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The Effect of AI-Supported Microlearning on the Development of Language Skills

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A B S T R A C T

Purpose: The present study aimed to investigate whether AI-supported microlearning significantly improves listening, speaking, reading, and writing skills of intermediate EFL learners compared with conventional language instruction.
Methods and Materials: This study employed a quasi-experimental research design with pre-test and post-test measures. Sixty intermediate Iranian EFL learners enrolled in a private language institute were selected through convenience and purposive sampling and randomly assigned to an experimental group (n = 30) and a control group (n = 30). Both groups followed the same Touchstone 3 curriculum for eight weeks; however, the experimental group received AI-supported microlearning activities in addition to regular instruction, while the control group received traditional instruction only. AI-supported microlearning consisted of short, adaptive digital learning units including listening exercises, pronunciation practice, vocabulary repetition, reading comprehension tasks, micro-speaking activities, and AI-based feedback mechanisms accessible via mobile and computer devices. Standardized pre- and post-tests assessing listening, speaking, reading, and writing skills were administered under controlled conditions. Data were analyzed using descriptive statistics, independent-samples t-tests, normality tests, and effect size calculations to determine the statistical and practical significance of learning gains.
Findings: Inferential analyses revealed no statistically significant differences between the experimental and control groups at the pre-test stage, confirming baseline equivalence across all four language skills. Post-test comparisons demonstrated statistically significant differences favoring the experimental group in listening ($p < .05$), speaking ($p < .01$), reading ($p < .05$), and writing ($p < .01$). Effect size estimates indicated moderate to large practical impacts of AI-supported microlearning across skills, with particularly strong effects observed in speaking and writing performance. These findings indicate that integrating artificial intelligence with microlearning significantly enhances overall language skill development beyond conventional instruction.
Conclusion: The results demonstrate that AI-supported microlearning constitutes an effective, learner-centered instructional approach capable of improving receptive and productive language skills simultaneously.
Keywords: *AI-supported microlearning, language skill development, EFL learners, listening, speaking, reading, writing, instructional technology, adaptive learning*

1. Introduction

The rapid transformation of educational environments driven by digital technologies has fundamentally reshaped teaching practices, learner engagement, and instructional design worldwide. Advances in information and communication technologies have enabled education systems to move beyond traditional teacher-centered models toward flexible, learner-centered environments characterized by accessibility, personalization, and continuous interaction (Adelsberger et al., 2008; Hawkridge, 2022; Lu, 2018). Contemporary educational paradigms increasingly emphasize adaptive learning ecosystems where technological innovation functions not merely as a supplementary tool but as a central component of pedagogical strategy. Within this context, artificial intelligence (AI) and microlearning have emerged as two of the most influential developments redefining modern language education.

Microlearning has gained substantial attention as an instructional approach that delivers content in short, focused, and manageable learning units designed to match learners' cognitive capacities and contemporary digital habits (Alias & Razak, 2025; Boumalek et al., 2025). Unlike traditional long-format instruction, microlearning structures knowledge into concise learning episodes that facilitate rapid comprehension, sustained attention, and flexible access through mobile and online platforms. Research indicates that the growing popularity of microlearning reflects broader changes in learner behavior, particularly the preference for on-demand, just-in-time learning experiences compatible with modern technological lifestyles (Lee, 2023; Leong et al., 2021). Systematic reviews further confirm that microlearning improves knowledge retention, learner motivation, and engagement by enabling distributed practice and frequent exposure to learning materials (Monib et al., 2025; Taylor & Hung, 2022).

The theoretical foundation of microlearning is closely connected to cognitive learning theories, especially cognitive load theory and multimedia learning principles. Cognitive load theory posits that learning becomes more effective when instructional materials reduce unnecessary mental processing and present information in optimally segmented forms (Sweller, 1988). Similarly, multimedia learning theory emphasizes segmentation and modality principles that allow learners to process information gradually rather than simultaneously, thereby enhancing understanding and long-term retention (Mayer, 2005). Microlearning operationalizes these principles by breaking complex knowledge into small units, enabling learners to focus on essential processing without experiencing cognitive overload. Consequently, microlearning aligns well with contemporary views of efficient digital pedagogy.

Empirical studies increasingly demonstrate that microlearning contributes positively to educational outcomes across various disciplines. Research has shown that microlearning environments enhance learning performance, motivation, and engagement when compared with conventional instructional approaches (Fidan, 2023; Sirwan Mohammed et al., 2018). In language education, microlearning supports incremental acquisition of linguistic skills through repetitive exposure, interactive activities, and mobile accessibility (Ghafar et al., 2023). Instructional designs grounded in microlearning have been successfully applied to reading development, critical thinking integration, and learner autonomy enhancement, particularly in English language learning contexts (Cahyanto et al., 2024; Sumarni & Salsabila, 2023). Furthermore, technology-supported microlearning applications demonstrate positive effects on learner motivation and usability experiences, highlighting their pedagogical practicality (Robles et al., 2023).

Despite these advantages, microlearning alone cannot fully address individual differences among learners, such as varying learning speeds, preferences, and proficiency levels. This limitation has led researchers to explore artificial intelligence as a complementary innovation capable of delivering personalized learning experiences. Artificial intelligence has rapidly evolved into a transformative force within education, enabling adaptive feedback, automated assessment, and individualized instructional pathways (Jafari & Yazdi, 2024; Kaswan et al., 2024). AI-based systems analyze learner behavior and performance data in real time, allowing instruction to adjust dynamically to learner needs—an instructional capability largely unattainable in traditional classroom settings.

