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Bibliometric Mapping of Microlearning Research (2014–2024): Thematic Evolution, Collaboration Networks, and the Shift Toward AI-Driven Personalization†

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Abstract

Microlearning has emerged as a prominent pedagogical strategy offering concise, focused learning experiences typically spanning three to ten minutes. Its responsiveness, flexibility, and alignment with contemporary digital learning behaviors make it particularly suitable for both educational and professional training contexts. Despite its growing adoption, the academic landscape still lacks a methodologically transparent, critically interpreted synthesis of microlearning research. This study addresses that gap through a systematic bibliometric analysis of the microlearning domain covering the period 2014–2024. Drawing on peer-reviewed literature extracted from the Scopus database and analyzed with the Bibliometrix R-package, following a PRISMA-inspired selection protocol, the study maps major research themes, identifies leading authors and prolific institutions, and delineates international collaboration networks. The final corpus comprises 651 documents from 444 sources, produced by 1782 authors, with an annual growth rate of 32.22%. Keyword co-occurrence analysis and thematic clustering reveal the progressive integration of artificial intelligence, mobile technologies, gamification, and adaptive learning into microlearning frameworks and point to a shift in research emphasis from descriptive, definitional work toward applied and, more recently, AI-driven personalization research. Beyond descriptive mapping, the study discusses the limits of raw publication and citation counts, situates the post-2019 acceleration relative to rather than as proof of the COVID-19-driven shift toward digital education, and identifies concrete methodological gaps (database and language coverage, search-term sensitivity, citation normalization, and clustering reproducibility) that should guide future bibliometric work on microlearning.

Keywords: microlearning; nanolearning; bibliometric analysis; personalized learning; digital pedagogy; artificial intelligence; adaptive learning; gamification; mobile learning; educational technology; thematic evolution

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1. Introduction

1.1. Establishing a Territory

Over the past decade, microlearning has attracted increasing scholarly attention as a modality offering short, focused learning experiences, typically between three and ten minutes in duration. The proliferation of digital technologies has restructured traditional educational paradigms, accelerating the shift toward more flexible, mobile, and accessible

forms of learning. In this changing context, microlearning has been identified as a potential approach to improve learner engagement, knowledge retention and skill acquisition in various educational and professional settings [1,2].

In terms of cognition, microlearning is well aligned with established learning theories, notably Sweller's [3] Cognitive Load Theory, which stresses the importance of decreasing extraneous cognitive load to achieve better learning outcomes. Microlearning breaks instructional content into small bites, reducing cognitive overload and increasing encoding of the information. This theoretical basis distinguishes microlearning from traditional e-learning methods and positions it as a pedagogically sound approach for the digital age.

The COVID-19 pandemic coincided with a swift institution-wide transition to asynchronous, modular, and technology-mediated instruction [4]. This contextual shift is accompanied by a pronounced increase in both microlearning implementations and related academic output, which motivates a systematic examination of the field's intellectual structure and thematic evolution while, as discussed in Section 4.2, correlation in publication timing should not be read as proof of a causal pandemic effect.

1.2. Establishing a Niche

Although the number of publications on microlearning is increasing, there is a lack of systematic bibliometric synthesis of the field in the literature. Key gaps include the absence of longitudinal analyses evaluating long-term learning outcomes, insufficient investigation of optimal content-design principles, and limited examination of microlearning's integration with existing curriculum frameworks. Prior bibliometric studies have also tended to rely on narrow temporal windows or single-database samples, which constrains the generalizability of their conclusions. Where this paper refers to very recent contributions published in 2025 (e.g., [5,6]), these works are cited only as contextual points of comparison for the discussion in Sections 2 and 5.3 and do not form part of the analyzed corpus, which is strictly restricted to documents indexed between 1 January 2014 and 31 December 2024.

This study addresses these limitations by conducting a comprehensive bibliometric analysis spanning 2014–2024, examining publication growth trajectories and annual trends; citation-impact metrics and high-influence sources; thematic research clusters and keyword co-occurrence networks; international and institutional collaboration patterns; and technological integration and the evolution of research emphasis.

1.3. Occupying the Niche

This paper contributes a systematic and reproducible bibliometric mapping of microlearning research from 2014 to 2024. Beyond descriptive visualization, the study offers a critical interpretation of thematic clusters, collaboration dynamics, and the research trajectories shaping the field, and it is explicit about the boundaries of what bibliometric evidence can and cannot support. The paper is structured as follows: a literature review is provided in Section 2; the methodology is described in Section 3 and the results are in Section 4; Section 5 presents a summary of the findings and their discussion, including methodological limitations; and Section 6 concludes with implications and future directions.

2. Literature Review

The academic literature on microlearning is varied in disciplines and demonstrates its pedagogical versatility and increasing embedding in technology. Alharbi and Drew [7] found that mobile microlearning had a positive impact on learner engagement in higher education, with increases in retention and satisfaction. Kapp [8] explored gamification of learning and instruction and identified game-based elements as drivers of learner motivation.

Dicheva et al. [9], in their review of MOOCs, pointed to the need for adaptive learning technologies that correspond to the principles of microlearning.

Hug [2] presents a basic theoretical framework that places microlearning in the larger context of digital and informal learning. Merrill [10] provides prescriptive design principles that align with the microlearning emphasis on problem-centered instruction.

More recent bibliometric studies have begun to systematically map the microlearning landscape, and their scope helps situate the present contribution. Monib et al. [4] documented an annual growth rate of 19.37% over 2007–2023. Mochamad [11] identified 459 publications concentrated between 2019 and 2023. Astaño [5] examined the intersection of microlearning and nanolearning, a conceptually adjacent but narrower strand that the present study's search strategy deliberately excludes from its quantitative corpus (see Section 3.1) while still engaging with it here as context. Kusworo et al. [12] applied bibliometric methods to microlearning in economics education. Silva et al. [6] reviewed microlearning's role in basic education, identifying dominant digital tools and theoretical frameworks.

Collectively, this body of literature confirms expanding scholarly interest in microlearning while revealing persistent gaps in longitudinal effectiveness research, standardized measurement frameworks, and cross-disciplinary integration studies gaps that the present bibliometric mapping is positioned to describe, though not to close on its own.

3. Methodology

3.1. Data Collection and Search Strategy

The Scopus database is the main source of data because of its wide multidisciplinary coverage, strict quality standards of peer review and native compatibility with Bibliometrix analytical tools. This is a conscious tradeoff, not a neutral default. Scopus has good coverage of computer science and engineering education venues where a large share of microlearning research can be found but does not fully overlap with Web of Science, ERIC, or PsycINFO. This database coverage bias, coupled with the English language restriction detailed below, is addressed as a limitation in Section 5.2. The temporal scope covers the time period from January 2014 to December 2024.

