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Artificial intelligence as a catalyst for transformation: EFL learners' perceptions of AI-powered language tools in delivering effective oral and written corrective feedback

Masoomeh Estaji [1] *, Yara Mirfendereski [2] and Klara Skogmyr Marian [3]

*Correspondence:
estaji@atu.ac.ir
Department of English Language and Literature, Faculty of Persian Literature and Foreign Languages, Allameh Tabataba'i University, South Allameh St, Modiriat Fly-over, Chamran Highway, Tehran, Iran
Full list of author information is available at the end of the article

Abstract

The integration of artificial intelligence (AI) in English as a Foreign Language (EFL) teaching and learning has reshaped corrective feedback (CF) practices, facilitating new opportunities for both oral and written language development. This study examined EFL learners' perceptions of AI-powered CF, focusing on the effectiveness of six types of oral corrective feedback (OCF), namely clarification request, elicitation, explicit correction, metalinguistic feedback, recast, and repetition, and three types of written corrective feedback (WCF), including direct, indirect, and metalinguistic feedback delivered through the AI tools Kippy and Pi. Adopting an ethno-phenomenological design, the study collected the data through a Likert-scale questionnaire and semi-structured interviews with 27 Iranian EFL learners at the B1 proficiency level. The results revealed that explicit correction and direct feedback were rated as the most effective CF types, while repetition and indirect feedback were perceived as the least helpful. The interview data supported these results, highlighting the learners' preferences for direct and immediate feedback that clearly signals errors and provides opportunities for correction. Participants reported that AI-generated CF enhanced their autonomy in self-correction, created space for language learning, and delivered instant, personalized feedback tailored to their individual language needs. However, they noted that AI tools prioritized linguistic accuracy over communicative meaning, requiring teacher intervention for deeper contextual understanding. This study offers a comprehensive understanding of how AI tools may support CF processes, contributing to the integration of AI into EFL pedagogy.

Keywords: artificial intelligence (AI), AI-driven EFL classes, corrective feedback, learners' perspectives

Introduction

Artificial Intelligence (AI) now plays a pivotal role in facilitating language education by transforming classroom interaction. The integration of AI tools into foreign language teaching and learning has enabled personalized learning experiences that adapt to individual needs, supporting language acquisition (Mohebbi, 2025; Song & Song, 2023), particularly in the delivery of Corrective Feedback (CF). AI-powered platforms offer real-time, individualized feedback through Natural Language Processing (NLP), aiming to enhance learners' language skills (Han & Li, 2024). CF refers to indications that a language learner's oral or written output is erroneous in some way (Nassaji & Kartchava, 2017) and helps them rectify those errors and recognize the gap between their developing language system and the desired target language (Su & Tian, 2016).

Providing CF on both speaking and writing skills is nevertheless time-consuming, which makes it difficult for teachers to deliver tailored feedback to all individuals in a class (Lim & Phua, 2019). In this regard, the use of technology offers language teachers more possibilities for providing individualized feedback (Ko, 2024). Despite the increasing implementation of AI tools in English as a Foreign Language (EFL) education, there is still limited empirical research exploring how learners perceive AI-generated CF, especially when both oral and written modalities are involved. Furthermore, learners' preferences for different types of feedback delivered through AI remain largely underexplored. This lack of understanding poses a challenge for teachers striving to implement AI-generated CF in a way that aligns with learners' expectations, preferences, and needs and enhances learning outcomes.

While prior research has focused on how AI-generated CF works within either writing classrooms (e.g., Guo et al., 2022; Mohammad & Khalid, 2025; Rahimi et al., 2025; Teng, 2024; Yang et al., 2024), or speaking classrooms (e.g., Kovalyova, 2024; Shadiev et al., 2024), the present study attempts to supplement these findings by adding substantial information on the efficacy of both AI-generated Oral Corrective Feedback (OCF) and Written Corrective Feedback (WCF) in EFL settings. Moreover, to the best of the researchers' knowledge, no previous study has investigated both learners' perceptions of AI-generated CF across two modalities (i.e., oral and written) and their preferences for specific feedback types.

Therefore, the purpose of this study is to examine Iranian senior high school EFL learners' perceptions of CF delivered through AI platforms (i.e., Kippy and Pi), and identify which types of feedback (i.e., clarification request, elicitation, explicit correction, metalinguistic feedback, recast, and repetition) learners find most effective. The study offers a comprehensive investigation of EFL learners' perceptions of different types of AI-generated CF, covering both OCF and WCF, within the understudied Iranian public senior high school context. Employing an ethno-phenomenological design, it provides rich, triangulated insights into how AI feedback supports speaking and writing skills, and where teacher intervention remains necessary. A clearer picture of how practitioners can use AI resources to efficiently provide CF to EFL learners can lend ecological classroom insights and enhance generalizability in the domain of CF research.

Literature review

CF in foreign language learning

CF is a type of reaction to learners' inaccurate production (Ellis & Shintani, 2014) and is often adopted by foreign language teachers (Ellis et al., 2006). Foreign language learners inevitably make errors when practicing and often seek feedback on these errors, particularly in oral practices (Liu et al., 2025). CF enhances their language output by helping them compare the non-target output with the correct one (Nassaji, 2016). It can be provided both orally and in written form, with each mode having distinct characteristics and taxonomies.

As proposed by Lyster and Ranta (1997) regarding various types of CF, OCF strategies are divided into a six-part taxonomy, namely explicit correction (i.e., rephrasing an erroneous utterance into a correct form and indicating the erroneous part), recast (i.e., rephrasing all or part of an erroneous utterance into a correct form), clarification request (i.e., occurring when an utterance is not fully understood and the learner is asked for clarification), metalinguistic cue (i.e., providing metalinguistic information), elicitation (i.e., eliciting the correct form), and repetition (i.e., repeating the erroneous utterance with a rising intonation) (Nassaji & Kartchava, 2021). WCF, presented by Ellis (2012), is categorized as direct (i.e., providing the correct form), indirect (i.e., indicating errors without correction), and metalinguistic (i.e., offering explanations). Both OCF and WCF play complementary roles in foreign language learning, and understanding their types and effects helps tailor effective teaching techniques.

Empirical research has demonstrated that appropriate CF significantly enhances both spoken and written skills in EFL contexts (Sheen, 2011). However, since there is an ongoing lack of conclusive evidence about the relative superiority of CF types, it indicates that the superiority of CF types is context-specific (Ferris, 2010). In the case of AI-driven OCF and WCF, there is yet no research conducted to see which CF type is most effective in EFL classrooms.

CF and AI integration

Mediation, a key concept in sociocultural theory (Vygotsky, 1978), stresses the role of tools in facilitating human activities. In an AI-driven classroom, the AI resources serve as a mediator between the teacher and the learners. They can provide effective responses to learners' speaking and writing issues based on teacher-input prompts (Han & Li, 2024). Teachers then utilize the output of AI tools to address the learners' specific linguistic needs. The concept of scaffolding (Bruner, 1985) further underpins this innovative feedback approach. AI assists teachers in performing feedback tasks that might otherwise be challenging to accomplish alone, while teachers guide students to bridge the gap between their current abilities and their potential development, i.e., their Zone of Proximal Development (ZPD) (Han & Li, 2024; Vygotsky, 1978). The principles of mediation and scaffolding inspire the teaching approach examined in this study, with Pi and Kippy acting as mediators to enhance EFL teachers' provision of both OCF and WCF, and as scaffolds to support language learners in improving their writing and speaking skills.