Within foreign language education, AI has significantly expanded the possibilities of computer-assisted language learning. Intelligent systems incorporating natural language processing, speech recognition, and generative AI technologies support speaking practice, pronunciation correction, listening comprehension, and writing development (Kuddus, 2022; Schmidt & Strasser, 2022). Systematic reviews reveal that AI-enhanced language learning environments improve learner autonomy, motivation, and self-regulated learning behaviors through immediate and personalized feedback mechanisms (Peña-

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Acuña & Corga Fernandes Durão, 2024). Studies further demonstrate that AI-driven learning interventions strengthen speaking skills and self-regulation by providing continuous adaptive interaction between learner and system (Qiao & Zhao, 2023).

Recent research highlights the growing role of generative AI in enhancing learners' confidence and self-efficacy within mobile language applications. For example, learners exposed to AI-supported environments show significant improvement in perceived competence and engagement during language learning activities (Kittredge et al., 2025). These findings suggest that AI not only enhances cognitive outcomes but also positively influences affective dimensions of learning, which are critical in second language acquisition.

The integration of AI into instructional design has consequently stimulated interest in combining artificial intelligence with microlearning methodologies. AI-supported microlearning represents a pedagogical model that merges microlearning's cognitive efficiency with AI's adaptive intelligence, producing a highly personalized learning environment. Generative AI can automatically create micro-content, recommend learning sequences, and provide real-time feedback tailored to learner performance (Boumalek et al., 2024; Hosler, 2025). Such integration enables a dynamic learning ecosystem in which instructional materials continuously evolve based on learner interaction patterns.

Emerging empirical evidence supports the effectiveness of this combined approach. Studies on AI-enhanced microlearning demonstrate improvements in motivation, higher-order thinking skills, and learner engagement when AI chatbots and adaptive systems are embedded into microlearning environments (Silitonga et al., 2024). Similarly, qualitative investigations of AI-supported microlearning modules reveal enhanced self-regulated learning and professional competence development among learners and teachers (Kohnke et al., 2025). Flexible teacher development programs increasingly adopt microlearning as a standard approach in online and blended education, reinforcing its growing institutional acceptance (Kohnke et al., 2024).

In language education specifically, AI-supported microlearning has shown promising results across different linguistic domains. AI-assisted microlearning media significantly improve grammatical understanding and learner motivation in foreign language instruction (Noverisa et al., 2025). Microlearning interventions have also been found to enhance writing ability through repeated practice and immediate feedback cycles that promote continuous improvement (Fauziah et al., 2023). Meta-analytic evidence indicates strong positive effects of microlearning on speaking proficiency among EFL learners, confirming its relevance for communicative skill development (Prasittichok & Smithsarakarn, 2024). Additionally, ecosystem-based microlearning environments integrating mobile and digital tools successfully improve listening and speaking competencies in higher education contexts (Amakhina et al., 2023).

Learner perceptions research further demonstrates that students view microlearning as accessible, motivating, and effective for improving learning outcomes, particularly when supported by technological innovation (Monib et al., 2024). The increasing convergence of AI and microlearning therefore represents a logical evolution in digital pedagogy, addressing both cognitive and personalization requirements simultaneously.

From a broader pedagogical perspective, the evolution toward AI-supported microlearning aligns with ongoing educational transformations emphasizing flexibility, lifelong learning, and digital competence development. The shift toward modular learning structures reflects the need for scalable instructional models capable of supporting diverse learner populations in rapidly changing knowledge economies (Alias & Razak, 2025). Furthermore, educational research increasingly stresses the importance of integrating innovative technologies responsibly through evidence-based instructional design and rigorous research methodologies (Creswell & Creswell, 2017; Fatehi Rad et al., 2025).

Although the independent effects of microlearning and artificial intelligence have been widely investigated, significant gaps remain in the literature. Many existing studies focus on isolated language components such as vocabulary acquisition or grammar learning rather than examining integrated language skill development. Moreover, empirical quasi-experimental studies evaluating the combined impact of AI-supported microlearning on listening, speaking, reading, and writing simultaneously remain limited. Scholars have therefore called for comprehensive empirical investigations that examine how AI-supported microlearning influences holistic language proficiency development across multiple skills and learning contexts (Kohnke et al., 2025; Monib et al., 2025).

Another important gap concerns intermediate EFL learners, a population representing a critical transitional stage between basic language competence and advanced communicative proficiency. While technological interventions have been explored among beginners or teacher trainees, fewer studies have examined controlled instructional interventions targeting intermediate learners in authentic educational settings. Understanding how AI-supported microlearning functions within this proficiency level is essential for validating its pedagogical applicability and scalability.

Consequently, integrating artificial intelligence with microlearning offers a theoretically grounded and pedagogically promising approach capable of addressing cognitive efficiency, learner personalization, engagement, and adaptive feedback simultaneously. By combining segmented instructional delivery with intelligent adaptive systems, AI-supported microlearning may function as a dual-scaffolding instructional model that enhances both cognitive processing and individualized learning pathways.

Therefore, the present study aims to investigate the effect of AI-supported microlearning on the development of listening, speaking, reading, and writing skills among intermediate EFL learners.

2. Methods and Materials

2.1. Study Design and Participants

A quasi-experimental design was employed in this current study. This design was employed due to the fact that it allows cause-and-effect relationships among instruction interventions and learning gains to be explored in real learning contexts where random assignment may be impractical (Creswell & Creswell, 2017; Fatehi Rad et al., 2025). The intervention compared two groups' performance, an experimental group that was exposed to AI-supported microlearning instruction and a control group that was exposed to regular instruction over an eight week instructional time frame.

Participants of the current research comprised 60 Iranian EFL learners enrolled in a private language school in Kerman, Iran. A combination of convenience sampling and purposive sampling was used to enlist participants. Convenience sampling was initially used to select easily accessible learners from the institute's available classes. Later, purposive sampling made sure that participants shared certain inclusion criteria, i.e., being at a comparable level of proficiency, in the same institute, and having completed the same level of course in the Touchstone series. Participants were 20- to 26-year-old male and female adult learners, a relatively homogeneous age group typical of young adult Iranian EFL learners. They were all intermediate (B1 level) on the Common European Framework of Reference for Languages (CEFR) and had completed Touchstone Level 2 and were ready to start Touchstone Level 3 at the time the study was conducted. Their homogeneous level of competence was also verified through a placement test, applied by the institute, with the purpose of ensuring comparability at the baseline level prior to the experimental intervention. The two intact classes were randomly assigned to one experimental group (n = 30) and a control group (n = 30).