The following Boolean search query was applied to the title, abstract, and keyword fields:

```
TITLE-ABS-KEY("microlearning" OR "micro-learning" OR "micro learning")
AND PUBYEAR > 2013 AND PUBYEAR < 2025 AND (LIMIT-TO(DOCTYPE,"ar") OR LIMIT-
TO(DOCTYPE,"cp") OR LIMIT-TO(DOCTYPE,"ch")) AND LIMIT-TO(LANGUAGE,"English")
```

The query was limited specifically to the terms "microlearning", "micro-learning" and "micro learning" so that the corpus is still focused on the terminology in which the field has largely organized itself. Semantically similar but conceptually narrower or adjacent terms like "bite-sized learning", "nanolearning", and "just-in-time learning" were not included in the primary query; their relationship to microlearning is instead discussed qualitatively in Section 2 through Astaño [5]. The current study did not perform a sensitivity query that included these adjacent terms; this is mentioned as a direction for future work in Section 5.3.

3.2. Inclusion and Exclusion Criteria and PRISMA-Inspired Filtering

A structured selection process was used for relevance and quality. The inclusion criteria for the documents were peer-reviewed articles, conference proceedings, or book chapters, in English, and related to education or technology applications of microlearning. Non-academic publications, patents, commercial documents, editorials and records with insufficient metadata were excluded. The filtering process involved de-duplication, which reduced the initial retrieval of 892 records to 751 and manual screening for thematic relevance and completeness of metadata further reduced this to 651 documents (Figure 1). The final

corpus is divided into 313 journal articles (48.1%), 279 conference papers (42.9%) and 59 book chapters (9.1%) in line with the inclusion criteria above.

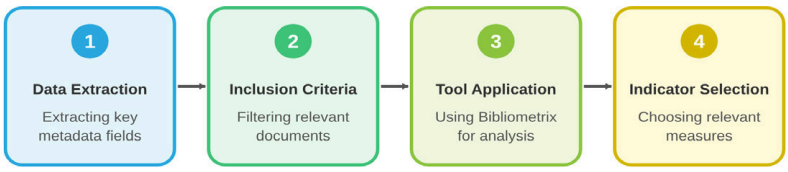


Figure 1. Bibliometric analysis process (Source: authors' own illustration).

Manual screening was conducted in two passes: a title/abstract pass to exclude records in which the search terms appeared in an unrelated technical context (e.g., non-educational uses of "micro-learning" as a compound term), followed by a full-text pass applied to borderline records. Screening was carried out collectively by the author team rather than under a formal multi-rater protocol; no independent-rater inter-agreement statistic (e.g., Cohen's κ) was computed, and this is acknowledged as a reproducibility limitation in Section 5.2. To support reproducibility, the corpus boundary was fixed at 31 December 2024; studies published in 2025 [5,6] are discussed in Sections 2 and 5.3 only as external comparators and were never included in the bibliometric computations reported in Section 4.

3.3. Analytical Tools and Selected Indicators

Bibliometric analysis was conducted using Bibliometrix (version not recorded at the time of the analysis) [13], an R-based package for systematic, quantitative analysis of scientific literature. The scientific impact was evaluated through citation analysis. The emerging thematic clusters were identified through keyword co-occurrence analysis. The collaboration patterns were analyzed through co-authorship network analysis. The contribution of the leading venues over time was assessed through source-production analysis. The international partnerships were visualized through country collaboration mapping.

Co-occurrence of keywords and thematic clustering of authors' keywords (DE field) were performed using the co-word analysis functions of Bibliometrix, following the general approach described by Aria and Cuccurullo [13]. The frequency table of Keywords Plus presented in Section 4.7 is only a complementary descriptive indicator and not the basis of the clustering procedure. Community detection was done using the default settings of Biblioshiny for keyword co-occurrence networks: the Louvain clustering algorithm with association strength normalization. This yielded the two-cluster partition shown in Section 4.6. The particular minimum keyword frequency threshold used was not separately recorded and is presented here as the software default rather than a manually tuned value. Section 4.3 presents the total citations by country and discusses citations-per-document as a normalized indicator that provides a more comparable picture of international scientific influence than raw citation counts.

4. Results

4.1. General Overview of the Corpus

The bibliometric analysis yielded a data set of 651 documents, published in 444 different sources. The research community is composed of 1782 authors, where 90 authors published single-authored documents. Scholarly output is growing at a sustained and accelerating rate, with an annual growth rate of 32.22%. The average number of co-authors per document (3.47) and the proportion of international co-authorship (17.2%) suggest a moderately collaborative research culture. The corpus cites 19,764 references with an average document age of 3.79 years and an average number of citations per document of 7.18 (Figure 2).



Figure 2. Research output summary (Source: Bibliometrix).

4.2. Annual Scientific Production

Scientific production shows a consistent upward trajectory from 2014 to 2024, with visible acceleration after 2019. Annual output rises from 9 documents in 2014 to 18 (2015), 14 (2016), 33 (2017), 33 (2018), 54 (2019), 58 (2020), 75 (2021), 89 (2022), 121 (2023), and 147 (2024) (Figure 3).

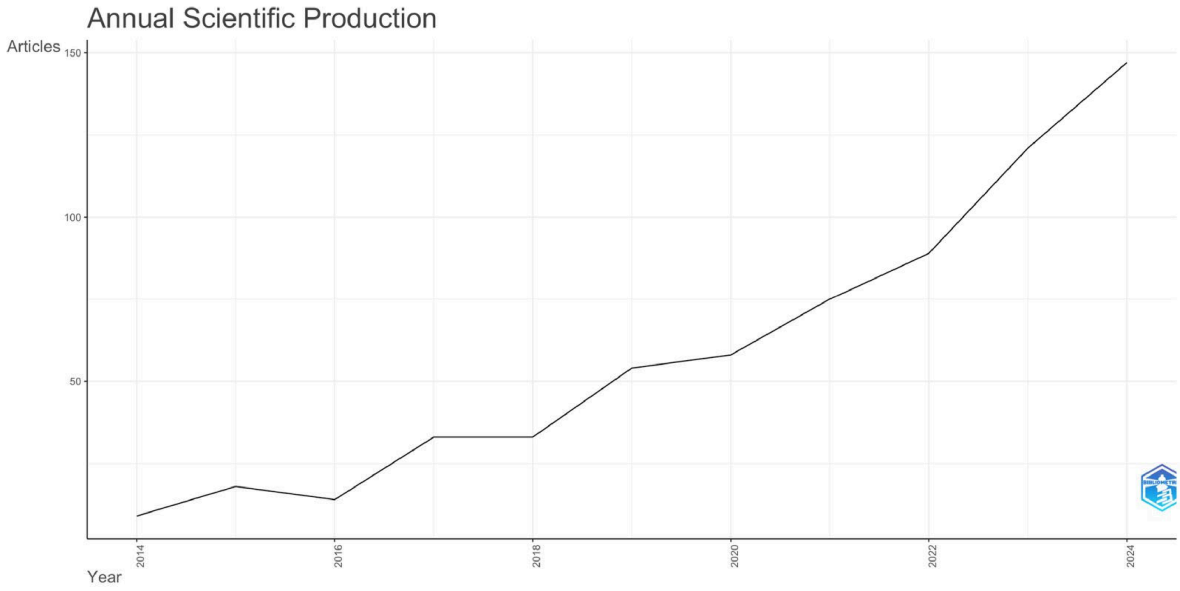


Figure 3. Annual scientific production, 2014–2024 (Source: Bibliometrix).

