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Where Microlearning Meets Language Learning and Cognitive Load: A Bibliometric and Content Analysis

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ABSTRACT

Microlearning has expanded rapidly, yet its links with language learning and cognitive load theory remain unclear. Using a bibliometric analysis and content analysis, this study mapped microlearning and examined where microlearning, language learning, and cognitive load intersect. The corpus comprised 758 English-language journal articles, retrieved from Scopus on 19 july 2026, of which 113 (14.9%) addressed microlearning; data were analysed with Biblioshiny and VOSviewer, complemented by a content analysis of 31 microlearning studies in language learning. Publications grew from 3 articles in 2015 to 231 in 2025, an annual growth rate of about 54%. China, the United States, and Indonesia were the leading countries, and higher education, artificial intelligence, and microlearning were the most frequent keywords. Language learning terms were scattered across several clusters. Cognitive load emerged as one of the newest themes, yet only four articles combined all three themes, and educational psychology and CALL sources formed separate co-citation clusters. All 23 empirical studies relied on perceptions or immediate post-tests; six studies referred to cognitive load theory or CTML, but none of these journal articles reported a cognitive load measure or a delayed post-test. Theory-informed microlearning designs for language learning have been proposed but not yet tested for their effects on cognitive load and retention. Future research should test such designs, measure cognitive load and delayed retention, and apply design-based research in EFL contexts.

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1. INTRODUCTION

Microlearning generally denotes brief learning activities built around small pieces of content, typically involving low time demands, compact units that address narrow topics, and fragmented formats such as short episodes or knowledge nuggets (Hug, 2012). Delivering learning content in short and focused units, has emerged as a growing global

research topic, with 476 relevant publications identified between 2006 and 2019 (Leong et al., 2021). Mobile microlearning platforms commonly use videos or multiformat materials such as text, audio, and quizzes (Lee et al., 2021). Language learning has been part of this development from the outset: the earliest microlearning publication indexed in Scopus proposed integrating second language learning into learners' daily routines through electronic devices (Sankaranarayanan et al., 2023).

This growth has not occurred in isolation. Microlearning is rarely implemented on its own and is often combined with other technology-enhanced approaches, such as mobile learning, flipped classrooms, gamification, and, more recently, AI chatbots. In workplace training, micro-learning interventions were found to be as effective as face-to-face and online interventions (Carter and Youssef-Morgan, 2022). In higher education, Fidan (2023) found that flipped classrooms improved pre-service teachers' learning performance, while microlearning support provided additional advantages in intrinsic motivation and engagement. A controlled study with MBA students likewise associated microlearning modules with better learning performance (Balasundaram et al., 2024). Because microlearning is increasingly combined with these approaches, its position as a distinct area within educational technology research has become less clear.

Several bibliometric studies have mapped microlearning research, particularly since the COVID-19 pandemic. Sankaranarayanan et al. (2023) analysed 208 Scopus publications, reported an annual growth rate of 33.5%, and identified four themes: design, implementation, evaluation, and the use of mobile devices. Dewi et al. (2025) analysed 127 Scopus documents published between 2005 and 2024 and reported an annual growth rate of 15.32%, while Susanti and Desa (2026) examined 201 Scopus documents published between 2016 and 2025. Moreover, Ranggana et al. (2025) found that 104 of 155 microlearning articles were published between 2020 and 2024. Altınpulluk et al. (2026) analysed 139 Web of Science publications, found that cognitive load theory occupied a limited position in the keyword map, and called for more theory-driven research. These studies map microlearning in general or in education broadly; none focuses specifically on its intersection with language learning and cognitive load.

In language learning, microlearning has been used both with learners and for teacher professional development. English teachers in higher education perceive microlearning as a flexible and low-pressure form of professional development (Kohnke et al., 2024a). For second language instruction, Khong and Kabilan (2022) observed that several microlearning studies lack theoretical grounding and proposed a model built on cognitive load theory, the cognitive theory of multimedia learning (CTML), and self-determination theory. A recent systematic review of 65 studies on microlearning in language education found that experimental and quasi-experimental studies, mostly with pre-test/post-test designs, formed the largest group (32%), and called for longitudinal studies to examine the long-term retention of learning through microlearning (Ekizer and Asma, 2026).

Cognitive load theory originated from the finding that conventional problem solving consumes a large amount of limited cognitive processing capacity, leaving less capacity for schema acquisition and thereby hindering learning (Sweller, 1988). The theory now distinguishes intrinsic load, determined by the complexity of the material and the learner's prior knowledge, from extraneous load caused by instructional features that do not support learning, while germane load refers to the working memory resources devoted to intrinsic load (Leppink et al., 2013; Sweller et al., 2019). CTML translates the idea of limited processing capacity into design principles such as segmenting, signalling, and removing extraneous information (Mayer, 2009). Cognitive load in multimedia environments has been reviewed extensively (Mutlu-Bayraktar et al., 2019), and a

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systematic review of 67 studies has examined cognitive load management in technology-assisted language learning (Bahari, 2022), although that review did not address microlearning. The segmenting principle intuitively aligns with microlearning, but whether microlearning designs for language learning have been tested against cognitive load and retention remains unclear.