2.2. Instruments and Materials

To gauge learners' performance in the four language skills, a set of standardised tests and courses from the Touchstone 3 second edition series, complemented with some extra AI-supported microlearning materials, were utilized. The Touchstone series published by Cambridge University Press formed the bulk of the course and assessment model. This series was mainly selected due to its use in the institute.

The research employed, for pre- and post-testing, an achievement test created by the authors of the Touchstone book itself, which is specifically designed to assess listening, speaking, reading, and writing capacity at the level of Touchstone 3. Validity and reliability of the test had already been established by the authors. The researcher also ensured the test's reliability and validity in the context of the study so that it could accurately and consistently measure learners' performance in the targeted skills. All the tests were administered in controlled conditions to the experimental and to the control group in order to ensure fairness and comparability.

The treatment group learned with the incorporation of AI-supported microlearning content, which presented bite-sized, focused digital learning segments. The microlearning modules were interactive exercises, listening clips, pronunciation practice, and short communicative activities, which aligned with the Touchstone lessons. The AI-enabled materials gave adaptive feedback to enable individualized learning and increased engagement. On the other hand, the control group was instructed with the regular Touchstone 3 curriculum without any AI-based supplements through classroom instruction only, textbook practice, and home assignments. In maintaining the same core curriculum for both groups, the study could attribute differences in

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performance noted later to the AI-supported microlearning intervention.

2.3. Data Collection and Analysis Procedures

The data collection procedure entailed three steps: pre-testing, intervention, and post-testing conducted within an eight-week period of teaching at a private language institute in Kerman, Iran. Initially, official consent was sought from the institute administration and participants. Participants had full knowledge of the research purposes and confidentiality measures. Entry was voluntary, and students were informed that attending or not attending would not influence their academic assessment. A total of 60 Iranian male and female EFL students aged 20–26 were sampled using a combination of convenience and purposive sampling. All the participants were intermediate students (B1 level according to CEFR), had completed Touchstone 2, and were supposed to start Touchstone 3.

Pre-test was administered to both groups before intervention in order to assess the baseline listening, speaking, reading, and writing skills. Pre-test items were adopted from the Touchstone teacher's guidebook (Cambridge University Press) keeping in view content validity and reliability. Reading and listening sections contained comprehension exercises from short dialogues and passages. Writing exercises required students to write brief paragraphs about universal topics, and speaking exercises were short interviews that tested fluency, accuracy, and pronunciation. The pre-test scores were used in establishing initial proficiency and testing group equivalence prior to treatment.

The intact classes were then assigned to an experimental group and a control group. Both groups received normal instruction based on the Touchstone 3 syllabus for eight weeks from the same experienced teachers in order to ensure consistency. The experimental group was instructed with AI-supported microlearning rather than traditional instruction, which comprised a series of interactive digital exercises designed to reinforce class learning. These activities included (1) AI-based vocabulary practice: learners practiced the target vocabulary through spaced repetition exercises with automated feedback, (2) Listening comprehension exercise: short audio passages with questions, allowing learners to receive automated feedback on right and wrong answers, (3) Pronunciation correction exercise: learners read out a word or sentence and the AI system provided immediate corrective feedback on stress and intonation, (4) Micro-speaking exercise: short, structured speaking exercises (e.g., describing a picture or answering a question) with AI feedback to practice fluency and accuracy, (5), Practice in grammar and sentence structure: learners completed short exercises on the targeted area of grammar practiced in class, with AI providing hints and feedback, (6) Reading comprehension exercise: learners read short online passages and responded to comprehension or vocabulary questions, receiving instant AI feedback, (7) Adaptive learning and tracking of progress: the system graded the difficulty of exercises and recommended further practice in areas where they were weaker, and (8) Computer and mobile accessibility: all AI-supported microlearning exercises were practiced outside class time so that the learners could practice flexibly and at their convenience.

The control group utilized the same Touchstone 3 curriculum but without microlearning and AI help. They also were taught in the classroom, did textbook exercises, and assigned regular homework, so differences in outcome may have been due to the AI-supported microlearning intervention. At the end of the eight weeks, a post-test as difficult and similar in format to the pre-test was administered under normal conditions to both the groups to evaluate their performance on all four language skills.

All quantitative data from post-tests and pre-tests were coded and examined in the Statistical Package for the Social Sciences (SPSS) version 26. Prior to carrying out the main analyses, the data were scanned for accuracy and suitability for parametric testing. Descriptive statistics of means, standard deviations were computed on each of the pre-test and post-test scores to track the distribution of the data and identify any potential outliers. Normality was also ascertained by using the Kolmogorov–Smirnov and Shapiro–Wilk tests. It was ascertained that all variables came close to normal distribution, satisfying the assumptions of the parametric analysis.

Independent-samples t-tests were run to compare post-test scores for the experimental group and the control group on each of the four language skills to test for the impact of AI-supported microlearning. Furthermore, effect sizes (Cohen's d) were also calculated for each skill to quantify the size of the differences achieved and provide information on the practical significance of the findings.

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3. Findings and Results

RQ1: Does AI-Supported Microlearning Significantly Enhance EFL Learners' Listening Skill?