This trajectory intersects with the larger digital education transformation induced by the COVID-19 pandemic [4], wherein many institutions shifted to modular, asynchronous, and technology-mediated instruction. But bibliometric data alone cannot demonstrate a causal link between the pandemic and the observed growth: publication counts reflect submission and review-cycle lags of one to three years, several other educational technology fields grew at similar rates over the same window, and no counterfactual exists. The association is thus described as a plausible context factor rather than a proven cause.

4.3. Geographic Distribution and Country Contributions

The geographic analysis identifies the United States as the most prolific contributor by document count, followed by China, Australia, Germany, and the United Kingdom. Other significant contributors include Iran, Spain, Hong Kong, India, Canada, the Czech Republic, Japan, Malaysia, Austria, the Netherlands, Romania, Singapore, Slovakia, Indonesia, and

France (Figure 4). This distribution reflects the global reach of microlearning scholarship while highlighting the concentration of output in a small number of English-speaking and East Asian research systems.

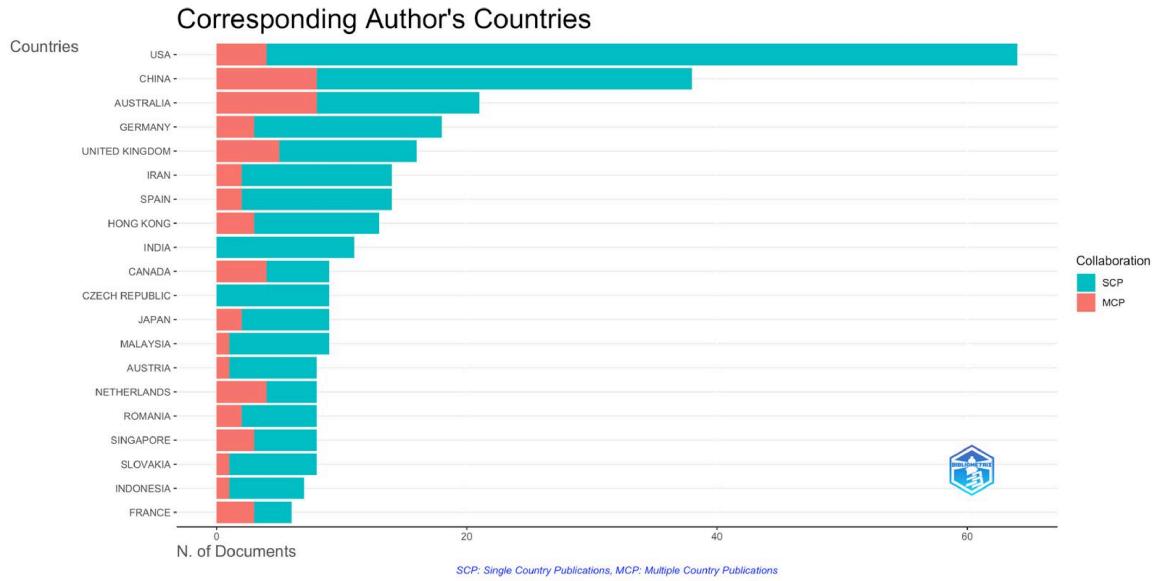


Figure 4. Corresponding author's countries—single- vs. multiple-country publications (SCP/MCP) (Source: Bibliometrix).

By total citation count, the United States leads with 620 citations, followed by China (407), Australia (205), the United Kingdom (185), India (142), Greece (139), Spain (137), Germany (118), Slovakia (102), and Italy (100) (Figure 5).

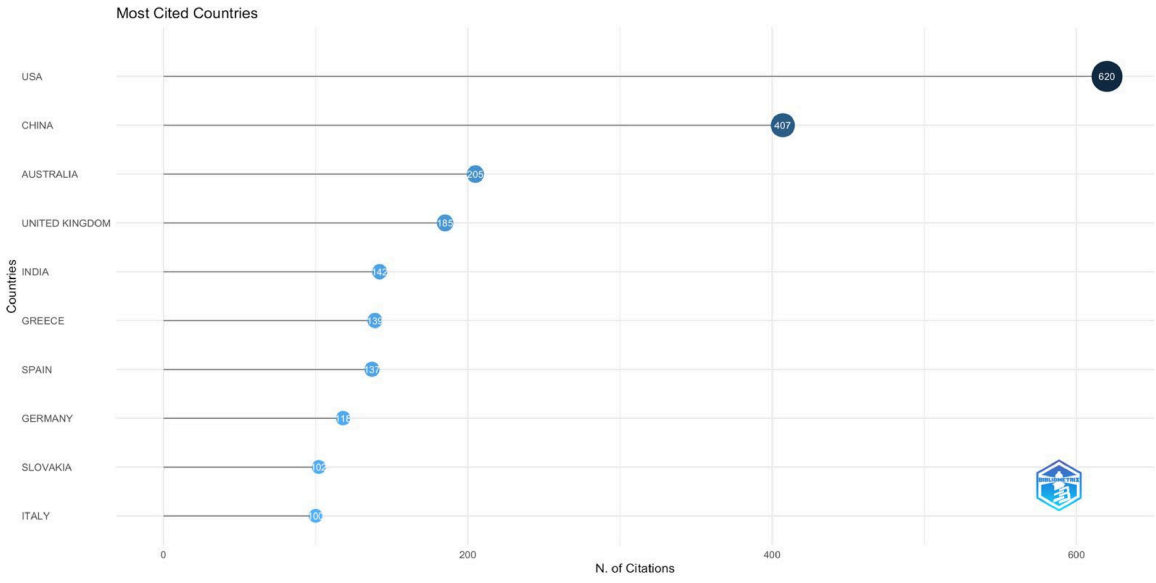


Figure 5. Most cited countries by total citation count (Source: Bibliometrix).