Bibliometric analysis enables systematic mapping of a research field through performance analysis and science mapping (Donthu et al., 2021). This study extends previous work by mapping the position of microlearning within the broader educational technology landscape, measuring its intersection with language learning and cognitive load, and examining through content analysis how microlearning studies in language learning have been designed and evaluated. Accordingly, this study addressed three questions: (1) how research that includes microlearning has developed in terms of publication trends, sources, countries, influential documents, and thematic and intellectual structure; (2) to what extent microlearning, language learning, and cognitive load intersect within this landscape; and (3) whether microlearning studies in language learning that draw on cognitive load theory have measured cognitive load and retention.

2. METHODS

This study employed bibliometric analysis comprising performance analysis and science mapping (Donthu et al., 2021). Data were obtained from the Scopus database on 19 July 2026. The corpus consists of 758 English-language journal articles, published between 1983 and 2026, and exported in CSV format with abstracts, keywords, affiliations, and cited references. No publication-year or subject-area restriction was applied at retrieval. Three term groups were applied to titles, abstracts, and keywords: (1) microlearning ("microlearning" OR "micro-learning" OR "micro learning"), together with the related formats "mobile learning" and "short video"; (2) language learning ("language learning" OR "language teaching" OR "language education" OR "EFL" OR "ESL" OR "second language" OR "foreign language" OR "vocabulary" OR "TESOL"); and (3) cognitive load ("cognitive load" OR "working memory" OR "multimedia learning").

Ten articles (1.3%) were published before 2015. Because of their small number, the performance analysis was restricted to 2015–2026 (748 articles). Data for 2026 covered only about seven months and were therefore not used to interpret trends. The annual growth rate was calculated between 2015 and 2025, the last complete year.

Performance analysis (2015–2026, n = 748), including annual trends, sources, authors, countries, keyword frequencies, and most-cited documents, was conducted with Biblioshiny, the web interface of the bibliometrix R package (Aria and Cuccurullo, 2017). Science mapping (full corpus, n = 758) was conducted with VOSviewer (van Eck and Waltman, 2010) through keyword co-occurrence analysis, overlay visualisation based on average publication year, and source co-citation analysis. The average publication year of selected author keywords was calculated from the exported data (n = 758).

To analyse the position of microlearning, language learning, and cognitive load, each of the 758 articles was tagged based on the occurrence of terms in its title, abstract, and keywords. The microlearning category was identified by the terms microlearning, micro-learning, and micro learning. The language learning category was identified by the terms language learning, language teaching, language education, EFL, ESL, second language, foreign language, vocabulary, and TESOL. The cognitive load category was identified by the terms cognitive load, working memory, and multimedia learning. Intersections between categories were then counted to determine how often the three themes appeared together. Because "working memory", "multimedia learning", and "vocabulary" may capture articles outside the intended categories, a sensitivity analysis was

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performed. Restricting the cognitive load category to the term "cognitive load" reduced it from 41 to 35 articles (microlearning × cognitive load: 13 to 11; language learning × cognitive load: 8 to 6), and removing "vocabulary" from the language learning category reduced it from 234 to 228 articles (language learning × cognitive load: 8 to 7). The microlearning–language learning intersection (35) and the three-way intersection (4) were unchanged in both cases.

To complement the bibliometric indicators, a content analysis was conducted on the 35 articles tagged as both microlearning and language learning. Their titles, abstracts, and author keywords were screened, and four articles were excluded because microlearning or language learning was not their focus, leaving 31 articles. Each article was coded on four dimensions, namely target group (learners or teachers), research design, primary outcome (learning performance or perception/self-report), and reference to cognitive load theory or CTML, and on three study features: the use of cognitive load measures, delayed post-tests, and video-based materials. Coding was carried out using a predefined coding sheet and was based on titles, abstracts, and author keywords; the absence of a feature therefore indicates that it was not reported in these sources, not necessarily that it was absent from the study.

3. RESULTS AND DISCUSSION

Sections 3.1–3.5 describe the broader research landscape in which microlearning is situated (research question 1). Because microlearning appears in only 113 of the 758 articles (14.9%), these sections characterise the context of the corpus rather than microlearning research itself. Sections 3.6 and 3.7 focus on the intersection of microlearning, language learning, and cognitive load (research questions 2 and 3).

3.1. Publication Trends

The 2015–2026 corpus comprises 748 articles from 313 sources written by 2,128 authors, with an average of 3.12 authors and 19.5 citations per article. Figure 1 shows that publications grew slowly until 2018 and then increased sharply from 49 articles in 2022 to 95 in 2023, 148 in 2024, and 231 in 2025. The annual growth rate for 2015–2025 was approximately 54%. The decline in 2026 reflects incomplete data at the time of retrieval rather than declining research interest.