The first research question of this study was whether microlearning enhanced by AI enhanced the listening skill of EFL learners more than the traditional way. Normality assumption was checked prior to conducting the significant inferential tests to confirm whether parametric tests would be applicable. For analyzing whether there was normal distribution of each group's listening score, Kolmogorov–Smirnov and Shapiro–Wilk tests were used. Table 1 shows the results of normality tests of experimental and control groups' pre- and post-test listening scores. Pre-test scores of the groups according to Kolmogorov–Smirnov and Shapiro–Wilk tests were normally distributed ($p > .05$). Normality for post-test was achieved in the control group ($p > .05$), whereas the experimental group showed a marginal deviation from normality in the Kolmogorov–Smirnov test ($p = .008$) but not the Shapiro–Wilk test ($p = .066$), which suggested around normality. Overall, data were appropriate for assumptions of parametric analysis, and independent-samples t-tests could be utilized in order to compare listening performance between groups.

Table 1

Tests of Normality for Listening Pre-test and Post-test Scores across Control and Experimental Groups

	Group	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Listening_Pre	Control	.140	30	.141	.964	30	.382
	Experimental	.107	30	.200*	.959	30	.289
Listening_Post	Control	.108	30	.200*	.961	30	.333
	Experimental	.189	30	.008	.935	30	.066

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Pre-test listening scores were nearly the same in groups: Control ($M = 11.667$, $SD = 2.808$) and Experimental ($M = 11.700$, $SD = 2.020$). This indicates similar baseline performance before intervention.

Table 2

Descriptive Statistics for Listening Pre-test Scores across Control and Experimental Groups

	Group	N	Mean	Std. Deviation	Std. Error Mean
Listening_Pre	Control	30	11.667	2.8080	.5127
	Experimental	30	11.700	2.0197	.3688

As disclosed from Table 3, pre-test t-test of scores indicated no group difference ($t(58) = -0.053$, $p = .958$), which identifies baseline equivalence. Levene's test assumptions ($p = .168$) and the t-test were fulfilled.

Table 3

Independent Samples t-test Results for Listening Pre-test Scores across Control and Experimental Groups

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Listening_Pre	EVA	1.950	.168	-.053	58	.958	-.0333	.6315	-1.2974	1.2308
	EVNA			-.053	52.67	.958	-.0333	.6315	-1.3002	1.2335

As is evident in Table 4, effect sizes for pre-test were small (Cohen's $d = -0.014$, Hedges' $g = -0.013$, Glass's delta $= -0.017$), once again confirming that the two groups were equivalent before intervention.

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Table 4

Effect Size Estimates for Listening Pre-test Scores

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Listening_Pre	Cohen's d	2.4459	-.014	-.520	.492
	Hedges' correction	2.4781	-.013	-.513	.486
	Glass's delta	2.0197	-.017	-.522	.490

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

Both the groups improved more at post-test: Control (M = 13.900, SD = 3.782) and Experimental (M = 15.900, SD = 2.975). The experimental group showed improvement in listening performance after intervention.

Table 5

Descriptive Statistics for Listening Post-test Scores across Control and Experimental Groups

	Group	N	Mean	Std. Deviation	Std. Error Mean
Listening_Post	Control	30	13.900	3.7815	.6904
	Experimental	30	15.900	2.9752	.5432

T-test determined a difference in listening following the post-test between the groups (t(58) = -2.277, p = .027) in the favor of the experimental group. Levene's test (p = .180) verified equality of variances and corroborated the usage of the standard t-test.

Table 6

Independent Samples t-test Results for Listening Post-test Scores across Control and Experimental Groups

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Listening_Post	EVA	1.840	.180	-2.277	58	.027	-2.0000	.8785	-3.7585	-.2415
	EVNA			-2.277	54.957	.027	-2.0000	.8785	-3.7605	-.2395

Post-test effect sizes indicated a large to moderate practical effect of AI-supported microlearning on listening performance. In other words, Cohen's d was -0.588, Hedges' g was -0.580, and Glass's delta was -0.672. The values indicate not only that the improvement in listening of the experimental group was statistically significant but also educationally significant, thereby sustaining the effectiveness of the AI-supported microlearning intervention.

Table 7

Effect Size Estimates for Listening Post-test Scores

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Listening_Post	Cohen's d	3.4023	-.588	-1.103	-.068
	Hedges' correction	3.4471	-.580	-1.088	-.067

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Glass's delta	2.9752	-.672	-1.202	-.132

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

The pre- and post-test listening scores of both groups presented in Tables 1–7 clearly establish the intervention's effect. The results confirm that while gain in listening might be possible via the traditional instruction augmented with AI-supported microlearning to a limited degree, it significantly enhances the learners' listening capacity with both statistical as well as educationally significant gains.

RQ2: Does AI-Supported Microlearning Significantly Enhance EFL Learners' Speaking Skill?

The second research question was if microlearning with AI boosted the ability of EFL learners in speaking more than traditional instruction. Before carrying out the main statistical tests, the normality of pre-test and post-test speaking scores was calculated. Table 8 displays results of normality tests for pre- and post-test speaking scores. The pre-test scores of both the control (Kolmogorov–Smirnov: p = .195; Shapiro–Wilk: p = .179) and experimental (Kolmogorov–Smirnov: p = .157; Shapiro–Wilk: p = .109) groups were normally distributed. Experimental group post-test scores proved to be normal (Kolmogorov–Smirnov: p = .200; Shapiro–Wilk: p = .424), whereas the control group did deviate on the Shapiro–Wilk test (p = .002). Thus, the results indicate that the data were nearly normally distributed, with the justification for applying parametric tests in subsequent analysis.

Table 8

Tests of Normality for Speaking Pre-test and Post-test Scores across Control and Experimental Groups

	Group	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Speaking_Pre	Control	.132	30	.195	.951	30	.179
	Experimental	.137	30	.157	.943	30	.109
Speaking_Post	Control	.157	30	.057	.874	30	.002
	Experimental	.110	30	.200*	.965	30	.424

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Table 9 shows that pre-test speaking scores were similar for groups, with the control group mean being 11.500 (SD = 2.991) and the experimental group mean being 12.767 (SD = 2.515). The experimental group mean was slightly higher, but this difference was not statistically found to be significant, meaning that the groups were quite comparable at the baseline.

