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Thirty years of mobile learning in higher education: A historical review and bibliometric analysis

Thuthukile Jita [a], Brian Shambare [b,*]

[a] Department of Curriculum and Higher Education Studies, University of the Free State, 205 Nelson Mandela Drive, Bloemfontein 9300, South Africa
[b] Department of Mathematics, Natural Sciences and Technology Education, University of the Free State, Private Bag X13, Phuthaditjhaba 9866, South Africa

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ABSTRACT

Mobile learning research has grown rapidly over the past three decades, yet the literature remains fragmented. This study presents a bibliometric analysis of 3980 records from the Web of Science, spanning the period from 1994 to 2024. We examined publication and citation trends, contributions from countries, institutions, authors, and journals, as well as emerging research themes. Analyses were conducted using Microsoft Excel, VOSviewer, and polynomial regression. Results show that 95.9 % of publications were published between 2010 and 2024, with a notable surge from 2020 to 2022, reflecting the impact of the COVID-19 pandemic. The United States, China, and Taiwan were the most prolific countries. Taiwan's National University of Science and Technology and National Normal University led institutional output. Hwang Gwo-Jen was the most influential author, while *Computers & Education* emerged as the most productive and cited journal. Recent research focuses on gamification, augmented reality, and self-regulated learning. Polynomial regression forecasts a rise in Virtual Reality and AI-driven mobile learning studies. These findings highlight evolving trends and guide sustainable, context-aware mobile learning practices.

1. Introduction

Mobile learning (m-learning) has evolved remarkably over the past thirty years. While the volume of articles published each year is indicative of strong scholarly interest, this growth has produced a diverse and fragmented body of work that makes it difficult for scholars to discern coherent research trajectories, identify shifting pedagogical priorities, and stay current with emerging trends. This fragmentation partly reflects the pace and complexity of technological change underpinning m-learning. Technological advancements have propelled this shift, transitioning students from rudimentary portable devices to sophisticated mobile applications (apps). Beyond a mere technological leap, this transformation is considered a fundamental change in human cognition. Historians and cognitive scientists, such as Harari [1] and Hasselbalch [2], have characterised the technological shift as an evolutionary turn, a revolution comparable to past moments in human history, such as the Agricultural Revolution and the Industrial Revolution. The Agricultural Revolution marked the transition from nomadic hunting and gathering to settled farming communities involved in plant and animal domestication [3]. Later, the Industrial Revolution introduced mechanisation and mass production, which reshaped economies and societies [4]. Similarly, this latest mobile technological revolution has expanded humans' capabilities by breaking the constraints of spatial immobility and redefined knowledge exchange beyond physical proximity.

The driving force behind this technological evolution is the rapid expansion of mobile connectivity, including in developing regions where digital infrastructure is advancing at an unprecedented pace. By 2025, Africa is expected to lead the world in mobile internet traffic at 75.62 %, followed by Asia at 71.29 %, while North America lags at 51.18 % [5]. The rise in smartphone network subscriptions further advances this momentum. In 2023, global subscriptions neared seven billion and are projected to surpass 7.7 billion by 2028, with the United States, China, and India leading the way [6]. The widespread diffusion of mobile technologies has generated a large and diverse body of m-learning research. However, this rapid expansion has also produced a fragmented literature, making it increasingly difficult to trace the field's development, identify dominant and emerging themes, and recognise influential scholarly contributions. Bibliometric analyses have therefore been used to systematically synthesise large volumes of research by mapping intellectual structures and longitudinal trends (e.g. [7,8],). Despite these efforts, important gaps remain. Most existing studies focus on publication growth and broad global patterns, while giving limited attention to

* Corresponding author.
E-mail addresses: JitaT@ufs.ac.za (T. Jita), ShambareB@ufs.ac.za (B. Shambare).

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the structural drivers of research production, such as technological infrastructure, research capacity, and funding availability. As a result, the understanding of how m-learning research evolves across diverse socio-economic and cultural contexts remains incomplete.

