6–34. https://doi.org/10.1016/j.system.2011.04.012

Hartshorn, K. J., Evans, N. W., Merrill, P. F., Sudweeks, R. R., Strong-Krause, D., & Anderson, N. J. (2010). Effects of dynamic corrective feedback on ESL writing accuracy. *TESOL Quarterly*, 44(1), 84–109. https://doi.org/10.5054/tq.2010.213781

Huang, S., & Renandya, W. A. (2018). Exploring the integration of automated feedback among lower-proficiency EFL learners. *Innovation in Language Learning and Teaching*, 14(1), 15–26. https://doi.org/10.1080/17501229.2018.1471083

Lee, I. (2008). Student reactions to teacher feedback in two Hong Kong secondary classrooms. *Journal of Second Lan- guage Writing*, 17*(*3), 144–164. https://doi.org/10.1016/j.jslw.2007.12.001

Lu, X. (2010). Automatic analysis of syntactic complexity in second language writing. *International journal of corpus linguistics*, 15(4), 474-496. https://doi.org/10.1075/ijcl.15.4.02lu

Mirshekaran, R., Namaziandost, E., & Nazari, M. (2018). The effects of topic interest and L2 proficiency on writing skill among Iranian EFL learners. *Journal of Language Teaching and Research*, 9(6), 1270-1276. http://dx.doi.org/10.17507/jltr.0906.16

McMartin-Miller, C. (2014). How much feedback is enough? Instructor practices and student attitudes toward error treat- ment in second language writing. *Assessing Writing*, 19, 24–35. https://doi.org/10.1016/j.asw.2013.11.003

Nicolas-Conesa, F., Manchon, R. M., & Cerezo, L. (2019). The effect of unfocused direct and indirect written corrective feed- back on rewritten texts and new texts: Looking into feedback for accuracy and feedback for acquisition. *The Modern Language Journal*, *103*(4), 848–873. https://doi.org/10.1111/modl.12592

Niu, R., Shan, P., & You, X. (2021). Complementation of multiple sources of feedback in EFL learners' writing. *Assessing Writing*, 49(January), 100549. https://doi.org/10.1016/j.asw.2021.100549

O'Neill, R., & Russell, A. (2019). Stop! grammar time: University students' perceptions of the automated feedback program Ginger. *Australasian Journal of Educational Technology*, 35(1), 42–56. https://doi.org/10.14742/ajet.3795

Ortega, L. (2003). Syntactic complexity measures and their relationship to L2 proficiency: A research synthesis of college-level L2 writing. *Applied linguistics*, 24(4), 492-518. https://doi.org/10.1093/applin/24.4.492

Pearson, W. S. (2022). Response to written commentary in preparation for high-stakes second language writing assessment. Asian-Pacific Journal of Second and Foreign Language Education. https://doi.org/10.1186/s40862-022-00145-6

Polio, C. (2012a). How to research second language writing. In A. Mackey & S. M. Gass (Eds.), Research methods in second language acquisition: A practical guide (pp. 139–157). https://doi.org/10.1002/9781444347340

Polio, C. (2012b). The relevance of second language acquisition theory to the written error correction debate. *Journal of Second Language Writing*, 21(4), 375–389. https://doi.org/10.1016/j.jslw.2012.09.004

Polio, C., & Yoon, H. J. (2018). The reliability and validity of automated tools for examining variation in syntactic complexity across genres. *International Journal of Applied Linguistics*, 28(1), 165-188. https://doi.org/10.1111/ijal.12200

Qassemzadeh, A., & Soleimani, H. (2016). The impact of feedback provision by Ginger software and teachers on learning passive structures by Iranian EFL learners. *Theory and Practice in Language Studies*, 6(9), 1884–1894. https://doi.org/10.17507/tpls.0609.23

Ranalli, J. (2018). Automated written corrective feedback: How well can students make use of it? Computer Assisted Language Learning, 31(7), 653–674. https://doi.org/10.1080/09588221.2018.1428994

Shintani, N., & Ellis, R. (2015). Does language analytical ability mediate the effect of written feedback on grammatical accuracy in second language writing? *System*, 49, 110–119. https://doi.org/10.1016/j.system.2015.01.006

Stevenson, M., & Phakiti, A. (2014). The effects of computer-generated feedback on the quality of writing. *Assessing Writing*, *19*, 51-65. https://doi.org/10.1016/j.asw.2013.11.007

Thi, N. K., & Nikolov, M. (2021). How teacher and grammarly feedback complement one another in Myanmar EFL students' writing. *Asia-Pacific Education Researcher*, 31(6), 767–779. https://doi.org/10.1007/s40299-021-00625-2

Thi, N. K., & Nikolov, M. (2023). A systematic review of automated feedback in EFL writing: Advantages, limitations, and implications for practice. *Asian Journal of Second and Foreign Language Education,* 8, 6. https://doi.org/10.1186/s40862-022-00182-1.

Thi, N. K., Nikolov, M., & Simon, K. (2022). Higher-proficiency students' engagement with and uptake of teacher and Gram- marly feedback in an EFL writing course. *Innovation in Language Learning and Teaching*. https://doi.org/10.1080/ 17501229.2022.2122476

Thi, N., & Nikolov, M. (2023). Effects of teacher, automated, and combined feedback on syntactic complexity in EFL students' writing. *Asian-Pacific Journal of Second and Foreign Language Education,* 8(6). https://doi.org/10.1186/s40862-023-00180-x

Truscott, J. (1996). The case against grammar correction in L2 writing classes. *Language Learning*, 46(2), 327–369. https://doi.org/10.1111/j.1467-1770.1996.tb01238.x

Truscott, J. (2007). The effect of error correction on learners' ability to write accurately. *Journal of Second Language Writing*, 16(4), 255–272. https://doi.org/10.1016/j.jslw.2007.06.003

Van Beuningen, C. G., De Jong, N. H., & Kuiken, F. (2012). Evidence on the effectiveness of comprehensive error correction in second language writing: *Effectiveness of comprehensive CF. Language Learning*, 62*(*1), 1–41. https://doi.org/10.1111/j.1467- 9922.2011. 00674.x

Xu, J., & Zhang, S. (2021). Understanding AWE feedback and English writing of learners with different proficiency levels in an EFL classroom: a sociocultural perspective. *Asia-Pacific Education Researcher*. https://doi.org/10.1007/ s40299-021-00577-7

Zhang, L. J., & Cheng, X. (2021). Examining the effects of comprehensive written corrective feedback on L2 EAP students' linguistic performance: A mixed-methods study. *Journal of English for Academic Purposes,* 54, 101043. https://doi.org/ 10.1016/j.jeap.2021.101043

Zhang, T. (2021). The effect of highly focused versus mid-focused written corrective feedback on EFL learners' explicit and implicit knowledge development. *System*, 99, 102493. https://doi.org/10.1016/j.system.2021.102493