Because raw citation totals mechanically favor countries with larger overall output, they should not be read on their own as a measure of scientific influence. Table 1 reports citations-per-document for the ten most-cited countries, computed directly from the underlying Scopus export by summing citation counts and document counts per corresponding-author country (country identified from the Correspondence Address field; 412 of 651 records, 63.3%, carry an identifiable corresponding-author country, so totals below are a close

approximation of the full-corpus figures rather than an exact reproduction of Figure 5 the reproduced citation totals matched Figure 5 exactly for eight of the ten countries, with a minor difference for China (396 vs. 407) attributable to records with an ambiguous or missing address).

Table 1. Citations-per-document by country, ranked by normalized impact, reproduced from the Scopus export (* China's citation total as independently reproduced; Figure 5 reports 407) (Source: authors' analysis of the underlying Scopus export).

Country	Documents	Citations	Citations/Document
Greece	2	139	69.50
Italy	4	100	25.00
India	11	142	12.91
Slovakia	8	102	12.75
China	34	396 *	11.65
United Kingdom	16	185	11.56
Spain	14	137	9.79
Australia	21	205	9.76
USA	64	620	9.69
Germany	18	118	6.56

The normalized ranking changes the picture substantially. Greece, with only two documents, records the highest citations-per-document ratio in the set (69.50) nearly seven times the USA's ratio (9.69) confirming quantitatively that its citation impact (Section 4.3, Figure 5) is concentrated in a very small, unusually high-impact body of work rather than distributed volume. Italy (25.00) and Slovakia (12.75) similarly outrank the three largest producers (USA, China, Australia) on a per-document basis despite an order of magnitude fewer documents. Germany, despite ranking fourth by total documents (18), has the lowest citations-per-document ratio in the table (6.56), indicating comparatively lower average impact per publication. This confirms that raw citation and document totals (Figures 4 and 5) and normalized impact (Table 1) support different, complementary conclusions and that neither should be read as a complete picture of "scientific influence" on its own.

Single Country Publications (SCP) dominate the corpus for most contributing nations, indicating that while cross-national collaboration is growing, a substantial share of microlearning research remains nationally bounded (Figure 4). The country collaboration map (Figure 6a) illustrates the resulting international research partnerships geographically, showing the densest ties among the United States, China, and Australia.

Disaggregating cumulative output by country (Figure 6b) makes the discussion on timing of the pandemic in Section 4.2 more detailed. The USA, Australia, China and Germany follow each other closely and grow at broadly similar rates through 2019; from 2020 the USA's trajectory steepens noticeably relative to the other three, overtaking Australia by 2021 and roughly doubling Australia's and China's output by 2024. India grows from a small base throughout the period without a comparable inflection. This country-level divergence around 2020 is consistent with the pandemic-timing association discussed in Section 4.2, but it also shows that the effect (if any) was not uniform across countries which further supports treating the COVID-19 link as a plausible contributing factor rather than a demonstrated, uniform cause.

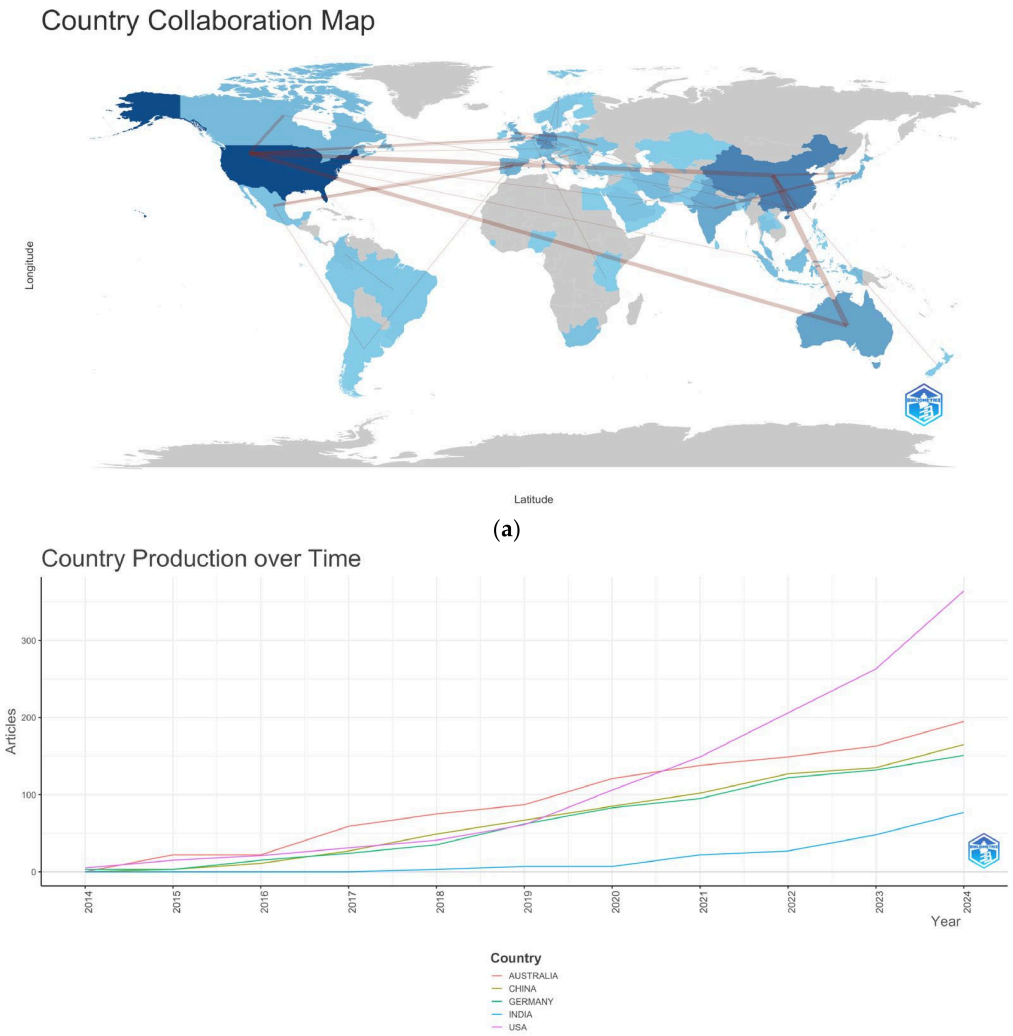


Figure 6. (**a**) Country collaboration map (Source: Bibliometrix). (**b**) Cumulative country production over time, 2014–2024, for the four leading contributors and India (Source: Bibliometrix).

4.4. Most Productive Authors and Local H-Index

The most prolific contributors are Shen Jun and Sun Geng (22 documents each), followed by Cui Tingru (21), Xu Dongming (16), and Chen Shiping (15). Additional prominent authors include Kohnke Lucas (12), Beydoun Ghassan (10), Javorcik Tomas (10), Lin Jiayin (10), and Skalka Jan (9) (Figure 7). These authors cluster around three thematic groups: educational technology, computer-supported collaborative learning, and intelligent tutoring systems, a grouping developed further in Section 4.6.