The impact of CF on students' oral and written performance has long been debated in language education. While it is widely acknowledged that CF can enhance writing and speaking to some extent, there is no consensus on the most effective type of feedback or its overall influence on language learning. Recent advancements in AI technologies have transformed feedback practices, particularly in EFL writing pedagogy, bringing Automated Corrective Feedback (ACF) into focus. However, little is known about how learners interact with AI-based feedback. Studies on Automated Written Corrective Feedback (AWCF) illuminates its potential for improving academic writing accuracy (Sanosi, 2022; Wang, 2024), fluency (Wang, 2024), self-efficacy and motivation (Teng, 2024), and for reducing writing anxiety (Wang, 2024). Research has also emphasized the importance of integrating AI tools into writing instruction for holistic development (Asadi et al., 2025), while drawing attention to concerns such as plagiarism, overreliance on AI, and the clarity of feedback (Asadi et al., 2025; Teng, 2024). Additionally, studies suggest that AI-powered synchronous CF, when supported by teachers, can enhance learners' writing proficiency, support more effective revisions, and address instructional challenges (Asadi et al., 2025; Han & Li, 2024; Sumedi, 2024).

Learner perspectives on AI-driven CF

As AI technologies, particularly generative AI, are increasingly integrated into language learning environments, learner perspectives have become a key point in understanding the efficacy and acceptance of AI-driven CF. Multiple studies have explored how learners perceive and interact with automated and hybrid feedback mechanisms across different EFL contexts. Fan et al. (2024) examined the nature of teacher feedback on writing and juxtaposed it with learners' perceptions of both teacher and AI-generated feedback. Their study highlighted the value of teacher feedback, which learners viewed as more context-sensitive and pedagogically grounded than current AI systems. In contrast, learners appreciated AI for its immediacy but cautioned against its generic nature. Zeevy-Solovey

(2024) similarly found that while learners viewed AI (i.e., ChatGPT) feedback as useful, it was most effective when combined with teacher feedback. Their participants preferred the teacher-generated WCF but acknowledged the practical value of ChatGPT's quick and clear feedback. Although learners appreciated peer feedback, it was the option they favored the least.

These results align with Fan et al. (2024), reinforcing the complementary rather than substitutive role of AI in feedback processes. In another study, Elmotri et al. (2025) focused on user perceptions of Automated Essay Scoring (AES) systems, accentuating learners' appreciation for the clarity, usefulness, and specificity of AWCF, particularly in reducing teachers' workload. Like Zeevy-Solovey (2024), Elmotri et al. (2025) concluded that students preferred targeted strategies over generic corrections, indicating a growing demand for personalized, adaptive feedback mechanisms. Expanding on learner experience with ChatGPT, Teng's (2024) quantitative results confirmed learners' improved writing motivation, engagement, and self-efficacy due to AI assistance. Interviews showed varied opinions; while several participants appreciated the help from ChatGPT, some expressed worries about depending too much on it and questioned its accuracy, aligning with Fan et al.'s (2024) point on the importance of teacher guidance.

Rahimi et al. (2025), guided by activity theory, compared AWCF with traditional WCF across writing subskills. Learners receiving AWCF demonstrated superior gains in grammar and task achievement, though no significant difference emerged in coherence and cohesion or lexical diversity. While learners engaged cognitively and behaviorally with AWCF, emotional ambivalence persisted. Tan et al. (2022) took a broader perspective by comparing three e-feedback modes: AWCF, Asynchronous Computer-Mediated Communication (ACMC), and their combination. Their study showed that the hybrid model (i.e., AWCF + ACMC) outperformed the others in complexity, accuracy, and fluency, and was rated more favorably by students. Yang et al. (2024) delved into learners' iterative interactions with Pigai, a Chinese AI tool. They found that learners initially focused on error correction but gradually shifted toward deeper engagement with linguistic resources, despite the AI's limited contextualization. Alanazi et al. (2025) assessed ChatGPT's impact and found greater writing improvement among AI users. Positive perceptions included ease of use and helpfulness of AI feedback, though concerns over privacy, bias, and relevance emerged. Guo et al. (2024) investigated the use of a chatbot in facilitating peer feedback with AI assistance. Their results showed enhanced feedback quality and writing improvement among EFL students, indicating AI's potential in scaffolding peer learning. Finally, Mohammad and Khalid (2025) provided evidence of AI feedback's psychological benefits, including increased motivation, peace of mind, and emotional intelligence, along with improved writing proficiency. This holistic view adds a fresh dimension to learner perspectives by linking affective outcomes with linguistic progress.

Moving beyond writing to speaking, Shadiev et al. (2024) introduced Speech-Enabled Corrective Feedback (SECF), integrating speech-to-text with ACF. Their findings revealed significant gains in pronunciation, grammar, vocabulary, and learner confidence. Importantly, learners reported reduced foreign language anxiety, a benefit reflected in Mohammad and Khalid's (2025) study on AI feedback in online writing. Both studies suggest that AI's immediacy and availability foster a safer, low-stakes environment for linguistic risk-taking and self-correction. Kovalyova (2024) also evaluated chatbot accuracy in text-based interaction, revealing improvements over earlier systems and suggesting issues in contextual appropriateness. Despite learners appreciating technological advancement, confusion and frustration were reported, mirroring concerns raised by Teng (2024) and Alanazi et al. (2025).

In sum, while AI-driven CF is widely acknowledged for its immediacy, consistency, and scalability, learners continue to value human feedback for its nuance, contextual understanding, and pedagogical depth. Studies consistently suggest that hybrid feedback models, where AI and human inputs are integrated, are most effective for fostering learner engagement, motivation, and language development. As research continues to evolve, learner perspectives remain pivotal for refining AI-assisted feedback systems in EFL contexts.

The present study

This study aims to address the mentioned research gaps by examining the role of two AI tools, Kippy and Pi, in providing both OCF and WCF to EFL learners. Employing an ethno-phenomenological research approach, the study addresses the following research questions.

1. Which types of OCF (i.e., clarification request, elicitation, explicit correction, metalinguistic feedback, recast, and repetition) and WCF (i.e., direct, metalinguistic, and indirect) provided by AI tools (Kippy and Pi) do EFL learners perceive as the most and least useful for developing their speaking and writing skills?
2. How do EFL learners perceive the overall effectiveness of AI-generated language tools in facilitating OCF and WCF processes?

Methodology

The present study employed a qualitative design to explore EFL learners' perceptions of AI tools in error correction and feedback provision, focusing on both OCF and WCF. To capture a comprehensive view of learners' experiences and preferences, the design integrated two qualitative data sources, namely survey responses and semi-structured interviews. Ethno-phenomenology was specifically chosen to investigate the patterns of values, beliefs, and experiences. Ethnography, a component of this design, allows researchers to examine culture-sharing groups and their practices (Creswell, 2007), including behaviors, language, and interaction, providing a contextualized understanding of the group's way of life and central beliefs (Denscombe, 2010; Hammersley & Atkinson, 2007). Phenomenology focuses on shared human experiences, aiming to uncover the essence of those experiences through the descriptions provided by participants (Creswell, 2007). By combining these methods, ethno-phenomenology enabled a deeper exploration of learners' experiences within the context of AI-mediated language learning.