Table 9

Descriptive Statistics for Speaking Pre-test Scores across Control and Experimental Groups

	Group	N	Mean	Std. Deviation	Std. Error Mean
Speaking_Pre	Control	30	11.500	2.9914	.5461
	Experimental	30	12.767	2.5146	.4591

Independent-samples t-test on pre-test scores also showed that there was no difference between groups (t(58) = -1.775, p = .081). The assumption of equality of variances was confirmed by Levene's test of equality of variances (F = 2.191, p = .144). This proves that the two groups were equal in speaking level prior to the intervention.

Table 10

Independent Samples t-test Results for Speaking Pre-test Scores across Control and Experimental Groups

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		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Speaking_Pre	EVA	2.191	.144	-1.775	58	.081	-1.2667	.7135	-2.6948	.1615
	EVNA			-1.775	56.33	.081	-1.2667	.7135	-2.6957	.1624

Pre-test effect sizes were negligible and negative (Cohen's d = -0.458; Hedges' g = -0.452; Glass's delta = -0.504), with no practical between-group difference in speaking ability before the intervention.

Table 11

Effect Size Estimates for Speaking Pre-test Scores

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Speaking_Pre	Cohen's d	2.7633	-.458	-.969	.056
	Hedges' correction	2.7997	-.452	-.957	.056
	Glass's delta	2.5146	-.504	-1.022	.023

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

Table 12 shows that post-test speaking scores were better in both groups but with the experimental group having a higher mean (M = 16.267, SD = 3.129) than the control group (M = 13.333, SD = 3.642). This shows that normal instruction and AI-supported microlearning improved speaking but more significantly by the experimental group.

Table 12

Descriptive Statistics for Speaking Post-test Scores across Control and Experimental Groups

	Group	N	Mean	Std. Deviation	Std. Error Mean
Speaking_Post	Control	30	13.333	3.6420	.6649
	Experimental	30	16.267	3.1287	.5712

Post-test marks t-test (Table 13) revealed that there was a significant difference between groups (t(58) = -3.346, p = .001) in favor of the experimental group. Levene's test also provided for equal variances (F = 0.136, p = .713). This indicates AI-supported microlearning intervention improved learning of speaking skills significantly over non-AI microlearning and traditional instruction.

Table 13

Independent Samples t-test Results for Speaking Post-test Scores across Control and Experimental Groups

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Speaking_Post	EVA	.136	.713	-3.346	58	.001	-2.9333	.8766	-4.6880	-1.1786
	EVNA			-3.346	56.711	.001	-2.9333	.8766	-4.6889	-1.1778

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Post-test effect sizes also showed a large to medium practical effect size: Cohen's d = -0.864, Hedges' g = -0.854, and Glass's delta = -0.938. All of these are positive values, showing that not only were the observed gains of the experimental group statistically significant but educationally significant as well, that is, AI-supported microlearning works in enhancing speaking performance.

Table 14

Effect Size Estimates for Speaking Post-test Scores

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Speaking_Post	Cohen's d	3.3951	-.864	-1.390	-.331
	Hedges' correction	3.4398	-.853	-1.372	-.326
	Glass's delta	3.1287	-.938	-1.491	-.371

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

Pre-test comparisons between the seven tables determine that experimental and control groups were equal prior to pre-test, with no statistical differences in speaking scores and a very small effect size. Both groups made gains due to the intervention of eight weeks, with the experimental group scoring significantly higher on post-test. The findings of the t-tests and the effect sizes determine that gains made through AI-supported microlearning were statistically significant and practically significant. Hence, AI-supported microlearning significantly enhanced the speaking competence of EFL learners compared to conventional instruction.

RQ3: Does AI-Supported Microlearning Significantly Enhance EFL Learners' Reading Skill Compared To Non-AI Microlearning And Traditional Instruction?

The third research question investigated if AI-supported microlearning has an appreciable effect on the reading competence of EFL learners compared to conventional instruction. Prior to conducting the main analyses, the normality of reading pre-test and post-test scores was determined by the administration of the Kolmogorov–Smirnov and Shapiro–Wilk tests (see Table 15). The pre-test reading score of the experimental group (p = .348 and .200) as well as the control group (p = .914 and .200) was normally distributed, according to the study. In post-test scores, normality was typically ensured with the exception that the control group was found to have a slight deviation for the Kolmogorov–Smirnov test (p = .012). Findings confirmed that data were comparable to assumptions needed in conducting parametric tests.

Table 15

Tests of Normality for Reading Pre-test and Post-test Scores across Control and Experimental Groups

	Group	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Reading_Pre	Control	.120	30	.200*	.962	30	.348
	Experimental	.097	30	.200*	.984	30	.914
Reading_Post	Control	.182	30	.012	.961	30	.326
	Experimental	.135	30	.169	.960	30	.311

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

Table 16 shows that pre-test reading scores were similar across groups: Control (M = 12.000, SD = 3.280) and Experimental (M = 12.600, SD = 2.500). The mean of the experimental group was a bit higher, but the difference was not significant, which indicated baseline comparability.

Table 16

Descriptive Statistics for Reading Pre-test Scores across Control and Experimental Groups

	Group	N	Mean	Std. Deviation	Std. Error Mean
Reading_Pre	Control	30	12.000	3.2800	.5988
	Experimental	30	12.600	2.4997	.4564

Independent-samples t-test (Table 17) also concurred that there was no group difference at pre-test (t(58) = -0.797, p = .429). Levene's test for homogeneity of variances (F = 2.035, p = .159) concurred that the variance was homogeneous. Hence, the groups were starting at equal levels of reading ability.

