



Enhancing Vocabulary, Grammar, and Discourse Competence through AI-Supported Microlearning among EFL Learners: A Quasi-Experimental Study

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Abstract

Recent research has examined artificial intelligence (AI) and microlearning as separate instructional approaches. However, their combined effect on the development of core language systems remains underexplored. This quasi-experimental study examined the impact of AI-supported microlearning on Iranian EFL learners' vocabulary, grammatical, and discourse competence. Accordingly, a total of 60 intermediate learners recruited from Tanin Language Institute in Kerman, Iran, participated in the study and were assigned to an experimental (n = 30) and a control group (n = 30). Over an eight-week instructional period, the experimental group engaged in AI-supported microlearning activities, while the control group received conventional instruction. Data were collected using vocabulary and grammar achievement tests, as well as a discourse production task administered at both pre-test and post-test stages. Analysis of covariance (ANCOVA) was employed in order to control for initial differences between the groups. The results indicated that learners in the experimental group significantly outperformed those in the control group across all three variables, with large effect sizes. These results suggest that integrating adaptive AI-based feedback with microlearning may support the development of multiple language systems in EFL contexts. Pedagogical implications for integrating AI-supported microlearning into EFL instruction, as well as directions for future research, are presented.

Keywords: AI-supported microlearning, artificial intelligence in language learning, vocabulary development, grammatical competence, discourse competence

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Introduction

The development of digital technologies has increasingly transformed classroom practices across educational contexts. In recent years, artificial intelligence (AI) has attracted increasing attention across educational contexts, particularly in the field of language education. AI-based tools are now able to support adaptive learning environments in which instructional content can be adjusted based on learners' needs and their ongoing performance (Ouyang & Jiao, 2021; Zawacki-Richter et al., 2019). In English as a foreign language (EFL), AI has been used for modifying instructional input and extending learning beyond the physical classroom (George, 2023; Yadav & Singh, 2025). These affordances male enable learners to experience more flexible exposure to language input and immediate responses to their performance.

Along with these developments, microlearning has emerged as a prominent trend in technology-enhanced learning environments. Microlearning refers to the delivery of instructional content in small and focused units, designed to address a specific learning objective (Alias & Razak, 2025; Ghafar et al., 2023; Taylor & Hung, 2022). This approach is often linked to cognitive load theory (CLT), which emphasizes the importance of presenting information in manageable segments. (Lopez, 2024; Plass & Kalyuga, 2019). Microlearning in language learning contexts may provide opportunities for repeated exposure and gradual consolidation of knowledge. A number of studies have suggested that microlearning can support learner motivation and accessibility, particularly in digital environments (Fidan, 2023; Holubnycha et al., 2025; Monib et al., 2024, 2025a). From a cognitive perspective, this study is informed by CLT, which suggests that learning is more effective when instructional materials are structured in a way that reduces unnecessary cognitive demands (Sweller, 1988; Plass & Kalyuga, 2019).

Recent investigations have started to consider the potential of combining AI with microlearning more recently. AI-supported microlearning environments can integrate some language learning features such as adapting content and tracking learner progress in a more individualized manner. Moreover, AI-driven microlearning environments can enhance self-regulated learning and higher-order thinking through adaptive feedback and personalized pathways (Hariyanti, 2026; Mrabet et al., 2024). Empirical studies (e.g., Almuqhim & Berri, 2025; Fadli, 2025; Monib et al., 2024, 2025a) showed that such environments may contribute to increased learner autonomy, motivation, and interaction with learning materials. In addition, microlearning-based interventions have been applied to different language skills such as reading, speaking, and writing often with positive outcomes (Amakhina et al., 2023; Boumalek et al., 2025; Prasittichok & Smithsarakarn, 2024). Therefore, technology-supported microlearning may offer useful possibilities for language development.

Despite these developments, existing research has largely focused on isolated language skills or learners' perceptions, with limited attention to the integrated development of core language systems. From the perspective of second language acquisition (SLA), language development involves more than the improvement of skills alone. It requires the development of underlying language systems, including phonology, vocabulary, grammar, and discourse. These systems form the structural

basis of communicative competence and impact meaningful language use (Scrivener, 2011).

Among these systems, Vocabulary knowledge forms the lexical foundation necessary for comprehension and expression (Nation, 2019). Grammar enables learners to organize the lexical items into meaningful structures and express relationships between ideas (Larsen-Freeman, 2015). Beyond sentence-level structures, discourse competence refers to the ability to produce coherent and contextually appropriate language across longer stretches of communication (Vásquez Fernández, 2025). These components contribute to the development of communicative competence in second language learning.