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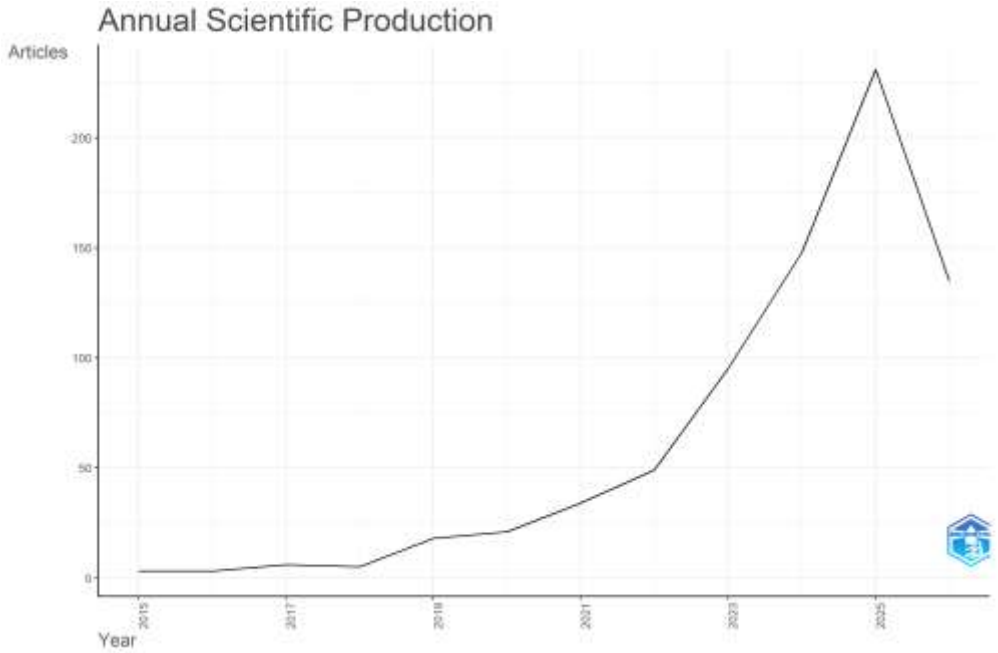


Figure 1. Annual scientific production (2015–2026, n = 748). Data for 2026 are partial (up to 19 July 2026).

3.2. Sources, Authors, and Countries

Nineteen core sources, identified using Bradford's law, contained 252 articles (33.7%), while the remaining articles were spread across 294 other sources. The Education and Information Technologies was the most productive source (48 articles), followed by Sustainability (20), Education Sciences (19), and Interactive Learning Environments (17). The only language-specific journal in the core zone was Computer Assisted Language Learning (9 articles). This distribution shows that the literature is widely dispersed and dominated by general education, educational technology, and multidisciplinary journals.

Lucas Kohnke was the most productive author (11 articles), followed by Di Zou (9), Behnam Behforouz (8), and Ali Al Ghaithi (8). Based on author affiliations, China (131 articles), the United States (87), and Indonesia (62) were the largest contributors, followed by Malaysia (59), Turkey (44), and Saudi Arabia (43).

3.3. Most Influential Documents

Table 1. Global most-cited documents (2015–2026).

No.	Document	Topic	Source	Citations	Citations per year
1	Chiu et al. (2024)	AI chatbot and student motivation	Interactive Learning Environments	519	173.0
2	Fan et al. (2025)	GenAI and metacognitive laziness	British Journal of Educational Technology	369	184.5
3	Essel et al. (2022)	Chatbot teaching assistant in HE	Int. J. of Educational Technology in Higher Education	352	70.4

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No.	Document	Topic	Source	Citations	Citations per year
4	Foroughi et al. (2024)	Intention to use ChatGPT	Int. J. of Human-Computer Interaction	349	116.3
5	Fathi et al. (2024)	AI-mediated EFL speaking	System	321	107.0
6	Turan and Akdag-Cimen (2020)	Flipped classroom in ELT	Computer Assisted Language Learning	267	38.1
7	de Santana Correia and Colombini (2022)	Neural attention models in deep learning	Artificial Intelligence Review	249	49.8
8	Mutlu-Bayraktar et al. (2019)	Cognitive load in multimedia learning	Computers & Education	249	31.1
9	Lin and Lin (2019)	Mobile-assisted vocabulary learning	Computer Assisted Language Learning	240	30.0
10	Lai et al. (2023)	Intrinsic motivation and ChatGPT adoption	Computers and Education: Artificial Intelligence	223	55.8

Table 1 shows that six of the ten most cited documents address chatbots, ChatGPT, or AI-mediated interaction, all published in 2022–2025. Three documents relate directly to language learning: a study of AI-mediated interaction for speaking skills (Fathi et al., 2024), a review of flipped classrooms in English language teaching (Turan and Akdag-Cimen, 2020), and a meta-analysis of mobile-assisted vocabulary learning (Lin and Lin, 2019). Only one document addresses cognitive load (Mutlu-Bayraktar et al., 2019). Thus, the most influential documents in this landscape concern AI and chatbots, whereas none focuses on microlearning and only one on cognitive load.