Table 17

Independent Samples t-test Results for Reading Pre-test Scores across Control and Experimental Groups

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Reading_Pre	EVA	2.035	.159	-.797	58	.429	-.6000	.7529	-2.1071	.9071
	EVNA			-.797	54.189	.429	-.6000	.7529	-2.1094	.9094

Effect sizes, as presented in Table 18, were small and negative (Cohen's d = -0.206, Hedges' g = -0.203, Glass's delta = -0.240) which depicted no differences of practical importance in reading skill prior to the intervention.

Table 18

Effect Size Estimates for Reading Pre-test Scores

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Reading_Pre	Cohen's d	2.9161	-.206	-.712	.303
	Hedges' correction	2.9545	-.203	-.703	.299
	Glass's delta	2.4997	-.240	-.748	.272

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

As can be seen in Table 19, both groups' post-test scores were improved: Control (M = 14.633, SD = 2.400) and Experimental (M = 15.833, SD = 2.119). There was greater reading performance gain by the experimental group, that is, there was some impact from both instructional methods but AI-supported microlearning produced bigger gains.

Table 19

Descriptive Statistics for Listening Post-test Scores across Control and Experimental Groups

	Group	N	Mean	Std. Deviation	Std. Error Mean
Reading_Post	Control	30	14.633	2.3995	.4381
	Experimental	30	15.833	2.1186	.3868

The t-test (Table 20) revealed a significant post-test reading score advantage (t(58) = -2.053, p = .045) for the experimental group. Equal variances were assumed by Levene's test (F = 1.312, p = .257). This suggests that AI-supported microlearning effectively enhanced reading performance compared to non-AI instruction.

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Table 20

Independent Samples t-test Results for Reading Post-test Scores across Control and Experimental Groups

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Reading_Post	EVA	1.312	.257	-2.053	58	.045	-1.2000	.5844	-2.3698	-.0302
	EVNA			-2.053	57.124	.045	-1.2000	.5844	-2.3702	-.0298

As suggested by Table 21, the effect sizes were also practically significant: Cohen's d = -0.530, Hedges' g = -0.523, and Glass's delta = -0.566. The readings suggest not merely that the changes that had been achieved by the experimental group were significant statistically but also significant in educational practice.

Table 21

Effect Size Estimates for Reading Post-test Scores

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Reading_Post	Cohen's d	2.2634	-.530	-1.043	-.013
	Hedges' correction	2.2932	-.523	-1.030	-.013
	Glass's delta	2.1186	-.566	-1.088	-.035

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

Analyses confirm that the pre-test experimental and control groups were similar, with no statistically significant differences between them, and extremely small effect sizes. Both groups learned after the eight-week instruction, but with significantly higher post-test scores in reading, as confirmed by t-test outcomes as well as moderate-to-large effect sizes. AI-supported microlearning did, in fact, enhance EFL learners' reading ability compared to traditional instruction.

RQ4: Does AI-Supported Microlearning Significantly Enhance EFL Learners' Writing Skill?

The fourth question of research probed whether AI-supported microlearning improved the EFL learners' writing skill more than traditional teaching. Prior to conducting inferential statistics, normality for pre- and post-test writing scores was verified using the Kolmogorov–Smirnov and Shapiro–Wilk tests. The findings indicated that the data were almost normally distributed in all the groups (pre-test: control, p = .299; experimental, p = .306; post-test: control, p = .356; experimental, p = .469). The normality was therefore established, and parametric tests could hence be employed for further analysis.

Table 22

Tests of Normality for Writing Pre-test and Post-test Scores across Control and Experimental Groups

	Group	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Writing_Pre	Control	.109	30	.200*	.959	30	.299
	Experimental	.111	30	.200*	.960	30	.306
Writing_Post	Control	.100	30	.200*	.962	30	.356
	Experimental	.119	30	.200*	.967	30	.469

*. This is a lower bound of the true significance.
a. Lilliefors Significance Correction

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The control group pre-test descriptive statistics presented in Table 23 show that the mean was 12.200 (SD = 2.987) and that of the experimental group was 11.733 (SD = 2.803). The groups were evenly distributed at baseline, and the control group mean was higher by only a small margin.

Table 23

Descriptive Statistics for Writing Pre-test Scores across Control and Experimental Groups

	Group	N	Mean	Std. Deviation	Std. Error Mean
Writing_Pre	Control	30	12.200	2.9873	.5454
	Experimental	30	11.733	2.8031	.5118

As is evident from Table 24, pre-test score t-tests ensured that there was no group difference (t(58) = 0.624, p = .535), and Levene's test showed similar variances (F = 0.000, p = .984). Both groups were therefore at similar levels of writing proficiency when they started.

Table 24

Independent Samples t-test Results for Writing Pre-test Scores across Control and Experimental Groups

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Writing_Pre	EVA	.000	.984	.624	58	.535	.4667	.7479	-1.0305	1.9638
	EVNA			.624	57.767	.535	.4667	.7479	-1.0306	1.9639

Pre-test effect sizes, as presented in Table 25, were small (Cohen's d = 0.161, Hedges' g = 0.159, Glass's delta = 0.166) and indicated negligible practical differences between groups at baseline.

Table 25

Effect Size Estimates for Writing Pre-test Scores

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Writing_Pre	Cohen's d	2.8967	.161	-.346	.667
	Hedges' correction	2.9348	.159	-.342	.659
	Glass's delta	2.8031	.166	-.343	.673

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

Table 26 shows descriptive statistics for control and experimental group post-test writing scores. Post-test scores were considerably enhanced in both groups, with the control group having a mean of 12.667 (SD = 4.020) and the experimental group a mean of 16.167 (SD = 3.495). The experimental group experienced significantly greater gain, suggesting that AI-supported microlearning was extremely effective in enhancing writing skill.