Despite the importance of language systems, very few studies have examined the development of these systems simultaneously within AI-supported microlearning environments. Some studies have either focused on isolated linguistic features or addressed general learning outcomes such as motivation. Moreover, research in the Iranian EFL context remains scarce, even though the use of digital tools in language classes has been gradually increasing.

Considering these gaps, this study aims to investigate the effect of AI-supported microlearning on vocabulary knowledge, grammatical competence, and discourse competence among Iranian EFL learners through a quasi-experimental design. This study aims to provide a more comprehensive understanding of how AI-supported microlearning may influence the development of core language systems. Based on these considerations, the following research questions are formulated:

- RQ1. Does AI-supported microlearning significantly improve Iranian EFL learners' vocabulary knowledge compared with conventional instruction?
- RQ2. Does AI-supported microlearning significantly improve Iranian EFL learners' grammatical competence compared with conventional instruction?
- RQ3. Does AI-supported microlearning significantly improve Iranian EFL learners' discourse competence compared with conventional instruction?

Literature Review

Theoretical Framework

From a cognitive perspective, this study is grounded in CLT, which explains how the limitations of working memory influence learning processes (Sweller, 1988; Plass & Kalyuga, 2019). According to CLT, learning becomes more effective when instructional materials are designed to reduce unnecessary cognitive demands and to support meaningful processing. When information is presented in smaller, manageable segments, learners are more likely to process and retain new knowledge. Microlearning aligns closely with the principles of CLT, as it structures learning content into brief, focused units that can reduce cognitive overload and facilitate gradual knowledge construction. This alignment has been empirically supported, with studies showing that microlearning designs grounded in CLT can enhance learning efficiency and reduce cognitive overload (Lopez, 2024). In language learning contexts, this approach may be particularly useful, as learners must simultaneously process vocabulary, grammatical

structures, and discourse-level information. Segmenting these elements into shorter learning episodes may support more efficient processing and retention. In addition, the integration of AI into microlearning environments introduces adaptive and feedback-driven features that can further optimize cognitive processing. AI-supported systems can adjust task difficulty, provide immediate feedback, and personalize learning pathways based on learners' performance (Monib et al., 2025b). These features may help regulate cognitive load by preventing excessive difficulty while maintaining sufficient challenge for learning. In this sense, CLT provides a useful lens for examining how AI-supported microlearning may influence the development of vocabulary, grammar, and discourse in EFL contexts.

Artificial Intelligence in Language Learning

AI has become part of technology-enhanced language learning (TELL) environments, influencing how teaching and learning processes are organized. AI-based systems are significant due to their ability to provide adaptive and personalized learning experiences (Ouyang & Jiao, 2021; Zawacki-Richter et al., 2019). Unlike traditional digital tools, AI systems can analyse learners' responses and adjust instructional content based on their performance and learning needs. AI technologies in EFL contexts have been integrated through a variety of tools, such as intelligent tutoring systems, automated writing evaluation systems, speech recognition tools, and chatbots (Kuddus, 2022; Schmidt & Strasser, 2022). The tools offer various opportunities for learners such as providing immediate feedback and helping learners to interact with language input more flexibly. In addition, these developments are consistent with broader trends in AI-supported educational innovation, where tutoring systems and microlearning approaches are increasingly combined to enhance learning flexibility and responsiveness (Mrabet et al., 2024). As a result, learners may experience greater autonomy and more opportunities for individualized learning (George, 2023; Yadav & Singh, 2025).

In addition, AI contributes to the development of adaptive learning environments in which instructional content is continuously adjusted. Since AI systems track learner performance, they can identify areas of difficulty and provide targeted support (Kaswan et al., 2024). From the learners' perspective, several studies have reported positive effects of AI integration on motivation, self-regulation, and language development. For example, Peña-Acuña and Durão (2024) reported increased motivation among learners. Qiao and Zhao (2023) found improvements in speaking performance and self-regulated learning. These findings show that AI can lead to more responsive and learner-centered language learning environments.

Microlearning in Language Education

Microlearning has become an important approach in digital learning environments. It refers to the delivery of content in small, focused units that target specific learning objectives and can be completed within short periods of time. These learning units are often delivered through digital platforms which make them accessible anytime and anywhere. Systematic reviews have emphasized that microlearning is not only a delivery format but also an instructional strategy that supports flexible, learner-centered environments (Alias & Razak, 2025). The theoretical basis of microlearning can be linked to CLT and the segmentation principle of multimedia learning (Mayer,

2005; Plass & Kalyuga, 2019). These perspectives suggest that learners process information more effectively when it is presented in smaller and manageable segments. In addition, instructional design models have demonstrated that structured microlearning sequences can improve learning outcomes by guiding learners through staged cognitive processing (Cahyanto et al., 2024). In this way, microlearning may help reduce cognitive overload and support more efficient processing of instructional material.