3.4. Thematic Structure and Emerging Themes

Based on the Biblioshiny keyword analysis, the most frequent keywords were higher education (78 occurrences), artificial intelligence (61), microlearning (57), education, e-learning and learning (38 each), and mobile learning (37). Figure 2 shows that microlearning is the largest node in the co-occurrence map, located in a cluster with e-learning, active learning, pedagogy, self-efficacy, and pre-service teachers. Other clusters centre on mobile learning and instructional design; motivation, engagement, and assessment; online learning, gamification, and social media; flipped classrooms and self-regulated learning; and generative AI and teacher education.

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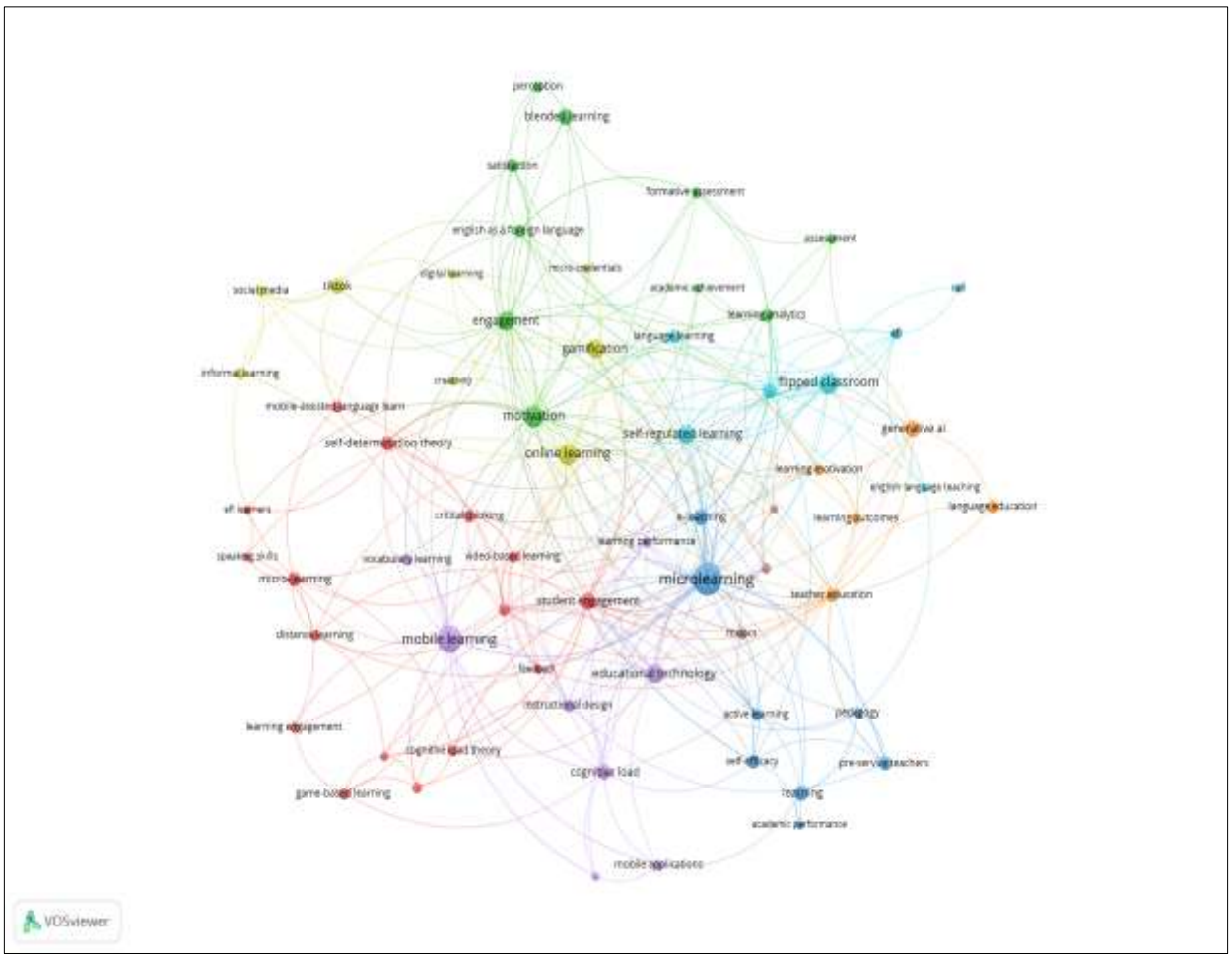


Figure 2. Keyword co-occurrence network.