AI tools in this study were conceptualized as mediational tools that support learners' EFL development in line with Vygotsky's sociocultural theory. By offering corrective feedback, they help learners notice, reflect on, and correct their linguistic errors. While the interviews provided in-depth personal accounts, the survey responses captured broader patterns in learners' perceptions of AI-generated CF, offering complementary insights. Together, they enhanced understanding of how learners interact with AI tools, providing a richer view of their experiences.

Context and participants

The participants were 27 EFL learners, recruited from senior high schools in Golestan Province, Iran, with B1 language proficiency level according to the Common European Framework of Reference for Languages (CEFR). The participants were from both genders (Females = 18, 66.6% and Males = 9, 33.3%) to ensure sample representativeness, and they did not have any prior experience using AI tools in their language learning journey. A purposive sampling method was employed to select participants for the study. The selection criteria were based on the participants' trajectories of change, tendencies, experiences, and abilities to provide rich information to the researcher. In other words, information-rich participants were purposefully selected to fit the aim of the study (Patton, 2002). This method was chosen to ensure that the participants could actively integrate AI tools into classroom activities and provide meaningful insights into the CF process. All participants were asked to participate in the interview sessions. The demographic information of the participants who took part in the study is shown in Table 1.

All participants were students at a Sampad high school[1] (i.e., a selective gymnasium for gifted students in Iran), where entry is granted through a rigorous nationwide entrance exam. As a result, they were largely homogeneous in terms of academic performance and exhibited higher-than-average English proficiency for their age group. Before the interviews, the participants were asked about their preferred language for the sessions, and all opted to conduct the interviews in English. To ensure full comprehension of the survey

[1] NODET: National Organization for Development of Exceptional Talents

and interview questions, a pilot test was conducted with a group of Sampad students not involved in the main study. The questions were reviewed for clarity and adjusted accordingly. During the interviews, the participants were encouraged to ask for clarification when needed, and the interviewer provided explanations to ensure mutual understanding.

It would be necessary to note that the participants were part of a larger study that introduced AI tools in EFL teaching, and that this study just focused on the learners' perceptions.

Table 1

Demographic information of the participants

N (Total)	N (Female)	N (Male)	Age range	Level of English language proficiency
27	18	9	15 - 18	B1

Instruments

The study employed a combination of various resources, AI-powered language learning tools, surveys, and semi-structured interviews to collect comprehensive data on the role of AI-generated CF in EFL learning. The following subsections describe each instrument in detail.

Oxford placement test

Before starting the sessions, the researchers administered the Quick Oxford Placement Test (QOPT) provided by Oxford University Press to homogenize the participants in the study. The QOPT consists of 60 questions designed to examine foreign language learners' knowledge of reading, grammar, and vocabulary. Results were reported instantly as an overall score, indicating the learner's English proficiency level from pre-A1 to C2, based on the Common European Framework of Reference for Languages (CEFR).

Kippy[2]

Kippy is an AI-powered language assistant designed to support learners in mastering vocabulary and grammar through gamified exercises and interactive activities. It focuses on enhancing language acquisition by engaging students in various tasks that promote vocabulary retention, grammatical accuracy, and pronunciation clarity. Kippy was utilized in this study to provide learners with structured practice opportunities in vocabulary and grammar. The interactive tasks and gamified approach encouraged engagement and

[2] https://kippy.ai/

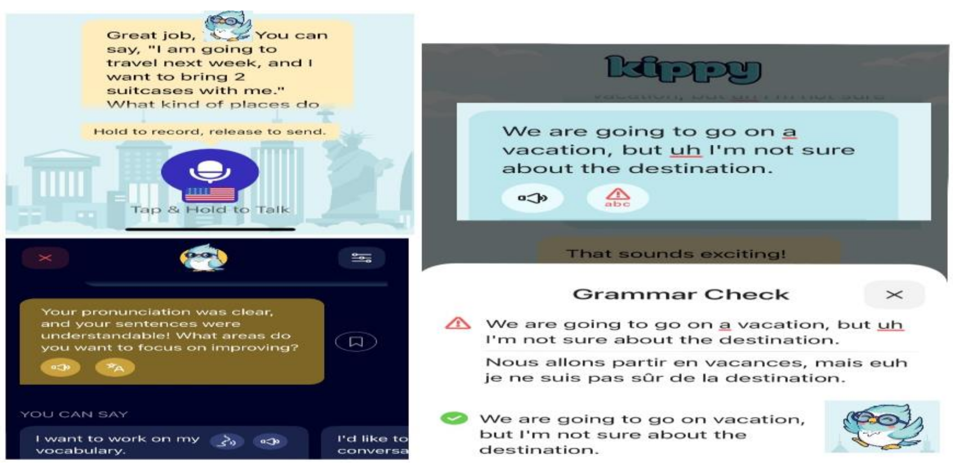
allowed learners to receive CF on their language use. Figure 1 shows some sample photos taken from Kippy.

Pi[3]

Pi is an AI-driven conversational language tool designed to facilitate language learning through interactive dialogues and personalized feedback. By simulating real-life conversations, Pi allows learners to practice their speaking and listening skills in a low-pressure environment. The tool adapts to individual learner needs, providing targeted vocabulary, grammar corrections, and pronunciation support based on the users' performance. In this study, Pi was used to assist learners in practicing their language skills through guided interactions. The tool provided CF and suggestions, allowing learners to self-correct and potentially improve their proficiency. Figure 2 presents some sample photos taken from Pi.

Figure 1

Kippy, a conversational AI platform



Survey on the effectiveness of CF types

Considering its proven utility in gathering factual, attitudinal, and behavioral data or traits from a defined population (Dörnyei & Taguchi, 2010), a questionnaire survey was selected as an appropriate method for this research. As no prior questionnaire addressing perceptions of CF types was available, the instrument for the study was developed based on Lyster and Ranta's (1997) taxonomy of OCF, categorized into six primary feedback strategies, and Ellis's (2012) classification of WCF, consisting of three types. The questionnaire was divided into three sections and contained a total of 14 items (Appendix

[3] https://pi.ai/

A): Background information questions (3 items), questions on the effectiveness of CF (9 items), and additional open-ended questions (2 items). The first section includes three demographic questions to gather general information about participants, such as their age, gender, and experience in learning a foreign language with AI tools. The second section is the core of the questionnaire, containing nine Likert-scale items, each evaluating a different type of OCF (i.e., clarification request, elicitation, explicit correction, metalinguistic feedback, recast, and repetition) and WCF (i.e., direct, indirect, and metalinguistic). Participants rated the effectiveness of each CF type on a five-point Likert scale (1 = Least Helpful, 5 = Most Helpful).