Microlearning in language learning may provide repeated exposure to linguistic input, which is essential for acquisition. Since language learning is gradual and cumulative, frequent interaction with small units of content can support retention and understanding over time (Monib et al., 2025a). This repeated exposure is particularly relevant in language learning, where microlearning has been shown to facilitate gradual acquisition and retention of linguistic knowledge (Ghafar et al., 2023). A growing body of research (e.g., Fidan, 2023; Monib et al., 2024, 2025a) has highlighted the role of microlearning in increasing learner motivation and accessibility in technology-enhanced environments.

Empirical studies have provided further support for the effectiveness of microlearning. Chen and Sitthiworachart (2023) found that mobile-based microlearning improved learners' vocabulary development and motivation. Shafiee Rad (2021) reported significant improvements in grammar achievement through microlearning-based instruction. Other studies (e.g., Amakhina et al., 2023; Fauziah et al., 2023; Prasittichok & Smithsarakarn, 2024) have shown positive effects on reading, writing, speaking, and overall communicative performance. However, many of these studies have focused on isolated language skills rather than underlying language systems. In addition to these findings, recent implementations in authentic educational contexts have reported that microlearning supports engagement and knowledge consolidation across different disciplines (Holubnycha et al., 2025).

AI-Supported Microlearning

The integration of AI and microlearning has led to the emergence of AI-supported microlearning, which combines adaptive technology with short, focused learning activities. In such environments, AI can adjust the level of difficulty, provide immediate feedback, and personalize learning pathways as learners engage with microlearning tasks (Boumalek et al., 2024; Chen et al., 2024; Monib et al., 2025b). This combination may enhance the pedagogical value of microlearning by making it more responsive to individual learner differences. AI-based analytics can monitor learner progress and provide targeted practice opportunities (Sajja et al., 2025). Thus, AI-supported microlearning may support self-regulated learning by creating continuous cycles of practice and adjustment. Such environments may also enhance higher levels of self-regulation and critical thinking by continuously adapting content to learner performance (Hariyanti, 2026). From a design perspective, microlearning frameworks supported by AI and mobile technologies have been shown to enable scalable and personalized learning experiences (Robles et al., 2023).

Related research has started to explore this combination in educational settings. For example, Arimbawa et al. (2025) and Silitonga et al. (2024) examined the use of AI chatbots within microlearning environments and reported improvements in motivation

and cognitive performance. Similarly, [Kohnke et al. \(2025\)](#) found that AI-supported microlearning enhanced confidence and self-regulated learning among pre-service teachers. Moreover, AI-driven microlearning has been associated with broader educational innovation trends, particularly in integrating adaptive tutoring systems with short-form learning content ([Mrabet et al., 2024](#)).

Despite these promising findings, research on AI-supported microlearning in language learning contexts is still limited. In many cases, AI and microlearning have been studied separately, and fewer studies have examined their combined effects using experimental designs. Moreover, systematic reviews indicate that integrated models of AI-supported microlearning remain underexplored, particularly in relation to comprehensive learning outcomes ([Alias & Razak, 2025](#); [Monib et al., 2025a](#)).

Language Systems in Second Language Acquisition

From the perspective of SLA, communicative competence develops not only through language skills but also through underlying language systems, including phonology, vocabulary knowledge, grammatical competence, and discourse competence ([Ellis, 2015](#); [Larsen-Freeman, 2015](#); [Scrivener, 2011](#)). These systems provide the structural foundation for meaningful communication.

Vocabulary knowledge plays an important role because it provides the lexical resources needed for both comprehension and production ([Nation, 2019](#); [Schmitt, 2019](#)). Grammar enables learners to organize these lexical items into meaningful structures and express relationships between ideas ([Larsen-Freeman, 2015](#)). At a broader level, discourse competence involves the ability to organize ideas coherently and use cohesive devices to produce contextually appropriate communication ([Celce-Murcia, 2008](#); [Vásquez Fernández, 2025](#)).

Although digital technologies are increasingly integrated into language learning, few studies have examined the simultaneous development of these language systems in AI-mediated environments ([Ouyang & Jiao, 2021](#); [Wang et al., 2024](#); [Zawacki-Richter et al., 2019](#)). This indicates a need for more comprehensive investigations that consider multiple dimensions of language development.

Empirical Gap and Rationale for the Study

Previous research highlighted the effectiveness of microlearning and AI in language education. Microlearning has been associated with improved learning outcomes and reduced cognitive load. AI has been linked to personalization, adaptability, and enhanced feedback mechanisms. However, several limitations can be identified in the literature. First, many studies have examined microlearning and AI separately rather than as an integrated instructional approach. In addition, most research has focused on individual language skills or general learner outcomes such as motivation and satisfaction. Furthermore, there is limited empirical evidence on the development of core language systems such as vocabulary, grammar, and discourse, particularly when these are examined together.