The local H-index shows that Chen Shiping, Cui Tingru, Shen Jun, and Sun Geng share the highest local H-index of 10, indicating consistent citation performance across multiple publications. The next best H-index is 8 for Beydoun Ghassan and Xu Dongming. Drlik Martin, Javorcik Tomas and Skalka Jan have a score of 6 (Figure 8a). The overlap between productivity (Figure 7) and local impact (Figure 8a) for most of the same authors shows a small, stable core of researchers anchoring the field's most cited work, rather than impact being evenly distributed across all prolific contributors.

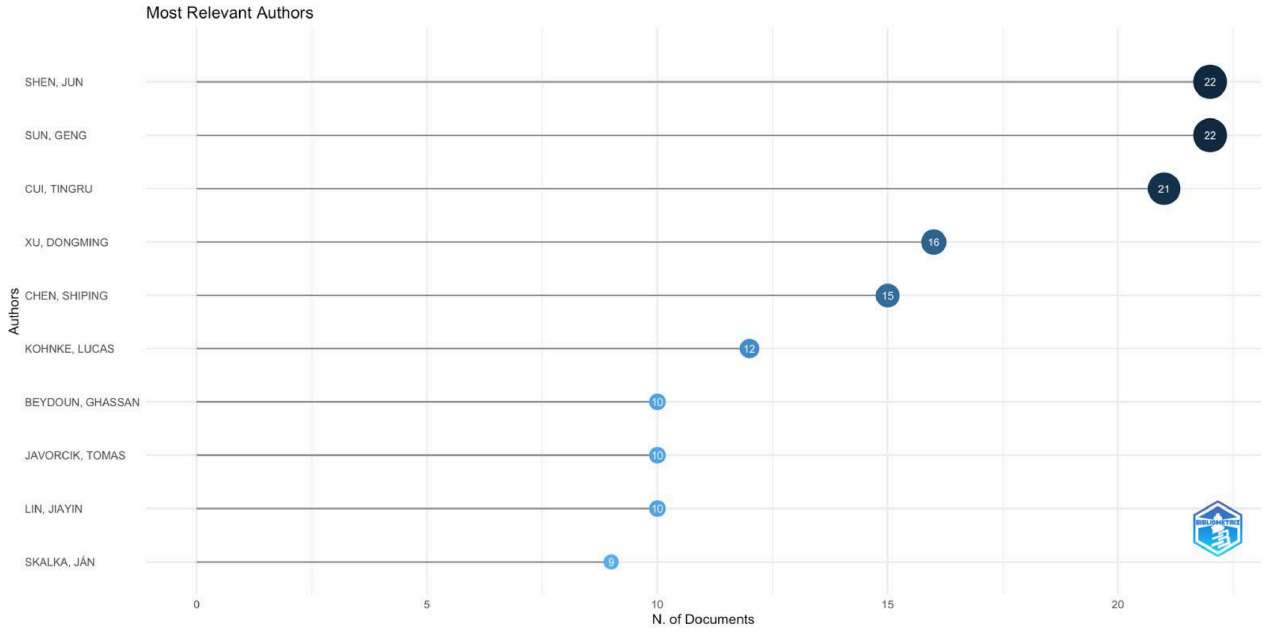


Figure 7. Most relevant authors by number of documents (Source: Bibliometrix).

The individual co-authorship network (Figure 8b) indicates that this productivity is structurally concentrated rather than broadly distributed: Shen Jun and Sun Geng anchor a single large, densely connected component, whereas the great majority of other productive authors appear in small, mutually disconnected pairs or triads (e.g., Javorcik Tomas–Polasek Radim; Drlik Martin–Skalka Ján). This pattern supports the moderate international co-authorship rate reported in Section 4.1 (17.2%) and suggests that, apart from the Shen/Sun cluster, microlearning research is now produced by many small, largely independent teams rather than a single integrated international network.

Institutional Contributions

Institutional analysis complements the author-level view in Section 4.4. The University of Wollongong is by far the most prolific affiliation (38 documents), followed by Constantine the Philosopher University in Nitra (21), the University of Nottingham Ningbo China (19), the University of Sydney (17), the Education University of Hong Kong and the University of Newcastle (14 each), Henan University of Science and Technology (12), Shiraz University of Medical Sciences and the University of Toronto (11 each), and Tehran University of Medical Sciences (10) (Figure 8c).

Two of the ten leading affiliations (Shiraz University of Medical Sciences and Tehran University of Medical Sciences) are medical sciences institutions rather than general or education-focused universities. This is consistent with, and helps explain, the separate red "clinical/medical" sub-network identified in the keyword co-occurrence analysis (Section 4.6): a meaningful share of the corpus originates from health-professions education research (e.g., clinical competence, controlled study, human experiment) rather than from computer science or general education venues, and this institutional split maps onto the two-cluster thematic structure rather than being an artifact of keyword indexing alone.



Figure 8. (**a**) Authors' local impact by H-index (Source: Bibliometrix). (**b**) Individual co-authorship network among the most productive authors (Source: Bibliometrix). (**c**) Most relevant affiliations by number of documents (Source: Bibliometrix).

4.5. Source Analysis and Publication Venues

Figure 9 illustrates the cumulative production of the leading sources over time and distinct adoption dynamics. Lecture Notes in Computer Science appears to have grown early and steadily since 2014, reflecting the field's origins in computer science venues. The ACM International Conference Proceeding Series also grew strongly from 2020 to 2021, a period that overlaps with the increase in educational technology research related to the pandemic discussed in Section 4.2. More recent venues such as Lecture Notes in Networks and Systems and Education and Information Technologies show steep growth after 2021, which indicates the diversification of the publication landscape and the entry of newer interdisciplinary outlets into the microlearning conversation.

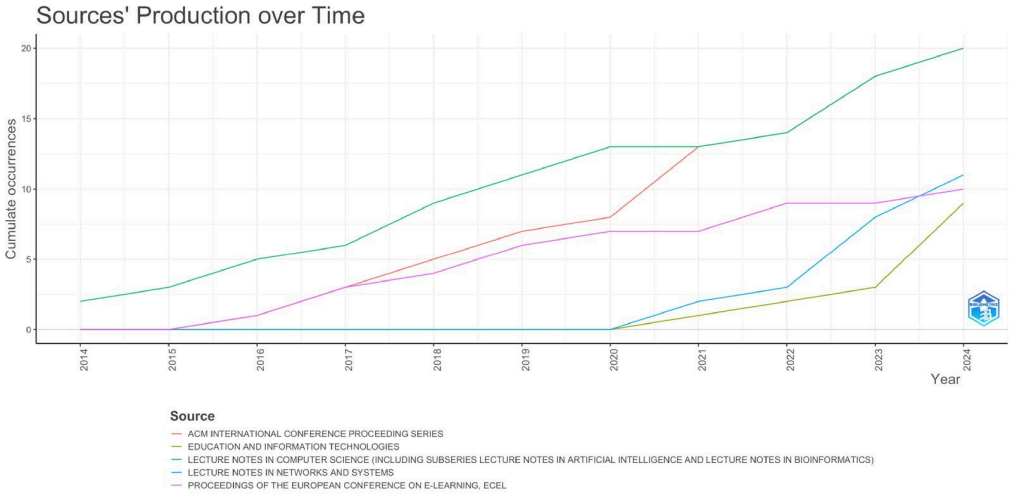


Figure 9. Cumulative source production over time, 2014–2024 (Source: Bibliometrix).