Each CF type was accompanied by a brief definition and an example to ensure clarity. The third section included two open-ended questions, allowing participants to elaborate on their preferences, perceptions, and suggestions for improving AI-based CF. The questionnaire was designed in English and administered individually to participants via one-on-one sessions. Data collection occurred following the completion of AI-supported instructional sessions. The questionnaire underwent evaluation by three field experts, comprising one university professor and two postdoctoral researchers with expertise in questionnaire design, who assessed its linguistic clarity and content relevance. The experts provided a limited number of suggestions to enhance the clarity of language and relevance of the questionnaire items. Accordingly, the researcher modified and finalized the items based on the experts' comments, ensuring their content validity. The instrument was prepared in English. Data were analyzed using Statistical Packages for Social Sciences (SPSS v.27) to calculate reliability and descriptive statistics. The Cronbach's alpha coefficient for the questionnaire yielded a reliability score of 0.89.

It is also noteworthy that the questionnaire was developed in line with the research objectives and based on clearly defined constructs, and each item was carefully designed to directly reflect the dimensions of interest, thereby avoiding any confusion for the students while responding. The number of items was intentionally limited to reduce participant fatigue and maintain clarity and focus, especially considering the length of the full data collection process, which included two qualitative components.

Semi-structured interviews

From among various types of interviews (e.g., structured, semi-structured, and unstructured), semi-structured interviews were used as they give the interviewers the chance to modify the questions and probe for deeper information (Gass & Mackey, 2016). In a semi-structured interview, although a specified number of interview questions are asked, there is a degree of flexibility in the sequence of the interview questions provided for participants, and they are allowed to elaborate on certain issues and are not limited to providing yes/no or short answers to interview questions (Dörnyei, 2007). Each one-on-

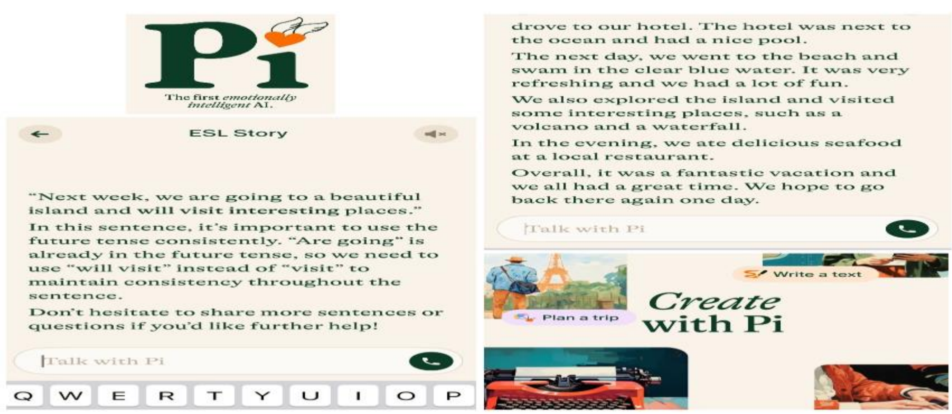
one interview lasted 15 to 20 minutes (Appendix B) and was recorded via a voice recorder for later transcription and analyses.

At the outset of the interviews, participants were reassured that their personal information and anonymity would be safeguarded both during and following the sessions, with their responses maintained as confidential and utilized solely for research purposes. Consent was secured to digitally record the interviews. Additionally, ethical standards were upheld by furnishing comprehensive details about the study and granting participants the autonomy to either engage in the research or withdraw at any point should they feel uneasy (Mackey & Gass, 2015). All interviews were conducted in English. It is worth noting that the interviewer was the main researcher herself, as she was thoroughly aware of the rationale of the study, the concept of AI-powered CF in EFL learning, and the purposes behind the research questions.

To establish the trustworthiness of the prompts (Nassaji, 2020), four experts in the field, comprising two university professors, one postdoctoral researcher, and one PhD graduate, with extensive experience in educational research, reviewed them for linguistic clarity and content relevance. Following the incorporation of the experts' feedback, the researcher revised the prompts to enhance their content validity.

Figure 2

Pi, a conversational AI platform



Data collection procedure

The process of collecting data spanned two months (i.e., twelve sessions) in three EFL classrooms in Iran, where AI tools were integrated into the curriculum, with the EFL teacher acting as a mentor for unexpected situations (for the sample lesson plan, see Appendix C). In each session, the learners were organized into three-member groups, given a smartphone, and interacted with Kippy and Pi, each for six sessions, while discussing the textbook topics. They also engaged in various interactive speaking and writing tasks facilitated by AI tools, focusing on speaking and writing skills, and common error-prone areas such as grammar, vocabulary, and pronunciation. Prior to each session, some clearly defined prompts, representing the oral and written feedback types, were given to the AI tool to ensure that the feedback was delivered to students in different formats. Following each session, all interactions between the AI tools and learners were carefully reviewed to verify which CF types were represented. While teacher mediation and task design helped ensure exposure to a wide range of feedback types, it was observed that some CF types occurred less frequently than others due to the AI apps' restrictions in their system.

Following the final session, the learners were asked to complete a survey designed to gather their perceptions of the effectiveness of each type of CF provided by AI tools. Simultaneously, they participated in a semi-structured interview to provide an in-depth understanding of their perceptions and experiences related to the effectiveness of AI tools in speaking and writing activities. The interviews focused on the learners' interactions with AI tools, exploring the specific ways in which these tools assisted or hindered their ability to correct language errors. Participation in all phases of the study was voluntary, and the learners provided consent for their feedback data to be used in this study. The study adhered to the ethical standards, ensuring the anonymity and confidentiality of the participant data.

Analytical procedures

Responses from the Likert-scale questionnaire were analyzed using descriptive statistics, focusing on the mean and standard deviation for each CF type. These measures provided an overall view of the learners' preferences and the perceived effectiveness of each feedback type. This analysis helped identify the most and least helpful OCF and WCF types provided by AI tools. All statistical analyses were conducted using SPSS (version 27), and the results were presented in tabular format for clarity. As for the interview data, they were transcribed, coded, and analyzed to identify EFL learners' perceptions of the effectiveness of the use of AI tools for speaking and writing activities. Adhering to the methodology outlined by Gao and Zhang (2020), the interview data were processed through a systematic sequence of steps, including data cleaning and coding, theme generation and categorization, and the subsequent reporting and interpretation of the resulting codes and themes (Figure 3). To ensure the consistency of the findings, two independent coders coded 20% of the data, achieving an inter-coder reliability coefficient of 0.86. All the analyses were conducted via MAXQDA (version 10) as using software for data analysis improves the credibility of the coding process in qualitative studies (Baralt, 2011).

Figure 3

The five-step data analysis model (Gao & Zhang, 2020)

Research findings

EFL learners' preferences regarding the usefulness of specific OCF and WCF types provided by AI tools

The first research question examined EFL learners' perspectives of the different types of OCF and WCF provided by AI tools in terms of perceived effectiveness. EFL learners rated each CF type on a 5-point Likert scale, with 5 representing "extremely helpful" and 1 representing "not helpful at all." Table 2 presents the descriptive statistics for each CF type, along with their ranking from most to least preferred.