This gap is evident in the Iranian EFL context, where the use of digital technologies is increasing but empirical research is limited. Therefore, there is a need

for studies that investigate how AI-supported microlearning influences multiple aspects of language development in a more comprehensive manner. To address this gap, the present study examines the effects of AI-supported microlearning on vocabulary knowledge, grammatical competence, and discourse competence using a quasi-experimental design. Focusing on these three interrelated language systems can provide a more complete understanding of the role of AI-supported microlearning in EFL learning.

Method

Research Design

This study employed a quasi-experimental design to examine the effect of AI-supported microlearning on the development of language systems among Iranian EFL learners. Quasi-experimental designs are commonly used in educational research when intact classes are involved and full randomization is not feasible (Creswell & Creswell, 2017). The study followed a pretest–posttest control group design. Two intact classes of intermediate EFL learners participated in the study. One class was assigned to the experimental group, which received AI-supported microlearning and the other class served as the control group and received conventional instruction. The intervention lasted eight weeks, and both groups followed the same core curriculum for instructional comparability. The independent variable in this study was AI-supported microlearning, while the dependent variables included vocabulary knowledge, grammatical competence, and discourse competence. As intact classes were used, the findings should be interpreted with caution in terms of causal inference.

Participants

A total of 60 Iranian EFL learners enrolled in Tanin Language Institute in Kerman, Iran, participated in this study. A combination of convenience and purposive sampling was used. Initially, learners who were available in the institute were selected through convenience sampling. Then, purposive sampling was applied to ensure that participants met the required criteria, particularly in terms of proficiency level and course enrolment. The learners were young adults aged between 20 and 26 years and were classified as intermediate-level (B1) based on the Common European Framework of Reference for Languages (CEFR). Prior to the study, all participants had completed Touchstone Level 2 and were studying Touchstone Level 3. This level was considered appropriate for the study, as learners at the intermediate stage are expected to demonstrate developing control over vocabulary, grammar, and discourse. To ensure group equivalence, the Oxford Placement Test (OPT) and pre-test measures were administered prior to the intervention, and the results confirmed that the two groups were comparable at the outset of the study. In addition, both groups were taught by experienced teachers and followed the same instructional materials, so that any observed differences could be attributed mainly to the instructional treatment. All participants were informed about the purpose of the study, and their participation was voluntary. Informed consent was obtained prior to data collection, and participants' anonymity and confidentiality were ensured.

Table 1*Demographic Characteristics of the Participants*

Variable	Experimental (n = 30)	Control (n = 30)	Total (N = 60)
Age (M ± SD)	23.1 ± 1.8	22.9 ± 1.9	23.0 ± 1.9
Age Range	20–26	20–26	20–26
Gender (M/F)	12 (40%) / 18 (60%)	14 (46.7%) / 16 (53.3%)	26 (43.3%) / 34 (56.7%)
CEFR Level	B1	B1	B1
Previous Instructional Level	Touchstone 2	Touchstone 2	Touchstone 2
Current Instructional Level	Touchstone 3	Touchstone 3	Touchstone 3

Note. M = mean; SD = standard deviation; M/F = male/female.

Instruments

Three instruments were used to collect the data, including a vocabulary achievement test, a grammar achievement test, and a discourse production task. These instruments were designed to measure learners' development in lexical knowledge, grammatical competence, and discourse organization.

Oxford Placement Test

To determine participants' language proficiency at the outset of the study, OPT was administered. The test consists of three sections: vocabulary, grammatical structures, and reading comprehension, including 40 vocabulary items, 40 grammar items, and 20 reading comprehension items. This test has been widely used in language research, with its reliability supported through large-scale piloting and its validity established through alignment with CEFR. The internal consistency of the test was estimated using Cronbach's alpha, yielding a coefficient of $\alpha = .84$, indicating acceptable reliability. To further support content validity, the test was reviewed by two experienced EFL instructors familiar with standardized language assessment.

Vocabulary Test

Vocabulary knowledge was measured using a researcher-developed test based on the lexical items presented in the Touchstone 3 textbook. The test included 20 items consisting of multiple-choice and contextualized questions. Each item was scored as one point, resulting in a total score range of 0 to 20. To ensure content validity, the test items were aligned with the instructional materials and reviewed by two experienced EFL experts. Based on their feedback, several items were revised for clarity. A pilot study was also conducted and minor modifications were made. Cronbach's alpha was used to

estimate the reliability of the test, and the results indicated an acceptable level of internal consistency ($\alpha = .84$).