The most relevant publication venues by document frequency are the ACM International Conference Proceeding Series and Lecture Notes in Computer Science (20 documents each), followed by Lecture Notes in Networks and Systems (11) and the Proceedings of the European Conference on E-Learning (10) (Figure 10). Source impact measured by local H-index confirms the primacy of Lecture Notes in Computer Science (H = 7), the ACM International Conference Proceeding Series (H = 6), and Education and Information Technologies (H = 5) (Figure 11).

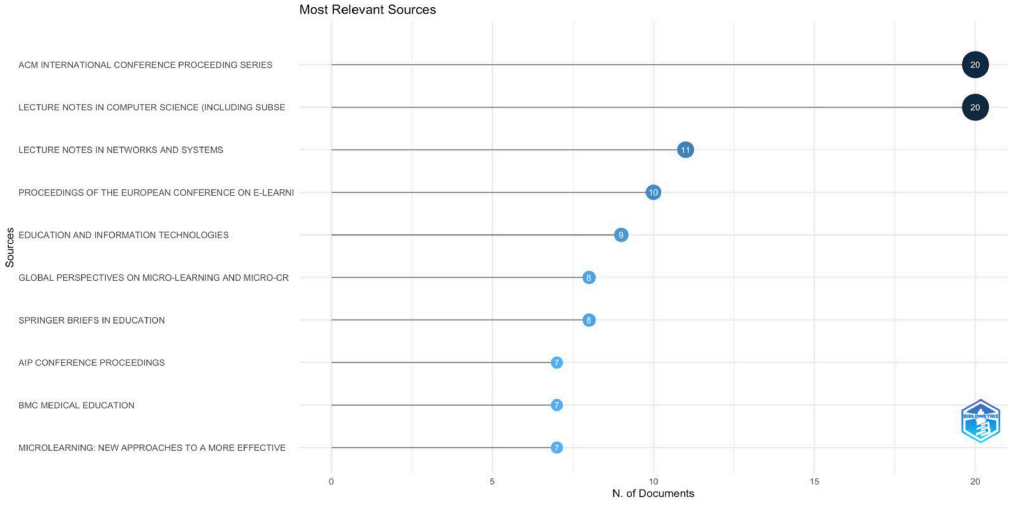


Figure 10. Most relevant sources by number of documents (Source: Bibliometrix).

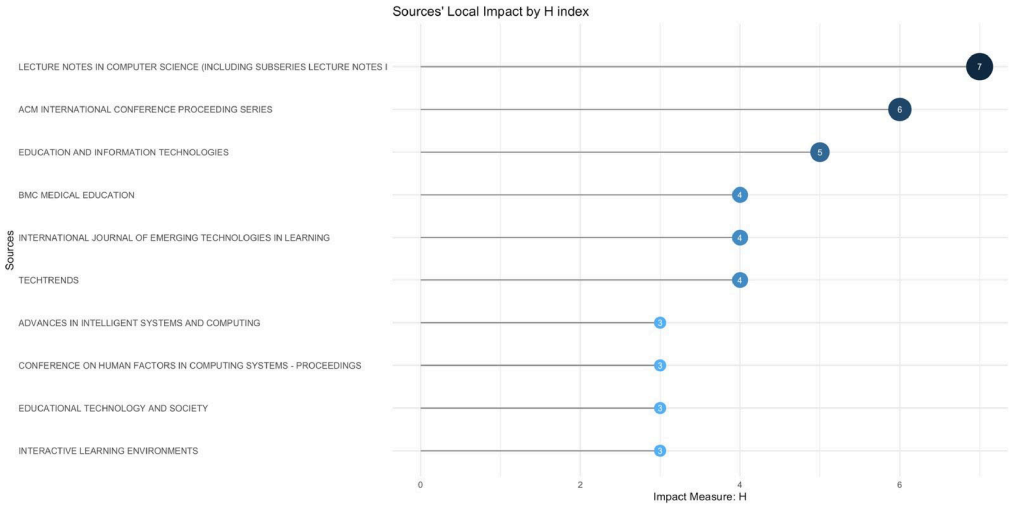


Figure 11. Sources' local impact by H-index (Source: Bibliometrix).

4.6. Keyword Co-Occurrence and Thematic Clusters

A keyword co-occurrence analysis was performed to identify the thematic architecture of the literature organized around several interconnected clusters. Figure 12 shows the word cloud, while Figure 13 shows the co-occurrence network. Micro-learning, e-learning and learning systems are the central nodes. Satellite clusters reveal distinct thematic orientations: a technology-mediated learning cluster encompassing mobile learning, artificial intelligence, and data mining; a pedagogical design cluster including gamification, blended learning, and virtual reality; an institutional and demographic cluster comprising students, curricula, medical education, and engineering education; and an assessment cluster featuring questionnaire, controlled study, and human-experiment methods.

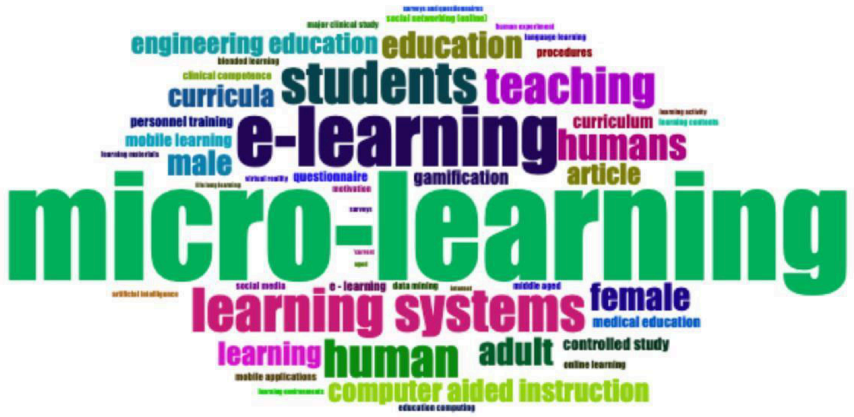


Figure 12. Keyword co-occurrence word cloud (Source: Bibliometrix).