Table 26

Descriptive Statistics for Writing Post-test Scores across Control and Experimental Groups

	Group	N	Mean	Std. Deviation	Std. Error Mean
Writing_Post	Control	30	12.667	4.0201	.7340
	Experimental	30	16.167	3.4947	.6380

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Table 27 presents Independent samples t-test results of post-test writing scores experimental vs. control group. The post-test t-test yielded a significant difference between groups (t(58) = -3.599, p = .001), with Levene's test equal variances (F = 1.288, p = .261). This indicates the AI-supported microlearning intervention yielded significantly improved writing scores compared to traditional instruction.

Table 27

Independent Samples t-test Results for Writing Post-test Scores across Control and Experimental Groups

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Writing_Post	EVA	1.288	.261	-3.599	58	.001	-3.5000	.9725	-5.4467	-1.5533
	EVNA			-3.599	56.898	.001	-3.5000	.9725	-5.4475	-1.5525

Effect sizes, presented in Table 28, were of large practical significance: Cohen's d = -0.929, Hedges' g = -0.917, and Glass's delta = -1.002. These results are in favor of the fact of the improvement of the writing skill of the experimental group, as stated, both being significant statistically and educationally.

Table 28

Effect Size Estimates for Writing Post-test Scores

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
Writing_Post	Cohen's d	3.7665	-.929	-1.459	-.392
	Hedges' correction	3.8161	-.917	-1.440	-.387
	Glass's delta	3.4947	-1.002	-1.562	-.427

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

The comparisons of all tables assure that the experimental and control groups were equivalent in pre-test with no difference in writing skill and negligible effect sizes. After the eight-week intervention, both groups showed improvement, with the experimental group recording much higher post-test scores. The outcomes of the t-tests and effect sizes demonstrate that AI-supported microlearning significantly enhanced EFL students' writing abilities in comparison to traditional instruction and confirm the effectiveness of AI-supported microlearning interventions toward productive language skill development.

4. Discussion and Conclusion

The present study investigated the effectiveness of AI-supported microlearning on the development of four essential language skills—listening, speaking, reading, and writing—among intermediate EFL learners. The findings consistently demonstrated that learners exposed to AI-supported microlearning achieved significantly greater improvements across all language skills compared with learners receiving conventional instruction. These results confirm the pedagogical value of integrating artificial intelligence with microlearning design and provide empirical support for contemporary theories of technology-enhanced language learning.

The improvement observed in listening skills indicates that AI-supported microlearning provides optimal conditions for processing auditory input. Both groups improved over time; however, the experimental group achieved significantly higher post-test scores, suggesting that microlearning combined with adaptive AI feedback enhances listening comprehension beyond traditional classroom exposure. From a theoretical perspective, this finding aligns with cognitive load theory, which emphasizes that learning effectiveness increases when instructional materials reduce extraneous processing demands (Sweller, 1988). Microlearning segments instructional content into

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manageable units, allowing learners to focus attention on specific listening tasks without cognitive overload. Similarly, multimedia learning principles emphasize segmentation and controlled information presentation as key mechanisms supporting comprehension (Mayer, 2005).

Empirical evidence supports this interpretation. Microlearning environments promote distributed exposure and repeated interaction with content, which improves retention and comprehension in language learning contexts (Ghafar et al., 2023; Taylor & Hung, 2022). The integration of AI further strengthens these mechanisms by adapting listening materials to learner performance and providing immediate corrective feedback. AI-based systems enable personalized learning pathways that continuously respond to learners' needs, thereby enhancing comprehension accuracy and learner confidence (Jafari & Yazdi, 2024; Kaswan et al., 2024). Studies examining AI-supported language applications similarly report increased learner self-efficacy and engagement during listening activities, confirming that adaptive technological environments facilitate auditory skill development (Kittredge et al., 2025). Therefore, the listening results suggest that AI-supported microlearning functions as a dual cognitive scaffold, combining structured input with individualized adaptation.

Regarding speaking development, the findings revealed the largest improvement among learners exposed to AI-supported microlearning. Speaking ability is widely recognized as one of the most challenging skills in second language acquisition because it requires simultaneous control of linguistic accuracy, fluency, and communicative confidence. The significant gains observed in the experimental group indicate that AI-supported microlearning creates conditions conducive to active language production. Constructivist perspectives of learning emphasize interaction and feedback as central to skill acquisition, and AI technologies simulate interactive communication environments by providing real-time responses and performance analysis (Kuddus, 2022; Schmidt & Strasser, 2022).

Previous studies reinforce this interpretation. Microlearning-supported instruction enhances learner engagement and motivation, which are crucial factors influencing oral communication performance (Fidan, 2023). Meta-analytic research has demonstrated strong positive effects of microlearning interventions on speaking proficiency through repeated short practice cycles and continuous reinforcement (Prasittichok & Smithsarakarn, 2024). Moreover, systematic reviews show that AI-enhanced language learning environments promote autonomy and self-regulated learning behaviors, both of which contribute to improved communicative competence (Peña-Acuña & Corga Fernandes Durão, 2024). The present findings extend this body of knowledge by demonstrating that when AI personalization is embedded within microlearning structures, learners receive individualized pronunciation feedback, adaptive speaking tasks, and low-anxiety practice opportunities that collectively enhance oral proficiency. These results also align with qualitative evidence showing that generative-AI microlearning modules improve learner confidence and self-regulation skills (Kohnke et al., 2025).

The findings related to reading development further confirm the effectiveness of AI-supported microlearning for receptive language skills. Although both groups demonstrated improvement, the experimental group achieved significantly higher gains, suggesting that adaptive microlearning environments enhance reading comprehension processes. Microlearning facilitates focused engagement with short texts and comprehension activities, enabling learners to apply reading strategies incrementally. Studies examining mobile microlearning approaches report improved learner motivation and reading strategy awareness due to flexible and accessible learning formats (Lee, 2023; Leong et al., 2021).