Language learning terms do not form a cluster of their own. English as a foreign language appears in the motivation cluster, EFL learners and speaking skills in the engagement cluster, vocabulary learning in the mobile learning cluster, and language learning and CALL in the flipped classroom cluster. Because no thesaurus was applied, part of this dispersion may reflect unmerged synonyms; for example, the variant spelling micro-learning appears as a node separate from microlearning. However, when spelling variants are merged, only 8 of the 70 articles with microlearning as an author keyword also have a language-learning author keyword, and the term-based tagging, which covers all spelling variants, shows that only 35 of the 113 microlearning articles involve language learning (Table 2). This pattern suggests that the link between microlearning and language learning is small and has not yet formed a distinct research agenda.

Figure 3 shows that vocabulary learning and mobile learning appear among the older themes, whereas generative AI and cognitive load appear among the newest. Calculated from the exported author keywords, earlier themes include vocabulary learning (2018.8), mobile learning (2021.6), and e-learning (2022.8), whereas the newest include generative AI (2024.9), cognitive load (2024.8), artificial intelligence (2024.6), and engagement (2024.4). Because the corpus itself is recent (mean publication year 2023.7), these values indicate relative rather than absolute recency. Cognitive load appeared as an author keyword in only 13 articles; all published from 2022 onwards and 12 of them from 2024 onwards; it is therefore a small but recent theme rather than an established one.

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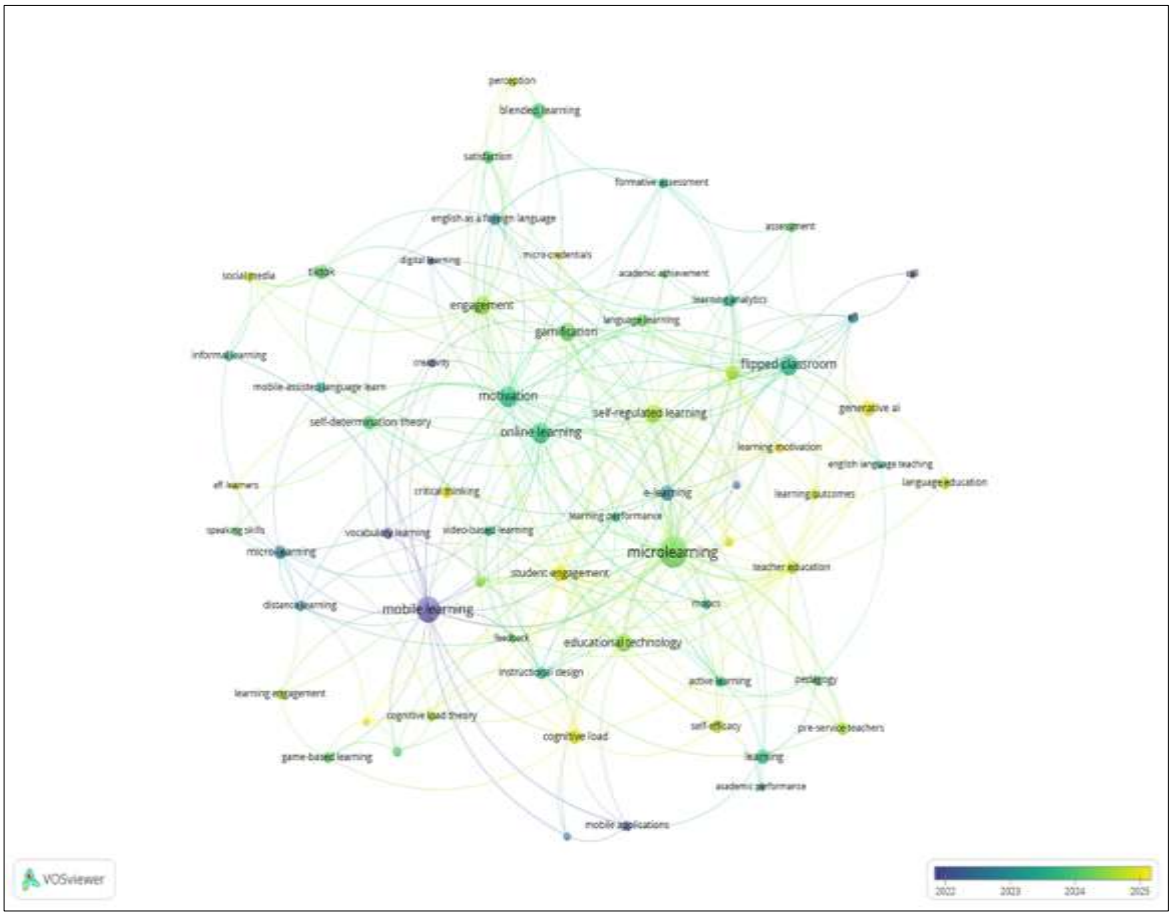


Figure 3. Keyword overlay visualisation by average publication year.