The network view (Figure 13) resolves into two dense sub-networks rather than a single undifferentiated cloud: a blue cluster anchored on micro-learning, e-learning, and learning systems, and a red cluster anchored on human, humans, and article, the latter reflecting the indexing conventions of health- and medical-education-related microlearning studies (e.g., clinical competence, controlled study) rather than a distinct pedagogical theme in its own right. Reading these two clusters as separate literatures, one methodological/technological, one clinical/educational-outcomes-oriented, helps explain why terms like "human experiment" and "micro-learning" co-occur at the corpus level without being conceptually close.

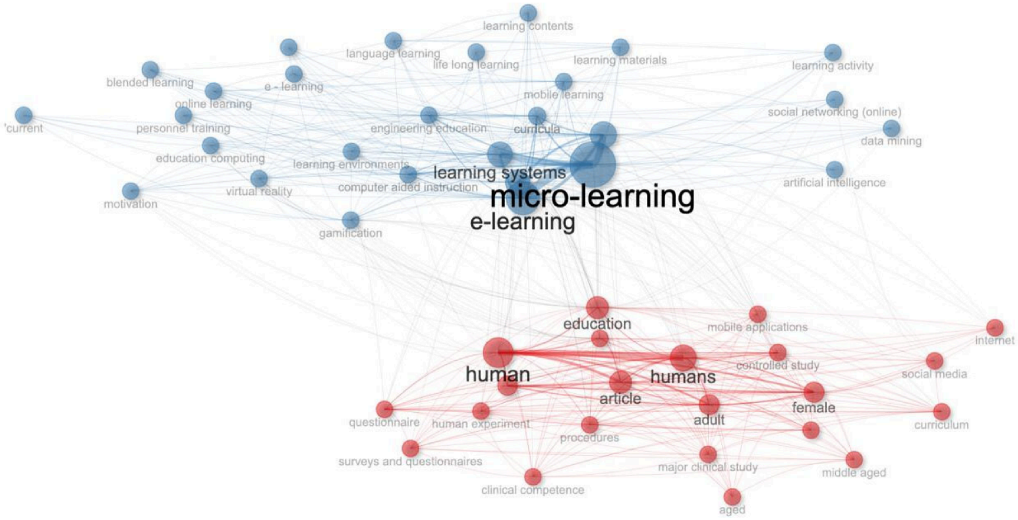


Figure 13. Key themes co-occurrence network in microlearning research (Source: Bibliometrix). Node colors indicate the two clusters: blue, anchored on micro-learning, e-learning and learning systems; red, anchored on human, humans and article.

The temporal distribution of keywords across the corpus is consistent with a shift from foundational, definitional work (2014–2016) toward applied technological integration (2017–2020) and, most recently, AI-enhanced personalization and adaptive learning systems (2021–2024). This periodization is an interpretive reading of the co-occurrence network and corpus timeline (Section 4.2) rather than the output of a separately validated trend-detection analysis (e.g., Bibliometrix's thematicEvolution() function was not run for this purpose), and it is presented as such.

4.7. Most Globally Cited Documents and Keyword Frequencies

Beyond the country- and cluster-level citation analysis in Sections 4.3 and 4.6, ranking individual documents by global citation count identifies the specific works driving the corpus's citation impact. The ten most globally cited documents are, in descending order: Yin [14] (2021, Journal of Educational Computing Research, 178 citations); Nikou (2018, Journal of Computer Assisted Learning, 137); Maity (2019, Journal of Management Development, 104); Leong (2021, Journal of Work-Applied Management, 82); Díaz-Redondo (2021, Multimedia Tools and Applications, 79); Dessì (2019, Computers in Human Behavior, 78); Cascio (2019, Human Resource Management Review, 72); Jahnke (2020, TechTrends [Technology, Knowledge and Learning], 68); Zhang [15] (2020, TechTrends, 63); and Sun (2018, IEEE Transactions on Services Computing, 63) (Figure 14).

Two features of this ranking are worth noting analytically rather than only descriptively. First, the leading document (Yin [14]) alone accounts for citations on the same order of magnitude as the combined total for the seventh- through tenth-ranked documents, indicating a strongly skewed, long-tailed citation distribution typical of emerging interdisciplinary fields rather than a uniformly cited core literature. Second, the venues represented (journals in human resource management (Cascio), work-applied management (Leong), and organizational behavior (Dessì) alongside educational technology outlets) confirm that the field's highest-impact work is not confined to educational technology journals, but draws citation attention from workplace learning and management research, reinforcing the corporate training thread identified in the literature review (Section 2). Zhang [15] (2020) corresponds to the Zhang and West [15] reference already discussed in this paper's literature review; the remaining nine documents are corpus entries not separately cited in

the reference list, consistent with standard bibliometric reporting practice of listing top-cited works by author/year/source rather than full citation.

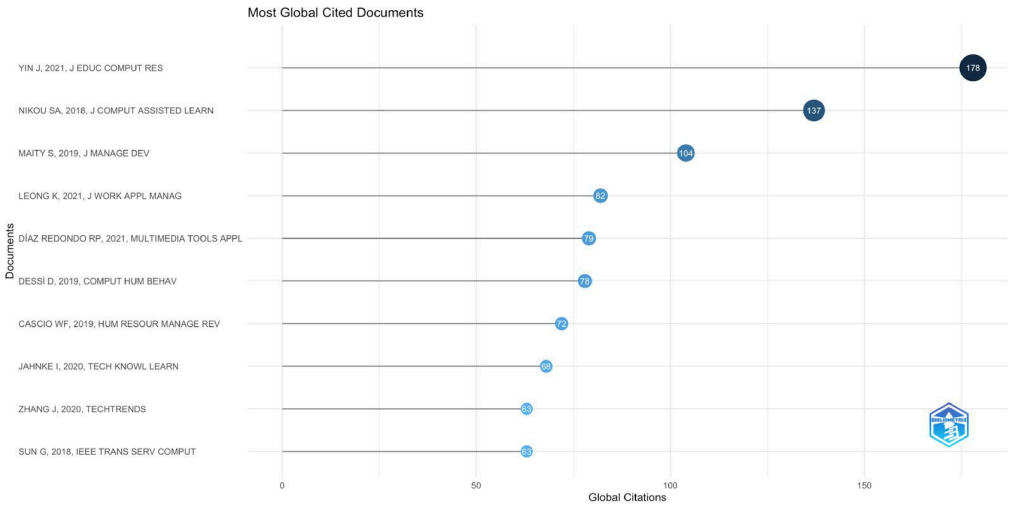


Figure 14. Most globally cited documents in the corpus (Source: Bibliometrix).

Table 2 reports the ten most frequent Keywords Plus terms in the corpus, complementing the word cloud and network views in Section 4.6 with exact frequencies and providing the keyword frequency context for the clustering methodology (Section 3.3).