Grammar Test

Grammatical competence was assessed using a grammar achievement test developed based on the grammar structures presented in the Touchstone 3 book. The test included 20 items, including sentence completion and multiple-choice questions. Each correct answer received one point, with a total score of 20. The test was reviewed by two experienced EFL instructors for content validity and alignment with instructional objectives. A pilot test was conducted, and the reliability of the instrument was confirmed through Cronbach's alpha ($\alpha = .82$), indicating acceptable internal consistency.

Discourse Task

A short written task was used to measure the discourse competence. In detail, learners were asked to produce a coherent paragraph on a familiar topic related to the course content. The responses were evaluated using an analytic rubric focusing on coherence, cohesion, and organization. Each component was scored on a scale, and the total score was calculated by summing the component scores. Scores ranged from 0 to 20, with higher scores indicating better discourse performance. To enhance scoring reliability, two experienced EFL instructors independently rated the written responses. Inter-rater reliability was estimated using the intraclass correlation coefficient (ICC), which indicated acceptable agreement between the raters (ICC = .82). Any discrepancies were discussed until consensus was reached.

Table 2

Reliability indices for study instruments

Instrument	Reliability Type	Coefficient
Vocabulary Test	Cronbach's Alpha	.84
Grammar Test	Cronbach's Alpha	.82
Discourse Measure	Inter-rater Reliability (ICC)	.82

Procedure

The study was conducted over eight weeks and was integrated into the regular instructional schedule of the institute. Both groups followed the same Touchstone 3 book to ensure consistency in instructional content. The data collection process consisted of three main stages of pre-testing, instructional intervention, and post-testing. At the beginning of the study, both groups completed pre-tests measuring vocabulary knowledge, grammatical competence, and discourse competence. These pre-tests were used to establish baseline equivalence between the groups.

Then, the experimental group participated in AI-supported microlearning activities in addition to regular classroom instruction. These activities were delivered through a digital platform accessible via mobile devices and computers. The

microlearning sessions were short (approximately 10–15 minutes) and included vocabulary tasks with spaced repetition, grammar-focused exercises, and short discourse-related activities. The system provided immediate feedback and adjusted the level of difficulty based on learners' performance. The AI-supported microlearning activities were designed to align with the vocabulary, grammar, and discourse objectives of the Touchstone 3 syllabus. Vocabulary tasks included matching, multiple-choice, and contextualized usage items with spaced repetition. Grammar activities focused on sentence-level practice, error correction, and form-focused exercises. Discourse tasks involved short paragraph construction, cohesion identification, and idea organization. The platform provided immediate feedback by indicating incorrect responses, offering brief explanations, and supplying additional practice when needed. Learners completed these activities outside class, and their participation was monitored by the instructor to ensure engagement.

In contrast, the control group received only conventional instruction, including teacher explanation, textbook exercises, and regular homework activities, without adaptive feedback or structured microlearning activities. At the end of the eight-week period, both classes completed the post-tests using the same instruments administered at the beginning of the study. Both groups received comparable instructional time to ensure that any observed differences were attributable to the treatment rather than differences in exposure.

Data Analysis

All data were analyzed using SPSS version 26. Before conducting the main analyses, assumptions of normality, homogeneity of variance, and homogeneity of regression slopes were examined and found to be satisfied. Analysis of covariance (ANCOVA) was used to examine the effect of the instructional intervention while controlling for pre-test differences. In each analysis, the post-test score was treated as the dependent variable, the instructional group as the independent variable, and the corresponding pre-test score as the covariate. Before conducting the main analyses, the assumption of homogeneity of regression slopes was tested by examining the interaction between group and pre-test scores. This interaction was not statistically significant which showed that the assumption was satisfied. Effect sizes were estimated using partial eta squared (η^2), with values of .01, .06, and .14 interpreted as small, medium, and large effects, respectively. The level of significance was set at .05 for all statistical tests.

Results

Preliminary Analyses

Before conducting the main analyses, preliminary checks were performed to examine whether the assumptions underlying ANCOVA were satisfied. Descriptive statistics indicated that the control and experimental groups were comparable at the pre-test stage across vocabulary, grammar, and discourse. Normality, homogeneity of variance, and homogeneity of regression slopes were assessed. The results are summarized in Table 3.

Table 3*Summary of Assumption Checks for ANCOVA*

Variable	Shapiro–Wilk p	Levene’s p	Group × Pre-test p
Vocabulary	.198	.092	.924
Grammar	.405	.842	.997
Discourse	.276	.072	.185

As shown in Table 3, the Shapiro–Wilk tests indicated that post-test scores were normally distributed ($p > .05$). Levene’s tests were non-significant, supporting the assumption of homogeneity of variances. In addition, the interaction between group and pre-test scores was not statistically significant for any of the variables, indicating that the assumption of homogeneity of regression slopes was met. Taken together, these results confirmed that ANCOVA was appropriate for the main analyses.