Table 2

EFL learners' preferences of the effectiveness of CF types provided by AI tools

	CF type	N	Minimum	Maximum	Mean	Std. deviation	Rank
OCF	Explicit correction	27	3	5	3.96	.64	1
	Recast	27	2	5	3.59	.84	2
	Metalinguistic	27	2	5	3.51	.84	3
	Elicitation	27	1	4	3.11	.75	4
	Clarification request	27	2	4	3.03	.70	5
	Repetition	27	1	3	2.48	.57	6
WCF	Direct	27	3	5	4.00	.87	1
	Metalinguistic	27	2	5	3.62	1.14	2
	Indirect	27	1	3	2.59	.57	3

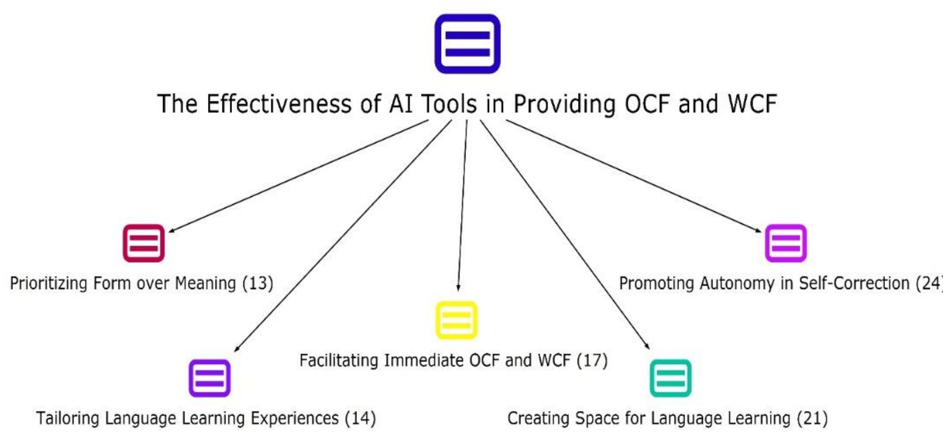
Explicit correction received the highest mean score (M = 3.96), indicating that learners perceived it as the most effective type of oral feedback. Recast and metalinguistic feedback followed, with mean scores of 3.59 and 3.51, respectively, showing moderate perceived effectiveness. Elicitation (M = 3.11) and clarification request (M = 3.03) were rated slightly lower. Repetition had the lowest mean (M = 2.48), suggesting it was perceived as the least effective oral feedback strategy. Direct feedback had the highest mean score (M = 4.00), showing that participants found this the most effective written feedback type. Metalinguistic feedback also received a relatively high score (M = 3.62), illustrating it was favorably viewed. Indirect feedback had the lowest mean in the WCF category (M = 2.59). Overall, explicit and direct forms of feedback were perceived as most effective. Less explicit forms (e.g., repetition and indirect) were rated lower, indicating that learners may struggle to interpret or act on them without additional support.

EFL learners' perceptions of the overall effectiveness of AI tools in providing OCF and WCF

This section presents the analysis from interviews with EFL learners, focusing on their perceptions of the effectiveness of AI tools (i.e., Kippy and Pi) in providing OCF and WCF. The findings are organized around five key themes: (1) promoting autonomy in self-correction, (2) creating space for language learning, (3) facilitating immediate CF, (4) tailoring language learning experiences, and (5) prioritizing form over meaning (Figure 4).

Figure 4

Themes extracted regarding the effectiveness of AI tools in providing OCF and WCF



Promoting autonomy in self-correction

Learners report to become more independent in their learning in AI-supported EFL classes than in non-AI-supported classes, particularly when it comes to correcting their own mistakes using AI tools. This independence helps learners feel more in control of their learning. As most of the learners have noted, AI tools help them take charge of their language learning journey. S5 commented as follows:

I've noticed that I can now correct my mistakes on my own. I don't wait for someone else to tell me what's wrong. I use AI tools to find and fix errors. This makes me feel more confident.

This suggests that AI-powered feedback encourages self-monitoring and boosts learners' confidence, leading to more active engagement in their language development. In addition, S8 reported:

I feel more confident because I can correct my mistakes myself. The AI shows me what's wrong, and I try to fix it before asking the teacher. When I ask for help, I already have some ideas on how to improve.

This suggests that increased autonomy not only empowers learners to manage their learning but also can help strengthening their problem-solving skills.

Creating space for language learning

It is important to create a comfortable and supportive environment for EFL learners to practice. According to multiple respondents, AI tools help learners feel less anxious and more engaged in their learning. They create a safe environment for learners to take risks, which is important for improving language skills. 21 participants report that AI tools give them the freedom to practice at their own pace, making language learning less stressful and more effective. S7 elaborated on this as follows:

Using Kippy makes me feel comfortable practicing my speaking skills. It's like a safe space where I can make mistakes without feeling embarrassed. I can try again until I get it right. It feels like having a practice friend.

This illustrates that AI tools function as nonjudgmental learning partners, providing learners with a supportive environment that encourages iterative practice. Moreover, S5 stated:

Pi helps me focus on areas where I need improvement. I can take my time to understand the feedback without pressure. This helps me feel more in control of my learning.

Such personalized pacing enables learners to internalize CF more effectively, reflecting learner-centered scaffolding.

Facilitating immediate OCF and WCF

AI tools in EFL classrooms can provide instant feedback, helping learners correct their mistakes quickly. This immediate feedback helps learners improve faster. Instant feedback helps learners improve faster and become more aware of their language use and work on their writing and speaking skills, which might enhance motivation. S4 emphasized these points:

The biggest change for me is how fast I can fix my errors. With AI, I get immediate feedback, especially in writing and pronunciation. It's like having a personal teacher who is always there for me. This keeps me motivated.

Certain respondents even suggested that real-time corrections might accelerate learning. As S10 stated:

I like that I can see my mistakes right away. When I write a sentence, the AI tells me if I used the wrong tense or word. I can correct it immediately, which helps me learn faster.

This indicates that immediate error correction enhances awareness and supports self-regulated learning.

Tailoring language learning experiences

AI tools create personalized learning paths based on each learner's needs, which might in turn make learning more effective and relevant. Personalized feedback helps learners focus on their specific challenges and improve their desired language skills. In this regard, S3 and S4 shared the following reflections:

The AI analyzes my progress and gives me exercises to practice my weak points, like sentence structure. This helps me feel more confident when speaking.

I like how Kippy adjusts its feedback based on my past mistakes, especially with pronunciation. It feels like it understands my language needs and helps me understand the correct sounds better.

These examples indicate that AI can target learners' gaps, improve confidence, and enable focused skill development. In other words, AI tools function as adaptive tutors, responding to individual learning needs through personalized scaffolding.

Prioritizing form over meaning

AI tools are good at correcting grammar, spelling, and pronunciation, but they sometimes miss the bigger picture. While they help correct form, learners still need teachers to explain the deeper meaning and context of language use. S6 emphasized this concern in the following ways:

Pi is great for catching grammar and pronunciation mistakes, but it doesn't always understand the context. Sometimes I need help to understand not just the correction but also why it's wrong.

This reflects a limitation of AI CF in handling semantic particularities, suggesting that teacher mediation remains essential for context-focused instruction. S2 declared:

The AI tool helps me with grammar and spelling, but sometimes I don't understand why my sentences are wrong. I still need my teacher to explain the meaning.