Table 2. Ten most frequent Keywords Plus terms in the corpus (Source: Bibliometrix).

Keyword	Occurrences
micro-learning	234
e-learning	129
learning systems	95
students	93
human	82
teaching	80
humans	67
adult	60
female	60
education	58

The frequency gap between the top term (micro-learning, 234) and the tenth (education, 58) shows that the co-occurrence network in Figure 13 is anchored by a small number of high-frequency hub terms rather than a flat distribution, which is consistent with the two dense sub-networks described in Section 4.6.

5. Discussion: Analysis and Synthesis of Findings

Taken together, the results describe a research domain in dynamic expansion, characterized by increasing output volume, broadening thematic scope, and growing technological sophistication. The 32.22% annual growth rate exceeds the growth rates reported for comparable educational technology domains by Monib et al. [4] and Mochamad [11], which is consistent with microlearning having gained scholarly momentum beyond that of a short-lived pedagogical trend though, as with the pandemic association discussed above, a higher growth rate relative to two other studies is suggestive rather than conclusive evidence of durability, since it may also reflect this corpus's more recent and slightly broader inclusion window.

Thematic cluster analysis is consistent with a field moving from descriptive conceptualization toward more prescriptive, design-oriented work. The early literature (2014–2016) is dominated by definitional and theoretical contributions; the intermediate period (2017–2020) shows a proliferation of empirical studies; and the most recent period (2021–2024) is characterized by AI-driven personalization, adaptive learning architectures, and immersive technologies as focal concerns (Section 4.6). This progression should be read as a description of what the corpus's keywords emphasize over time, not as an independently validated causal account of how the field's research paradigm changed.

The convergence of microlearning, gamification, user-centered design and learning analytics (Section 4.6) suggests microlearning is increasingly considered not as a standalone format, but as part of integrated, adaptive, data-informed learning ecosystems. The relevance of data-driven personalization in such ecosystems is also reinforced by recent work on behavioral clustering, which shows how learner interaction data can be used as a basis for adaptive learning [16]. The geographic distribution (Section 4.3) is indicative of structural asymmetries: the concentration of high-impact output in USA, China, Australia and a few European countries reflects, at minimum, uneven distribution of research infrastructure and funding in the contributing countries of the field. The bibliometric data by itself cannot differentiate this explanation from other contributing factors such as differences in publication strategy or database indexing coverage by country.

5.1. Contributions and Practical Implications

From a theoretical perspective, bibliometric cluster analysis provides a structured frame to locate microlearning along the cognitive, technological and organizational dimensions. In practice, mapping of high-impact authors, institutions and sources (Sections 4.4 and 4.5) provides educators, program designers and policy makers with evidence-based reference points for identifying active research groups and venues. The intersection of mobile technologies, gamification and adaptive learning (Section 4.6) provides a justification for the inclusion of microlearning within formal education programs, and policymakers developing lifelong-learning frameworks, particularly for professional development and vocational training, may find the identified thematic clusters and leading venues helpful as an initial map of the field, while noting that this study does not itself provide evidence of effectiveness for any particular intervention.

5.2. Methodological Limitations

- Database coverage: Solely using Scopus may miss works indexed in Web of Science, ERIC or PsycINFO and grey literature, especially in regional or practitioner outlets.
- Sensitivity of search terms: the keyword-based approach may not catch semantically similar ideas like "bite-sized learning" or "nanolearning". A sensitivity analysis with a broadened search term would be useful to quantify how much this restricts the corpus.
- Language bias: restriction to English-language publications excludes relevant work published in other languages, which may under-represent non-English-speaking research communities.
- Screening reproducibility: the author team performed manual screening collectively, rather than under a formal multi-rater protocol, and no inter-rater agreement statistic was calculated (Section 3.2). This limits the ability to assess inter-rater reliability and should be taken into account when interpreting the reproducibility of the selection procedure.
- Descriptive versus causal interpretation: co-citation and keyword co-occurrence analysis describe conceptual structure and thematic association, but do not describe causal relationships or quality of individual studies; in particular, growth of publication

volume should not be interpreted as a direct indicator of scientific maturity or research quality (Section 5).

- Citation normalization: raw citation and publication counts by country favor larger research systems; Table 1 (Section 4.3) reports citations-per-document for the ten most-cited countries, reproduced directly from the underlying Scopus export, and shows that the normalized ranking (led by Greece, Italy, and Slovakia) differs substantially from the raw-total ranking (led by the USA, China, and Australia).
- Clustering transparency: the thematic clusters in Figure 13 were produced with Biblioshiny's default Louvain clustering algorithm and association-strength normalization (Section 3.3); the exact minimum keyword-frequency threshold applied was not separately recorded, so the two-cluster partition is reproducible in its general method but not to the last configuration detail. This limitation is explicitly reported to facilitate cautious interpretation and future replication.

5.3. Future Research Directions

Future bibliometric studies should expand database coverage to include Web of Science, ERIC, and regional repositories, and should report a term-sensitivity analysis that incorporates adjacent terminology such as nanolearning and bite-sized learning [5]. Text mining, natural language processing, and machine-learning approaches applied to bibliometric data could enable richer semantic analysis than keyword co-occurrence alone. The current bibliometric mapping documents research attention, rather than demonstrated learning outcomes, and longitudinal, controlled studies of long-term microlearning effectiveness in diverse populations remain a priority. Emerging frontiers: Priority areas for future research building on the thematic shift identified in Section 4.6 are microlearning's intersection with generative AI, learning analytics, and immersive environments.

6. Conclusions

This bibliometric analysis of microlearning research from 2014 to 2024 charts a field in sustained and accelerating growth, driven by the progressive integration of digital technologies, the pandemic-era shift to digital education, and the increasing sophistication of AI-mediated learning systems. The corpus includes 651 documents from 444 sources, written by 1782 authors, with an annual growth rate of 32.22%. This indicates the global reach and interdisciplinary character of the field.

Thematic cluster analysis suggests a trajectory from basic conceptualization toward applied, increasingly AI-driven, personalization, with convergent engagement across gamification, mobile learning, adaptive systems, and user-centered design. Geographic analysis confirms the USA, China and Australia as leaders in citation impact, and indicates the increasing, and in some cases disproportionately high-impact, contributions of individual European research communities such as Greece (Section 4.3). Methodologically, the study offers a systematic bibliometric mapping based on Scopus and Bibliometrix, and an explicit indication of where the evidence is descriptive rather than causal or evaluative, along with transparent reporting of the remaining methodological limitations concerning screening protocol and clustering configuration. Future research should focus on longitudinal effectiveness studies, bibliometric syntheses across databases, and empirical investigations of emerging technology–microlearning interfaces involving generative AI, learning analytics, and immersive environments.

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