3.5. Intellectual Structure

Figure 4 shows that source co-citation forms six groups of literature. The educational psychology group includes Educational Psychology Review, Journal of Educational Psychology, Learning and Instruction, and Computers & Education. The CALL group includes Computer Assisted Language Learning, ReCALL, System, and Language Teaching Research. The other four groups represent educational technology journals (e.g., Education and Information Technologies, Interactive Learning Environments), distance and open education journals together with British Journal of Educational Technology and TechTrends, multidisciplinary journals (e.g., Sustainability, IEEE Access), and a smaller group around Educational Technology Research and Development.

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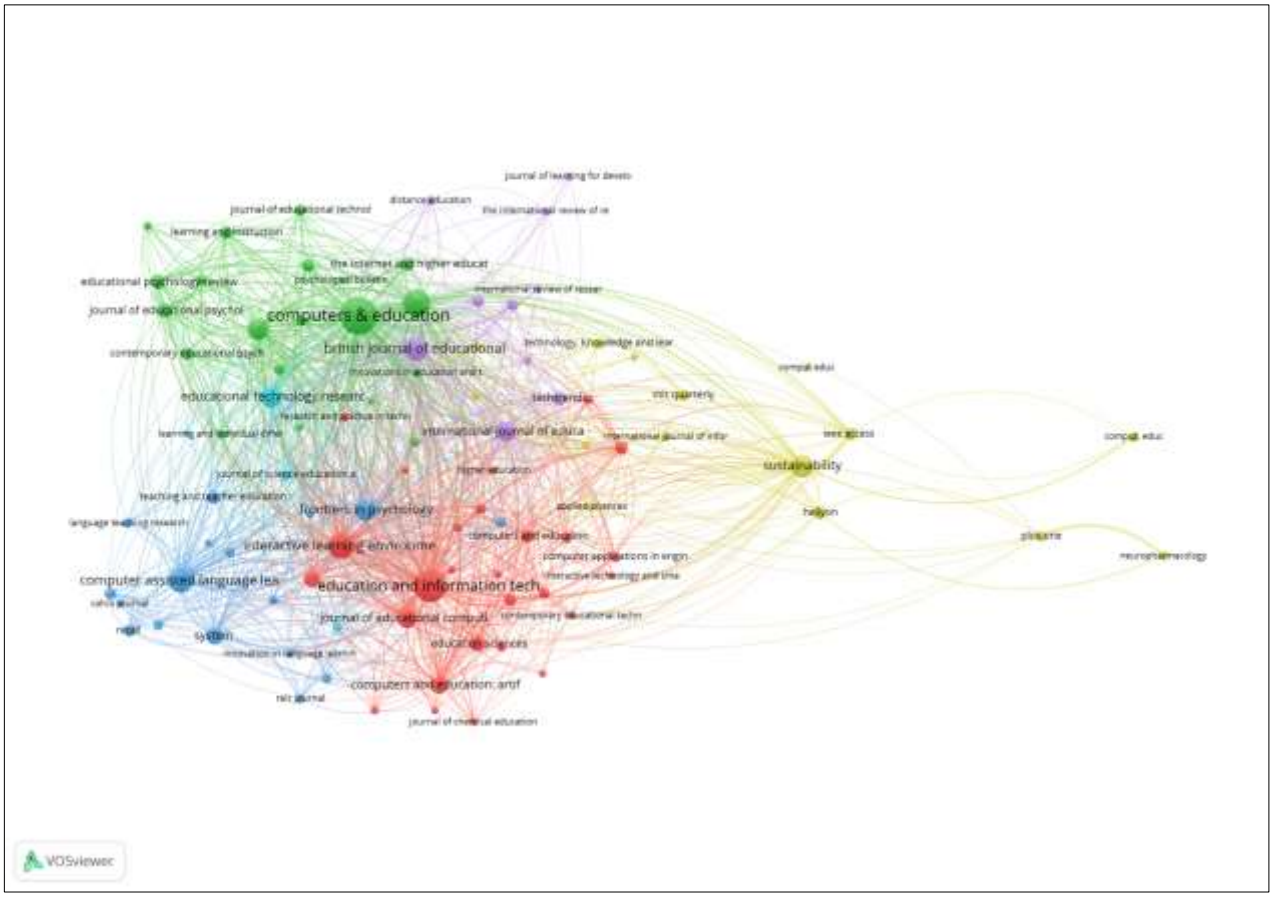


Figure 4. Source co-citation network.

The educational psychology and CALL groups form separate clusters, although they are adjacent and linked. Co-citation overlap (Jaccard index) between the core journals of each group confirms this: it was lowest for educational psychology and CALL (0.28), compared with educational psychology and educational technology (0.33) and CALL and educational technology (0.41). This indicates that sources on learning and cognition and sources on language learning are less often cited together by the same articles, suggesting that the two research bases are only partly integrated.