This underlines the necessity of combining AI and teacher feedback to ensure comprehension of context and meaning, highlighting the complementary role of human guidance in AI-assisted learning.

Discussion

Drawing on Vygotsky's (1978) sociocultural theory, this study aimed to explore EFL learners' perceptions of the effectiveness of AI tools (i.e., Kippy and Pi) in delivering OCF and WCF, with a focus on how different types of CF are perceived in facilitating the repair process. This study specifically addressed learners' experiences and preferences with AI-generated feedback during classroom interactions. The findings revealed that the use of AI tools promoted learners' autonomy in self-correction, created space for language learning, facilitated immediate CF, and tailored learning experiences to meet individual language needs. However, learners reported that these tools prioritize form over meaning in giving feedback. Additionally, among the different types of OCF and WCF, explicit and direct feedback were perceived as the most effective, with explicit feedback being the most effective for OCF and direct feedback for WCF. In contrast, repetition and indirect feedback were considered the least effective.

In general, the findings align with Shadiev et al. (2024) and Wang and Li (2019), who reported the positive impact of ACF on EFL learners' speaking ability. They also echo the conclusions of Rahimi et al. (2025), who found that AI-powered tools significantly enhance learners' writing performance. However, contrasting evidence by Fan (2023), who observed mixed learner attitudes toward AWCF, further suggests that learners' responses to AI feedback are context-dependent. The current findings reflect this complexity, revealing both perceived benefits and concerns. One salient theme was learners' enhanced autonomy in self-repair. This theme is consistent with findings from Chacón-Beltrán (2017) and Ko (2024), who reported that automatic feedback fosters learner independence. According to Chacón-Beltrán (2017), ACF enables learners to make self-corrections with greater confidence, which positively affects their writing and speaking performance. This reported level of independence reflects how AI tools seem to act as a supportive framework that helps learners move from relying on external guidance to managing their own performance independently through self-correction.

Similarly, Ko (2024) emphasized that individualized online feedback strengthens learners' problem-solving abilities, supporting greater autonomy in recognizing and rectifying language-related errors. This is also in line with Yang et al. (2024), who found that long-term engagement with AI tools can lead to self-initiated revisions. Another key finding was learners' appreciation of immediacy in AI-generated feedback. This is consistent with Mohammad and Khalid (2025), who found that immediate feedback enhances learners' motivation to revise their writing. According to Rahimi et al. (2025), timely feedback can increase learners' engagement. Similarly, Barrot (2023) emphasizes that synchronous metalinguistic explanations help learners notice and address errors more efficiently. Given that the teacher WCF often comes with a time delay (Ellis, 2009), the real-time nature of AI feedback may offer a significant advantage in maintaining learners' motivation and progress. This immediacy not only supports performance but also sociocultural principles of mediated learning.

Concerning the specificity of AI-generated feedback, the analysis revealed that learners benefited from the tailored language learning experiences offered by Kippy and Pi. These tools allowed students to focus on their specific writing and speaking needs in a personalized and consistent learning journey. This finding supports Lee et al. (2023), who found that AI tools that adapt content based on learners' interests increase engagement and ongoing improvement. Similarly, Mohammad and Khalid (2025) found that feedback specificity increases learners' motivation by offering targeted suggestions, which aligns with the current study. These insights affirm that personalized and real-time AI feedback can enhance learners' motivation, competence, and autonomy. In addition to these benefits, learners also described how AI tools create a reflective "space for learning," a concept emphasized by Walsh and Li (2013) as central to effective classroom interaction. Learners reported that AI-enabled feedback allowed them to process and revise their language output without the immediate social pressure of classroom correction.

However, the study uncovered a limitation of AI feedback, which is its focus on linguistic form rather than contextual meaning. In other words, while AI feedback effectively targets grammatical accuracy, it often fails to convey meaning and context. The participants noted that although AI tools are effective in identifying grammar and structural errors, they often overlook semantic issues. These findings are consistent with those of Shadiev and Feng (2024), who asserted the inability of ACF tools to understand context-dependent meanings or analyze complex sentence structures accurately. Likewise, Bai and Hu (2017) reported that that although AI tools are effective in identifying grammatical mistakes, they have difficulty recognizing errors related to collocations and pragmatic use. Although Ko (2024) suggests that learners' dissatisfaction may not prevent them from understanding the feedback, it can hinder motivation and depth of learning, an issue also raised by Thompson and Lee (2012) and Wihastyanang et al. (2020). While AWCF can be effective for certain linguistic features (Sanosi, 2022), learners may still experience confusion and frustration due to occasional inappropriate responses from AI tools (Kovalyova, 2024; Long, 2024). Therefore, there is a need for complementary instructional support that combines AI feedback with synchronous teacher input to enhance the effectiveness of AI-driven CF (Asadi et al., 2025; Fan et al., 2024; Sanosi, 2022; Sumedi, 2024; Wang, 2024; Zeevy-Solovey, 2024). It emphasizes that while AI tools can assist with structural aspects of language, teacher guidance remains crucial for understanding meaning and context. This suggests that an effective approach involves a combined effort, with both AI and teachers working together to support language learning.

Regarding the learners' preferences for different CF types, the participants in the present study found explicit and direct feedback to be the most helpful, followed by recast and metalinguistic. This preference for explicit correction aligns with the interview findings, where learners emphasized the importance of clarity and immediacy in feedback. The participants appreciated the directness of explicit and direct correction, which enabled them to recognize and correct errors efficiently. This consistency between datasets reflects learners' desire for straightforward feedback. These findings align with Elmotri et al.

(2025), who identified that learners favor explicit WCF from AI, and that direct correction remains important in human-student interaction. This preference also corroborates Ellis et al. (2006), who found that explicit CF supports language learning more effectively than implicit feedback. Aghajanloo et al. (2016) and Roothooft and Breeze (2016) similarly reported the benefits of direct correction across teacher-led contexts. These findings emphasize that learners tend to favor clear, straightforward feedback that enables rapid and effective self-correction.

While learners valued clarity and immediacy, they were less satisfied with indirect and implicit feedback types. Indirect, repetition, clarification request, and elicitation feedback received the lowest ratings. This contradicts findings from Li and He (2017), who emphasized a preference for indirect feedback in teacher-guided instruction. However, the divergence may be explained by the nature of AI feedback, which often lacks sensitivity to context and relies on user interpretation. This reflects Vygotsky's (1978) view that meaningful learning happens when the learner is developmentally prepared for it. Explicit feedback often matches a learner's ZPD more closely, making it easier for them to understand and apply what they receive. In contrast, indirect feedback can sometimes go beyond their current capabilities, which may make it harder for learners to grasp and use effectively.

As Sheen (2007) and Ellis (2009) argue, implicit feedback, such as indirect, repetition, clarification request, and elicitation, which were less preferred by the learners in the study, requires higher levels of metalinguistic awareness and may not fall within learners' ZPD. The learners' preference for clear and straightforward feedback shows the indirect approach may fail since it provides learners with insufficient information to resolve complicated errors (Bitchener & Knoch, 2009). Recast, the second most helpful type of OCF, though implicit, was highly valued by most learners. This aligns with previous research (Llinares & Lyster, 2014; Sheen, 2004), suggesting that the focus on fluency rather than accuracy, along with minimal disruption to communicative flow, contributes to learners' preference for this feedback type. Metalinguistic feedback, despite being favored by some learners, was rated lower than explicit correction and recast. This suggests that while learners value understanding the underlying rules of language, they may prioritize the immediate benefits of direct correction. This aligns with Han and Li's (2024) observation that AI-generated feedback, though informative, can sometimes be perceived as less accessible or too abstract.