RQ1: Effect of AI-Supported Microlearning on Vocabulary Knowledge

Descriptive statistics for vocabulary scores are presented in Table 4. The two groups showed comparable performance at the pre-test stage. However, at the post-test stage, the experimental group obtained higher scores than the control group.

Table 4*Descriptive Statistics for Vocabulary Scores by Group*

Group	Pre-test M	Pre-test SD	Post-test M	Post-test SD
Control	11.67	1.81	13.63	2.06
Experimental	11.73	1.93	17.80	2.30

To determine whether this difference was statistically significant while controlling for pre-test scores, an ANCOVA was conducted.

Table 5*ANCOVA Results for Vocabulary Post-test Scores*

Source	F	p	Partial η^2
Vocab_Pre	211.34	< .001	.788
Group	244.99	< .001	.811

As can be seen in Table 5, the results indicated that vocabulary pre-test scores significantly predicted post-test performance. More importantly, the effect of instructional group was statistically significant, suggesting that learners who received

AI-supported microlearning achieved higher vocabulary scores than those in the control group after controlling for initial differences. The effect size was large (partial $\eta^2 = .811$), indicating that the instructional intervention accounted for a substantial proportion of variance in vocabulary outcomes.

RQ2: Effect of AI-Supported Microlearning on Grammatical Competence

Descriptive statistics for grammar scores are presented in Table 6. While both groups were comparable at the pre-test stage, the experimental group demonstrated higher post-test scores than the control group.

Table 6

Descriptive Statistics for Grammar Scores by Group

Group	Pre-test M	Pre-test SD	Post-test M	Post-test SD
Control	13.13	2.00	15.03	2.24
Experimental	13.03	1.90	19.43	2.14

An ANCOVA was conducted to examine whether this difference remained significant after controlling for pre-test scores.

Table 7

ANCOVA Results for Grammar Post-test Scores

Source	F	p	Partial η^2
Grammar_Pre	191.44	< .001	.771
Group	270.78	< .001	.826

The ANCOVA results (Table 7) revealed that grammar pre-test scores significantly predicted post-test performance. In addition, the effect of instructional group was statistically significant which indicates that AI-supported microlearning led to improved grammatical competence compared with conventional instruction. The effect size was large (partial $\eta^2 = .826$). This shows a strong impact of AI-supported microlearning on grammatical competence.

RQ3: Effect of AI-Supported Microlearning on Discourse Competence

Descriptive statistics for discourse scores are shown in Table 8. As with the other variables, the two groups were comparable at the pre-test stage, while the experimental group achieved higher post-test scores.

Table 8*Descriptive Statistics for Discourse Scores by Group*

Group	Pre-test M	Pre-test SD	Post-test M	Post-test SD
Control	10.83	2.09	13.13	2.18
Experimental	11.63	1.94	17.50	1.74

To evaluate the statistical significance of this difference, an ANCOVA was conducted.

Table 9*ANCOVA Results for Discourse Post-test Scores*

Source	F	p	Partial η^2
Discourse_Pre	325.51	< .001	.851
Group	325.53	< .001	.851

The results in Table 9 indicated that discourse pre-test scores significantly predicted post-test performance. More importantly, the effect of instructional group was statistically significant, suggesting that AI-supported microlearning was associated with a substantial effect on learners' discourse competence. The effect size was particularly large (partial $\eta^2 = .851$), indicating that the intervention had a strong influence on learners' discourse performance.

Across all three research questions, the results consistently showed that AI-supported microlearning significantly improved learners' vocabulary knowledge, grammatical competence, and discourse competence compared with conventional instruction. In all three variables, the effect sizes were consistently large (partial η^2 ranging from .811 to .851), highlighting the substantial impact of the intervention.

Discussion

This study aimed to examine the effects of AI-supported microlearning on Iranian EFL learners' vocabulary knowledge, grammatical competence, and discourse competence. The findings showed that, after controlling for pre-test differences, learners in the experimental group outperformed those in the control group in all three language systems. This pattern suggests that AI-supported microlearning may provide a supportive learning environment within the context of this study. More specifically, the results indicate that combining microlearning with AI-based feedback may help learners engage more actively with language content. The presence of short learning units, together with immediate and adaptive feedback, seems to create conditions in which learners can process language more gradually but also more effectively. From a cognitive perspective, this pattern can be interpreted through the lens of CLT, which suggests that structuring information into manageable segments can reduce cognitive

overload and facilitate more efficient processing (Lopez, 2024; Plass & Kalyuga, 2019). In this sense, the findings of the study are generally consistent with previous research on technology-supported learning environments, which emphasizes the role of adaptive feedback and structured input in supporting language development (Mrabet et al., 2024; Monib et al., 2025a; Ouyang & Jiao, 2021).