3.6. Position of Microlearning, Language Learning, and Cognitive Load

Microlearning appeared in 113 of the 758 articles (14.9%), and 88 of them (78%) were published from 2023 onwards. Table 2 shows that the number of articles drops sharply when the three themes are narrowed simultaneously.

Table 2. Intersection of microlearning, language learning, and cognitive load.

No.	Category or Intersection	Articles	Percentage (%)
1	Language learning	234	30.9
2	Microlearning	113	14.9
3	Cognitive load	41	5.4
4	Microlearning and language learning	35	4.6
5	Microlearning and cognitive load	13	1.7
6	Language learning and cognitive load	8	1.1
7	Microlearning, language learning, and cognitive load	4	0.5

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The intersection of all three themes contains only four articles (Table 3). All four refer to cognitive load theory or CTML, but only Aljawarneh et al. (2026) tested a cognitive-load-informed design experimentally, and none reported a measure of cognitive load or a delayed post-test.

Table 3. Articles combining microlearning, language learning, and cognitive load.

No.	Study	Design	Refers to CLT/CTML	Measures cognitive load	Delayed post-test
1	Khong and Kabilan (2022)	Conceptual (theoretical model)	Yes	Not applicable	Not applicable
2	Rahman (2025)	Qualitative (YouTube Shorts vs long-form videos)	Yes	No	No
3	Kohnke and Moorhouse (2026)	Qualitative (pre-service teachers, generative AI)	Yes	No	No
4	Aljawarneh et al. (2026)	Quasi-experimental (Voscreen short videos)	Yes	No	No

3.7. Content Analysis of Microlearning Studies in Language Learning

Table 4 summarises the coding of the 31 microlearning studies in language learning. Eighteen studies (58.1%) targeted language learners, while ten (32.3%) focused on teachers, mostly through microlearning-based professional development. Experimental or quasi-experimental designs and qualitative designs were equally common (eight studies each), followed by conceptual papers (five), mixed methods (four), surveys (three), and design and development studies (three).

Table 4. Content analysis of microlearning studies in language learning (n = 31).

No.	Dimension and Category	Articles	Percentage (%)
1	Target group: learners	18	58.1
2	Target group: teachers (pre-service and in-service)	10	32.3
3	Target group: general (conceptual papers)	3	9.7
4	Design: experimental or quasi-experimental	8	25.8
5	Design: qualitative	8	25.8
6	Outcome: learning performance	10	32.3
7	Outcome: perception or self-report	13	41.9
8	Refers to cognitive load theory or CTML	6	19.4
9	Measures cognitive load	0	0.0
10	Uses a delayed post-test	0	0.0

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No.	Dimension and Category	Articles	Percentage (%)
11	Uses video-based materials	4	12.9

Empirical studies were defined as those reporting learning performance or perception outcomes; the five conceptual papers and three design and development studies, which reported no such outcomes, were excluded. Among the 23 empirical studies, 13 (56.5%) relied primarily on perceptions or self-reports, and ten (43.5%) measured learning performance, all through immediate post-tests. Six studies referred to cognitive load theory, CTML, or cognitive overload, but most did so conceptually or as a design rationale. Based on titles, abstracts, and keywords, no study reported a direct measure of cognitive load, and none reported a delayed post-test to examine retention. Video-based microlearning appeared in only four studies, two of which were perception studies of TikTok and YouTube Shorts (Chuah and Ch'ng, 2023; Rahman, 2025).

3.8. Discussion

Publication growth in this study (about 54% per year for 2015–2025) is higher than in previous bibliometric studies of microlearning, which reported annual growth rates of 33.5% (Sankaranarayanan et al., 2023) and 15.32% (Dewi et al., 2025). Because only three articles were published in 2015, this rate is sensitive to the starting point; however, starting from 2019 (18 articles) still yields about 53%. The direction of the trend also differs across databases: Ranggana et al. (2025) found that most ScienceDirect articles appeared between 2020 and 2024, whereas Altınpulluk et al. (2026) reported that Web of Science publications peaked at 19 in 2017 and 2020 and declined to 8 in 2025. These differences likely reflect variations in databases, search terms, and scope. The broader corpus in this study also includes research on artificial intelligence and chatbots, which rose from 5 of 49 articles in 2022 to 80 of 231 in 2025; excluding these articles, the annual growth rate for 2015–2025 is still about 48%, so AI-related research explains only part of the higher growth.

The concepts associated with microlearning in this study, such as higher education, e-learning, and online learning, are consistent with those identified in the Web of Science, where cognitive load theory also occupied a limited position in the keyword map (Altınpulluk et al., 2026). Beyond these similarities, the present study shows that microlearning has become connected with teacher education since 2023 and with generative AI since 2025, as seen in studies on generative-AI-supported microlearning for pre-service teachers (Kohnke et al., 2025) and on developing teachers' professional digital competence through microlearning (Kohnke et al., 2024b).