Clarification requests and repetition, which received lower ratings, were seen as less effective in facilitating repair. This is consistent with Kovalyova's (2024) findings, which demonstrated that certain AI tools, such as chatbots, may provide frustrating responses, hindering the learning process. It also stresses that the effectiveness of different AI feedback types depends on how well they match learners' needs and align with their ZPD.

In sum, although a big part of the analysis was grounded in the previous literature, this study was one of the first to fill the gap exploring EFL learners' preferences toward the effectiveness of AI-generated CF types in speaking and writing repair practices. By linking these findings to sociocultural theory and empirical research, the study contributes to a growing body of knowledge on the integration of AI into language learning. The process aligns with Vygotsky's view of mediation, illuminating how language learners' development is co-constructed through engagement with tools and social interaction. To optimize the effect of AI in feedback practices, a blended approach that combines the strengths of AI with human mediation appears most promising. Continued investigation into learners' evolving needs and adaptive technologies will be essential in advancing effective AI-supported language education. Nevertheless, an important uncertainty in the present study relates to the distribution of CF types provided by the AI tools. Prior to each session, clearly defined prompts were given to the AI tools to ensure that feedback was delivered in different formats; however, some CF types occurred less frequently due to systemic restrictions in the AI tools. This uneven distribution may have influenced learners' preferences and perceived effectiveness of certain feedback types. Therefore, this uncertainty should be considered when drawing broader conclusions.

Conclusion and implications

In light of the results, this study provided insights into the use of AI tools, namely Kippy and Pi, in facilitating CF. The analysis of learner perspectives suggested that AI-driven feedback promotes autonomy in self-correction, provides immediate support, creates opportunities for focused language learning, and tailors feedback to individual needs. However, the tendency of AI tools to prioritize form over meaning raised concerns about the balance between grammatical accuracy and communicative goals of language learning. Given this understanding, it is essential to integrate AI tools thoughtfully into EFL classrooms, ensuring that they complement, rather than replace, teacher feedback and interactive peer discussions. The findings also emphasized that explicit and direct corrections are the most preferred feedback types due to their clarity and immediacy, while repetition and indirect feedback were rated as the least effective feedback type because they merely echo the error without offering additional cues or explanations, making it less useful for learners who require more structured feedback to facilitate their learning process.

The results of this study suggest several pedagogical implications for EFL instruction. The CF ranking provides insights for AI tool developers to prioritize more explicit CF types when designing or integrating AI feedback systems in EFL contexts. Given learners' strong preferences for explicit correction and recasts as OCF, and direct and metalinguistic feedback as WCF, teachers could consider integrating AI tools that prioritize these feedback types, while also supporting learners in developing the ability to process more implicit forms of feedback. Additionally, the study demonstrates the role of AI in fostering learner autonomy, suggesting that teachers could incorporate AI-assisted practice sessions to supplement classroom instruction. However, as AI feedback is primarily form-focused, educators should provide complementary feedback on meaning, discourse, and pragmatics to ensure holistic language development. Furthermore, training learners to critically evaluate AI-generated feedback can enhance their ability to discern accurate corrections and apply them effectively in authentic communication. Overall, these findings contribute to the broader discourse on AI-assisted language learning, reinforcing the importance of integrating AI tools strategically alongside teacher feedback to ensure a comprehensive learning experience.

The study has several limitations that should be acknowledged. First, the data primarily relied on learners' self-reports, which may be influenced by memory biases. Second, while the study focused on learners' perceptions, it did not measure actual language development or long-term learning outcomes after receiving AI-generated feedback. Additionally, the study examined only two AI tools, Kippy and Pi, which may not represent the variety of technologies currently in use. Therefore, the generalizability of the findings to other AI platforms or EFL contexts may be limited. Another limitation is the limited number of items in the current survey instrument per measured feedback type. While the questionnaire was designed with an emphasis on clarity and brevity to enhance participant engagement, future research may benefit from including a larger number of items to more comprehensively evaluate reliability and validity. Despite efforts to ensure balanced exposure to all CF types, some were observed less frequently during AI-student interactions. This may have influenced learners' preferences and perceptions.

Future studies could explore how different AI-generated CF types affect learners' preferences at various proficiency levels, as individual differences may influence the effectiveness of AI feedback. Another interesting area of research would be to develop an instrument to measure the efficacy of CF types based on both teachers' and learners' perspectives in AI-driven EFL contexts. Additionally, longitudinal research examining the long-term effects of AI-mediated CF on language learning would provide invaluable insights into its impact on learner development. Another promising avenue is investigating how AI tools can be designed to provide more balanced feedback, integrating both accuracy-focused and meaning-oriented corrections. By addressing these areas, future research can contribute to refining AI-driven language learning strategies and optimizing their role in EFL education.

Appendix A

In the version provided to the students, the jargon (i.e., feedback type names) was removed. Instead, the questionnaire was divided into two sections, namely speaking and writing, with explanations and examples provided for each item, which were labeled with numbers.

Survey on the Effectiveness of Corrective Feedback (CF) Types Provided by AI Tools

Introduction:

Dear Participant,

This survey aims to understand your perspectives on the effectiveness of different types of corrective feedback (CF) provided by AI tools during language learning. Please read the definitions of each CF type carefully and rate how helpful you find each type on a scale from 1 (Least Helpful) to 5 (Most Helpful).
Your responses will contribute to research on AI-assisted language learning. Thank you for your time and participation!

Section 1: Background Information

Age: ……

Gender: Female ☐ Male ☐ Prefer not to say ☐

Have you ever used AI tools to improve your English? Yes ☐ No ☐

Section 2: Corrective Feedback (CF) Types and Their Effectiveness

Below are the CF types provided by AI tools. Please read the definitions and rate each type based on how helpful you find it in improving your language skills.