AI-Supported Microlearning and Vocabulary Knowledge

The first research question examined whether AI-supported microlearning leads to improvement in vocabulary knowledge. The results demonstrated a statistically significant difference between the experimental and control groups, with higher performance observed among learners who received AI-supported microlearning. This finding aligns with previous studies suggesting that microlearning can support vocabulary development by presenting lexical items in small and manageable units. Such an approach helps learners to encounter new words repeatedly over time, which is important for retention and use (Ghafar et al., 2023; Nation, 2019). This repeated exposure is particularly important in vocabulary learning, as it supports both form–meaning connections and long-term retention. For example, Chen and Sitthiworachart (2023) reported that mobile-based microlearning improved vocabulary learning as well as learner motivation and satisfaction. The present study extends these findings by showing that the addition of AI-based adaptivity may further strengthen these effects (Hariyanti, 2026; Sajja et al., 2025).

In addition, the role of AI in providing immediate and personalized feedback should also be considered. Some studies (e.g., Ouyang & Jiao, 2021; Zawacki-Richter et al., 2019) in AI-supported language learning have emphasized that timely feedback and adaptive support can facilitate more efficient learning processes. In this study, such features may have helped learners notice gaps in their knowledge and revisit difficult items more frequently. A possible explanation for the observed improvement is that vocabulary learning benefits from repeated exposure, focused attention and feedback. The microlearning format, by dividing content into smaller units, may reduce cognitive overload and aid learners to concentrate on specific lexical items (Lopez, 2024). At the same time, AI-based systems can adapt to learners' performance and provide additional practice when needed. This combination likely created more opportunities for noticing and consolidation, which are essential processes in vocabulary development. These factors may explain the significant gains observed in vocabulary knowledge. This interpretation is also consistent with CLT, as reduced cognitive demands may enable learners to allocate more attention to lexical processing and consolidation.

AI-Supported Microlearning and Grammatical Competence

The second research question addressed grammatical competence. It was found that learners in the experimental group performed significantly better than those in the control group after controlling for pre-test scores. This finding may indicate that AI-supported microlearning can also be effective in supporting grammar learning. This result is consistent with previous research indicating that microlearning can be beneficial for grammar instruction, especially when grammatical structures are presented in smaller and more focused units (Alias & Razak, 2025; Cahyanto et al., 2024). For instance, Shafiee Rad (2021) found that microlearning-based instruction

improved both grammar achievement and learner motivation. The present study contributes to this line of research by examining grammar as part of a broader language system rather than as an isolated outcome. One possible reason for this finding is that grammar learning often requires careful attention and timely correction. This immediacy may help learners process grammatical forms while the input is still active in working memory, which can facilitate more effective form–function mapping. In traditional classrooms, such conditions may not always be fully available. However, in an AI-supported microlearning class, learners may receive more immediate feedback on their responses, which can help them identify and correct errors more effectively (Ouyang & Jiao, 2021; Sajja et al., 2025). In addition, the segmented nature of microlearning may enable learners to focus on specific grammatical forms without being overwhelmed by large amounts of information.

It also seems that the adaptive nature of AI plays an important role here (Hariyanti, 2026; Kaswan et al., 2024). By adjusting the level of difficulty and revisiting problematic areas, the system may support a more individualized learning process. In this way, learners may engage more actively with grammatical structures and develop a clearer understanding of how these structures function in context. This could explain the relatively strong improvement observed in grammatical competence.

AI-Supported Microlearning and Discourse Competence

The last research question addressed the effect of AI-supported microlearning on discourse competence. The results showed that the experimental group significantly outperformed the control group, even after controlling for pre-test differences. This finding is significant, as discourse competence is generally considered more complex to develop compared to vocabulary and grammar. Discourse competence involves organizing ideas, maintaining coherence, and using appropriate cohesive devices in extended stretches of language (Celce-Murcia, 2008; Vásquez Fernández, 2025). Therefore, improvement in this area usually requires first exposure to language forms and then opportunities to practice organizing and connecting ideas. Such processes require linguistic knowledge as well as the ability to integrate multiple elements of language in a coherent manner.

Although relatively fewer studies have directly examined discourse competence in AI-supported microlearning environments, the present findings are broadly consistent with research showing positive effects of such environments on communicative skills, including speaking and writing (Amakhina et al., 2023; Fauziah et al., 2023; Prasittichok & Smithsarakarn, 2024). Since these skills rely on discourse-level organization, it may be argued that that improvements in these areas may reflect underlying gains in discourse competence.