These findings indicate that cognitive load research and language learning research remain only weakly connected in this corpus. The educational psychology and CALL groups form separate clusters in the source co-citation map (Figure 4); only four articles combine all three themes (Table 2), and although six of the 31 microlearning studies in language learning referred to cognitive load theory, CTML, or cognitive overload, none reported a measure of cognitive load (Table 4). Cognitive load can nonetheless be measured in microlearning, as shown by quasi-experimental studies outside language learning (Li, 2026; Zhu et al., 2024), and it has been assessed through questionnaires and interviews in a qualitative study of online learning (Susilana et al., 2022) and examined as a mediator in mobile language learning outside microlearning (Puri et al., 2025). The only study identified that measured cognitive load in microlearning for language learning, Salem (2025), reported improved functional writing skills and reduced cognitive load among business English students; as a proceedings chapter, it lies outside the corpus.

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The most important gap concerns retention. In the content analysis, 13 of the 23 empirical studies relied on learners' or teachers' perceptions, the ten studies that measured learning performance all used post-tests administered immediately after the intervention, and none reported a delayed post-test (Table 4). One study in the corpus nevertheless claimed long-term effects; Jubran (2024), reported better short- and long-term retention of English idioms after administering a single post-test. This pattern is consistent with a systematic review of 65 studies on microlearning in language education, in which experimental and quasi-experimental studies, typically with pre-test/post-test designs, formed the largest group (32%), and which called for longitudinal studies to examine the long-term retention of learning through microlearning (Ekizer and Asma, 2026). It also echoes the call of Altınpulluk et al. (2026) for more diversified and theory-driven microlearning research. By combining bibliometric mapping with a content analysis, the present study indicates that this gap is particularly evident in microlearning for language learning, where theory-informed designs are proposed but their effects on retention remain untested.

These findings point to several directions for future research. First, the theoretical model of micro-learning for second language instruction identified at the intersection of the three themes (Table 3), which combines cognitive load theory, CTML, and self-determination theory, should be tested empirically. Second, because none of the 31 studies reported a measure of cognitive load or a delayed post-test (Table 4), future studies should measure cognitive load directly with validated instruments and examine retention through delayed post-tests. Third, short-video microlearning deserves attention, as only four of the 31 studies used video-based materials, and three of these examined perceptions rather than learning outcomes. Fourth, design-based research could be used to develop and refine microlearning design principles for language learning iteratively, linking design decisions to measured cognitive load and retention.

In practice, EFL teachers and instructional designers could build microlearning units on multimedia principles such as segmenting and signalling (Mayer, 2009) and assess them with delayed tests rather than immediate tests or satisfaction alone. This is particularly relevant for Indonesia, the third largest contributor, where only one article combined microlearning and language learning.

This study has several limitations. The data came only from Scopus and were limited to English-language journal articles, so relevant studies published in conference proceedings were not captured by the bibliometric analysis. The corpus covers a broad educational technology landscape, so some documents relate only indirectly to microlearning. In addition, category tagging relied on term occurrence, so articles discussing cognitive load without using the term were not detected, and the intersection counts should be read as lower bounds. No thesaurus was applied in the science mapping, so some synonyms appear as separate nodes in Figures 2 and 3. Finally, the content analysis was based on titles, abstracts, and keywords, not full texts, and was conducted by a single coder. Some studies may have measured cognitive load or used delayed post-tests without reporting this in their abstracts.

4. CONCLUSION

Educational technology research that includes microlearning grew rapidly between 2015 and 2025; higher education and artificial intelligence are the most frequent keywords, and most of the most cited documents address chatbots or AI-mediated interaction. Microlearning is the largest node in the keyword map and a strengthening theme, yet it shares a cluster with broader concepts such as e-learning and active learning

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rather than forming a separate research area, while language learning is scattered across several thematic clusters. Cognitive load is among the newest themes, yet very few articles combine it with microlearning and language learning, and the educational psychology and CALL literatures form separate clusters in the source co-citation map. The content analysis shows that all empirical microlearning studies in language learning relied on perceptions or immediate post-tests; although several referred to cognitive load theory or CTML, none of the journal articles in the corpus reported a measure of cognitive load or a delayed post-test. Theory-informed microlearning designs for language learning have thus been proposed but not yet tested for their effects on cognitive load and retention.

Future research should test microlearning designs for language learning based on cognitive load theory and CTML, measure cognitive load and delayed retention, and adopt design-based research in EFL contexts. Future bibliometric studies could also use multiple databases, include conference proceedings, and combine bibliometric mapping with full-text content analysis to obtain a more complete picture.

5. AUTHOR'S NOTE

The author declares that there is no conflict of interest regarding the publication of this article. The authors confirmed that the paper was free of plagiarism.

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