	Corrective Feedback Type	Definition	Effectiveness Rating (1 = Least Helpful, 5 = Most Helpful)
Oral Corrective Feedback (OCF)	Clarification Request	The AI tool signals that there is an issue by asking for clarification, encouraging you to rephrase or correct the sentence. *Example:* **Learner:** "She go to the park." **AI:** "Sorry, I didn't understand. Can you say that again correctly?"	1☐ 2☐ 3☐ 4☐ 5☐
	Elicitation	The AI tool prompts you to self-correct by pausing or repeating part of the sentence with a rising intonation. *Example:* **Learner:** "She go to the park." **AI:** "She...?"	1☐ 2☐ 3☐ 4☐ 5☐
	Explicit Correction	The AI tool directly provides the correct form and explains the mistake. *Example:* **Learner:** "He go to school every day." **AI:** "It should be 'He goes to school every day' because in the present simple tense, we add -s to third-person singular verbs."	1☐ 2☐ 3☐ 4☐ 5☐

	Metalinguistic Feedback	The AI tool provides a comment or question about the error without giving the correct answer. *Example:* **Learner:** "He go to school every day." **AI:** "Remember, in English, we need to use a different verb form for third-person singular. Can you correct it?"	1☐ 2☐ 3☐ 4☐ 5☐
	Recast	The AI tool subtly corrects the error without direct explanation by reformulating your sentence correctly. *Example:* **Learner:** "She go to the park." **AI:** "Oh, she goes to the park? That sounds nice!"	1☐ 2☐ 3☐ 4☐ 5☐
	Repetition	The AI tool repeats the incorrect part of the sentence, often with a questioning tone to highlight the error. *Example:* **Learner:** "He go to school every day." **AI:** "He go?"	1☐ 2☐ 3☐ 4☐ 5☐
Written Corrective Feedback (WCF)	Direct	The AI tool provides the correct form of the error explicitly in your written output. *Example:* **Learner:** "She go to school every day." **AI:** "It should be "She goes to school every day."	1☐ 2☐ 3☐ 4☐ 5☐
	Indirect	The AI tool indicates that an error exists without providing the correct form, often through underlining, highlighting, or brief comments. *Example:* **Learner:** "He walk to work every day." **AI:** "There seems to be a verb tense issue here: "walk.""	1☐ 2☐ 3☐ 4☐ 5☐
	Metalinguistic	The AI tool gives a brief explanation of the grammatical rule related to the error without correcting it directly. *Example:* **Learner:** "They was happy with the result." **AI:** "Subject-verb agreement: "They" needs a plural verb."	1☐ 2☐ 3☐ 4☐ 5☐

Section 3: Additional Feedback

Which type of OCF and WCF do you find most effective? Why?

……………………………………………………………………………………………………..

Which type of OCF and WCF do you find least effective? Why?

……………………………………………………………………………………………………..

End of Survey

Thank you for your participation! Your responses will help improve AI-based corrective feedback in language learning.

Appendix B

Interview Questions:

1. Please tell me about your experience using Pi and Kippy in class.
2. What did you enjoy most or least about working with these two AI tools?
3. Did you find them helpful in practicing speaking or writing?
4. Is there anything else you would like to share about your experience using AI tools in your English learning process?

Appendix C

Sample Lesson Plan: AI-Driven EFL Class Using Pi and Kippy

Level	B1 (Intermediate)
Duration	90 minutes
Materials & Tools	Smart phones for accessing Pi and Kippy Prompts for tasks (uploaded to AI tools beforehand). A whiteboard or digital screen for collaborative activities.
Topic	How to plan my vacation
Objective	Students will improve their speaking and writing skills by using Pi and Kippy to engage in both individualized and group tasks.
Introduction (10 minutes)	a) Icebreaker Activity: Teacher asks students to share one fun fact about their weekend using simple English. AI Integration: Pi listens to their responses and provides real-time pronunciation tips. b) Objective Explanation: The teacher explains that students will use Pi and Kippy to practice their language skills through both individualized and group activities.
Individualized Tasks (30 minutes)	a) Writing Task with Pi (15 minutes): Students write a short story about their favorite hobby that they want to do on an upcoming vacation. Pi provides immediate feedback on grammar, spelling, vocabulary, and sentence structure. Students revise their writing based on Pi's suggestions. b) Listening & Speaking Practice with Pi & Kippy (15 minutes): Pi reads a paragraph about planning a vacation (e.g., a short story or news excerpt). Students are supposed to talk to Pi about the provided story, using present progressive and simple future tenses. Students practice retelling the story to Kippy, which provides feedback on pronunciation and accuracy.
Group Tasks (40 minutes)	a) Reading and Discussion Activity with Pi (20 minutes): Students are divided into small groups. Each group reads a short paragraph suggested by Pi, tailored to their interests. Groups discuss the main points, using Pi to clarify unfamiliar vocabulary and phrases. One student from each group summarizes the discussion to the class. b) Role-Playing Activity with Pi & Kippy (20 minutes): Students role-play real-life scenarios (e.g., booking a tour or activity on vacation) Pi acts as a virtual partner, while Kippy provides hints for correct language use. Groups perform their scenarios for the class, receiving feedback from Kippy on accuracy and fluency.
Wrap-Up (10 minutes)	a) Class Discussion (5 minutes): Students share one thing they learned or found challenging. b) Feedback (5 minutes): The teacher provides additional guidance based on the feedback provided by AI tools.

Abbreviations

ACF: Automated Corrective Feedback; ACMC: Asynchronous Computer-Mediated Communication; AES: Automated Essay Scoring; AI: Artificial Intelligence; AWCF: Automated Written Corrective Feedback; CEFR: Common European Framework of Reference; CF: Corrective Feedback; EFL: English as a Foreign Language; NLP: Natural Language Processing; OCF: Oral Corrective Feedback; QOPT: Quick Oxford Placement Test; SECF: Speech-Enabled Corrective Feedback; WCF: Written Corrective Feedback.

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Author's contributions

All authors have materially participated in the research and paper preparation. Additionally, all authors have approved the final manuscript.

Author's information

Masoomeh Estaji is a professor and faculty member in Applied Linguistic at Allamch Tabataba'i University (ATU) in Tehran, Iran. Her research activities have been recognized with several awards, including the Exemplary University Researcher at ATU in 2025 and the national Top Researcher Award in the Humanities in 2024. She has also received the Top Researcher Award at ATU in 2018, 2020, 2022, and 2024. Her research interests are in language testing and educational assessment, ESP, and teacher education. She has presented and published numerous papers on methodology, language testing, and second language acquisition (SLA) in various national and international journals, including Teaching and Teacher Education, International Journal of Testing, Language Assessment Quarterly, Educational Assessment, Language Learning in Higher Education, Reading Psychology, The Asian ESP, Asia TEFL, Educational Technology & Society, and Classroom Interaction.

Yara Mirfendereski is a PhD candidate in Applied Linguistics at the Department of English Language and Literature, Allameh Tabataba'i University, Tehran, Iran. She is also an English Language Teacher at the Ministry of Education. Her research focuses on discourse analysis, second language (L2) pragmatics, and technology-mediated language learning. She aims to enhance the understanding of how language functions in various communicative contexts and to improve language learning methodologies through the integration of technology.

Klara Skogmyr Marian is an associate professor of Bilingualism with a specialization in social dimensions of multilingualism and second language learning. Her main research interest is in the interface between second language learning and social interaction.

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Author details

Masoomeh Estaji: Professor of Applied Linguistics, Department of English Language and Literature, Faculty of Persian Literature and Foreign Languages, Allameh Tabataba'i University, Tehran, Iran. Email: estaji@atu.ac.ir / mestaji74@gmail.com

Yara Mirfendereski: PhD Candidate in Applied Linguistics, Department of English Language and Literature, Faculty of Persian Literature and Foreign Languages, Allameh Tabataba'i University, Tehran, Iran. Email: yara.mirfendereski@su.se / yara_mirfendereski@atu.ac.ir

Klara Skogmyr Marian: Associate Professor of Bilingualism, Center for Research on Bilingualism, Department of Swedish Language and Multilingualism, Faculty of Humanities, Stockholm University, Stockholm, Sweden. Email: klara.skogmyr-marian@su.se

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