An explanation for this finding is that microlearning may enable learners to focus on specific aspects of discourse, such as sequencing ideas or maintaining coherence, in a step-by-step manner (Cahyanto et al., 2024). At the same time, AI-based feedback may help learners monitor how effectively they organize their ideas and make necessary adjustments (Sajja et al., 2025). In this sense, AI-supported microlearning may act as a bridge between sentence-level learning and more extended language production. From a cognitive perspective, this may suggest that AI-supported

microlearning can support discrete language elements and higher-level integration processes by managing cognitive load and providing structured feedback (Lopez, 2024; Plass & Kalyuga, 2019).

Another important point is that these findings provide an alternative perspective on the assumption that microlearning is mainly suitable for discrete-point learning. While it is sometimes argued that breaking content into smaller units may limit the development of more complex skills, the present results suggest that, when supported by appropriate instructional design and adaptive feedback, microlearning may contribute to higher-level language abilities, such as discourse competence, when supported by appropriate instructional design and adaptive feedback.

In sum, the findings of this study suggest that AI-supported microlearning may influence language development through multiple mechanisms, including reduced cognitive load, increased opportunities for repeated exposure, and the provision of adaptive feedback (Ghafar et al., 2023; Lopez, 2024; Sajja et al., 2025). These mechanisms appear to operate across different language systems, from vocabulary and grammar to discourse-level organization. While the relative contribution of each factor cannot be determined in the present study, the overall pattern indicates that the integration of AI and microlearning may offer a more responsive and cognitively supportive learning environment for EFL learners.

Conclusion

The present study examined the effects of AI-supported microlearning on vocabulary knowledge, grammatical competence, and discourse competence among Iranian EFL learners. The findings showed that learners who engaged in AI-supported microlearning outperformed those who received conventional instruction in all three language systems. Therefore, AI-supported microlearning may play a meaningful role in supporting language development beyond what may be achieved through traditional classroom practices alone. The results also indicate that this instructional approach appears encourage more active engagement with language content. Through short, focused learning activities combined with adaptive feedback, learners appear to have more opportunities to process, revisit, and consolidate language knowledge over time. In this sense, AI-supported microlearning may be considered as a supportive extension to classroom instruction rather than a replacement for it.

The findings of this study offer some implications for language teaching practice. One implication of these findings is that AI-supported microlearning can be meaningfully integrated into existing instructional programs as a complementary approach. Rather than replacing traditional teaching methods, it may function as an additional layer of support that enhances learners' interaction with language systems. A related implication concerns the importance of instructional design. The effectiveness of AI-supported microlearning does not appear to depend only on the presence of technology, but also on how learning activities are structured. Short, clearly focused tasks combined with timely and adaptive feedback may create conditions that support gradual and sustained learning. Therefore, teachers and instructional designers need to carefully align microlearning activities with learning objectives and learner needs. In addition, the findings suggest that AI-supported microlearning may help address

individual differences among learners. Since the system can adjust content and feedback based on performance, it can provide more personalized learning experiences. This could be useful in EFL contexts where learners often have different levels of proficiency and learning pace.

Despite these contributions, several limitations should be acknowledged. One limitation relates to the sample, which consisted of only 60 intermediate-level learners from a single private language institute in Kerman, Iran. Because of this, the findings may not be easily generalized to learners with different proficiency levels or learning contexts. Future studies could address this issue by including larger and more diverse samples in order to examine whether similar patterns can be observed in different populations. A second limitation concerns the duration of the intervention. The study was conducted over a period of eight weeks, which, although sufficient to observe short-term improvement, does not allow strong conclusions about the long-term sustainability of the results. In this regard, longitudinal research designs would be useful to investigate whether the effects of AI-supported microlearning are maintained over time in terms of retention and continued development.

A further limitation is related to the research design. While the quasi-experimental design was appropriate for the classroom context, it does not provide the same level of control as fully randomized experimental designs. As a result, some uncontrolled variables may have influenced the findings. Future research may therefore benefit from employing fully randomized designs in order to strengthen causal interpretations. In addition, discourse competence was assessed only through a written paragraph task. This type of assessment may not fully capture learners' ability to use discourse in different communicative situations, especially in spoken interaction. Future studies could adopt a more comprehensive approach by including both written and spoken measures of discourse competence to gain a more complete understanding of learners' abilities. Finally, the present study relied mainly on quantitative data. Although this is useful for identifying general patterns, it may not fully capture learners' experiences during the learning process. For this reason, future research could incorporate qualitative methods, such as interviews or reflective reports, to explore learners' perceptions and engagement with AI-supported microlearning in more depth.

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