The addition of artificial intelligence strengthens these benefits through dynamic difficulty adjustment and individualized feedback mechanisms. AI systems analyze learner responses and provide targeted vocabulary support, comprehension monitoring, and scaffolding, which help maintain an optimal challenge level during reading tasks (Qiao & Zhao, 2023). Previous research demonstrates that microlearning-based instructional design enhances reading performance and critical thinking integration in English learning materials (Cahyanto et al., 2024; Sumarni & Salsabila, 2023). Furthermore, design-based studies of microlearning applications indicate improvements in usability, motivation, and reading comprehension outcomes (Robles et al., 2023). The present findings therefore reinforce the argument that combining AI adaptability with microlearning segmentation creates ideal cognitive conditions for reading skill acquisition.

Writing skill development showed particularly strong gains in the experimental group, indicating that AI-supported microlearning is highly effective for productive language abilities requiring higher cognitive processing. Writing involves complex processes such as idea generation,

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linguistic organization, grammatical accuracy, and revision. Microlearning addresses these demands by dividing writing instruction into smaller, manageable stages that reduce cognitive burden and enable gradual skill mastery. Research demonstrates that microlearning significantly improves learners' writing performance through iterative practice and focused feedback cycles (Fauziah et al., 2023).

Artificial intelligence enhances this process by providing automated error correction, linguistic suggestions, and real-time feedback, thereby accelerating learning cycles and encouraging self-revision. AI-based learning environments enable personalized instruction that responds instantly to learner performance, an advantage rarely achievable in traditional classrooms (Schmidt & Strasser, 2022). Studies examining AI-assisted microlearning media similarly report improvements in comprehension, motivation, and language production accuracy (Noverisa et al., 2025). Moreover, AI-integrated microlearning environments promote higher-order thinking and learner engagement, which contribute to improved written communication outcomes (Silitonga et al., 2024). The large effect sizes observed in writing development therefore support the claim that AI-supported microlearning effectively integrates instruction and formative assessment into a continuous learning process.

Across all four language skills, the findings reveal a consistent pattern demonstrating the superiority of AI-supported microlearning compared with conventional instruction. This consistency strengthens the theoretical assumption that integrating adaptive intelligence with segmented learning design produces synergistic pedagogical effects. Microlearning reduces cognitive complexity and increases accessibility, while AI provides personalization, adaptive feedback, and continuous monitoring. Together, these mechanisms create a learner-centered instructional ecosystem aligned with contemporary digital education frameworks (Boumalek et al., 2024; Hosler, 2025).

The results also support broader trends in educational transformation emphasizing flexible and technology-mediated learning environments. The integration of innovative digital technologies has reshaped teaching practices toward adaptive and individualized instruction (Adelsberger et al., 2008; Hawkridge, 2022). Research increasingly identifies microlearning as a dominant model for flexible professional development and online education (Kohnke et al., 2024). Systematic reviews confirm that microlearning improves learning outcomes across disciplines by promoting engagement, autonomy, and knowledge retention (Monib et al., 2025). Learner perception studies likewise demonstrate that students view microlearning as motivating and effective for skill acquisition (Monib et al., 2024).

Importantly, the findings of this study extend prior research by empirically validating the combined application of AI and microlearning within an integrated language-skills framework rather than isolated linguistic components. Previous investigations often examined grammar, vocabulary, or single skills independently. By demonstrating improvements across listening, speaking, reading, and writing simultaneously, the study provides stronger evidence supporting AI-supported microlearning as a holistic instructional model. The methodological rigor of a quasi-experimental design further strengthens the causal interpretation of results, consistent with recommendations for educational research design emphasizing controlled comparisons in authentic learning environments (Creswell & Creswell, 2017; Fatehi Rad et al., 2025).

Overall, the discussion suggests that AI-supported microlearning represents an evolution in language pedagogy rather than a simple technological addition. The approach integrates cognitive theory, adaptive learning, and digital flexibility into a unified instructional framework capable of addressing both cognitive and affective dimensions of language learning. The consistent improvement observed across all language skills indicates that AI-supported microlearning may function as a comprehensive model for future EFL instruction.

Despite its significant findings, this study has several limitations. First, the sample size was relatively small and limited to learners from a single private language institute, which restricts generalizability to broader educational contexts. Second, the duration of the intervention was limited to eight weeks; therefore, long-term retention and transfer effects of AI-supported microlearning were not examined. Third, learner variables such as motivation level, digital literacy, and prior technology experience were not controlled, although they may influence learning outcomes. Additionally, the study focused only on immediate performance gains rather than longitudinal language development. Finally, the reliance on standardized achievement tests may not fully capture communicative competence or authentic language use outside classroom settings.

Future research should investigate long-term effects of AI-supported microlearning through longitudinal designs examining retention, transferability, and sustained learner engagement. Larger and more diverse samples across

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multiple institutions and educational levels would strengthen external validity. Comparative studies examining different AI tools, feedback modalities, or microlearning delivery platforms could identify optimal instructional configurations. Mixed-methods approaches incorporating qualitative data such as learner interviews, classroom observations, and reflective journals may provide deeper insights into learner experiences and cognitive processes. Future studies may also explore moderating variables including learner autonomy, learning styles, age differences, and technological readiness to better understand individual differences in AI-mediated learning environments.

From a practical perspective, educators should consider integrating AI-supported microlearning as a complementary component of language instruction rather than a replacement for classroom teaching. Teachers can design short, goal-oriented learning activities supported by AI feedback to extend learning beyond classroom time. Language institutes and curriculum designers should develop structured microlearning modules aligned with existing syllabi to ensure pedagogical coherence. Professional development programs are necessary to enhance teachers' digital competencies and ethical awareness when using AI technologies. Educational policymakers may also invest in accessible AI platforms to support personalized learning opportunities. Encouraging learners to engage regularly with microlearning activities through mobile devices can promote autonomous learning habits and continuous skill development.

Authors' Contributions

All authors significantly contributed to this study.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

In this study, to observe ethical considerations, participants were informed about the goals and importance of the research before the start of the interview and participated in the research with informed consent.

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