Addressing this limitation, the present study makes four key contributions in providing a more nuanced and context-sensitive bibliometric examination of m-learning research. First, it offers a 30-year longitudinal analysis that captures the field's growth and evolution. Second, its broad geographical and institutional scope reveals global patterns of productivity, collaboration, and scholarly influence. Third, by integrating network analysis with polynomial regression, the study moves beyond descriptive mapping by incorporating forward-looking trend modelling. Fourth, the rapid advancements in mobile technology demand continuous evaluation to ensure that research remains relevant. Thus, incorporating the most recent studies, this research delivers a comprehensive and updated perspective on m-learning research trends to inform future research.

2. Related studies

To synthesise the key strands of existing bibliometric work, the salient studies are summarised in Table 1.

2.1. Research gaps and justification for contribution

As summarised in Table 1, prior bibliometric studies address the m-learning literature unevenly across analytical dimensions. Most studies primarily align with RQ1, documenting publication growth and citation patterns at a global level (e.g. [8,9]a,), but remain largely descriptive. Fewer studies partially address RQ2 and RQ3 by identifying productive countries and institutions (e.g. [16,17],), often relying on simple frequency or citation counts. Analyses related to RQ4-RQ6 (author, publication, and journal influence) are typically embedded within broader trend studies and lack longitudinal or integrative perspectives. Research addressing RQ7 has identified dominant and emerging themes (e.g. [12,14],); however, these studies are often limited by their short time spans or narrow contexts. Overall, existing work tends to examine these dimensions in isolation and within constrained temporal windows. Addressing these limitations, the present study simultaneously engages RQ1-RQ7 through a 30-year bibliometric analysis that integrates productivity, impact, collaboration, thematic evolution, and polynomial regression, offering a comprehensive and predictive understanding of mobile learning research in higher education. Building upon and extending these prior analyses, the following research questions (RQ) guide this bibliometric analysis.

2.2. Research questions (RQs)

To address these objectives in a systematic and methodologically transparent manner, this study aligns each research question with a specific bibliometric analytical technique, as outlined in Table 2 below.

3. Methodology

To identify research trends and influential contributions in the field, this study employed bibliometric analysis [18] using data indexed in the Web of Science (WoS) core collection.

3.1. Justification for bibliometric methods

We applied bibliometric methods to systematically examine m-learning research, enabling a comprehensive and predictive analysis of the field [19,20]. Bibliometric analysis helped us to map publication growth, citation impact, collaboration networks, and thematic evolution, allowing us to identify prolific authors, leading journals and institutions, and emerging research trends [21,22]. Unlike narrative

Table 1
Synthesis of Bibliometric Studies in m-learning.

Focus Area	Study	Data Scope & Period	Analytical Emphasis	Key Insights	Key Limitations
Global Trends & Publication Patterns	Irwanto et al. [8]	2477 articles from Scopus; 2002–2022	Longitudinal publication trends	Identified the exponential growth of m-learning research	Focused on growth metrics; limited thematic or contextual analysis
	Wang & Hasim [9]	8352 articles from Scopus; 2002–2023	Global output patterns	M-learning is positioned as a core digital education strategy	Emphasis on volume over explanatory drivers
	Sweileh [10]	4576 articles from Scopus; All the times up to the end of 2020	Science education disciplinary growth trends	Rapid expansion of m-learning research in STEM	Restricted to science education context
	Goksu [11]	5167 studies from the Web of Science, as of September 2019	Bibliometric mapping	Identified pedagogical and technological clusters	Lacks longitudinal trend prediction
	Gulzar et al. [12]	7404 studies from the Scopus 1984–2020	Keyword evolution	Shift from device-centric to pedagogical focus. Emergence of AI and learning analytics	Limited analysis of institutional or regional factors. Does not link themes to adoption contexts
	Sobral [13]	450 highly cited articles from Web of Science and Scopus; Up to 2020	Citation analysis	Growing m-learning adoption in higher education	Citation-based focus may overlook emerging research
Specific Themes & Contextual Applications	Panackal et al. [14]	277 Higher education publications from Web of Science; 2006–2023	Thematic and trend analysis	Identified collaboration, engagement, AI, and adaptive learning	Context-specific; limited cross-sectoral comparison
	Guo et al. [7]	6843 publications from Web of Science and Scopus; 2013–2023	Bibliometric, content & scientometric	Smartphones reshape learning but pose challenges	Limited predictive or longitudinal modelling
	Rachman et al. [15]	6623 articles from the Dimensions database; 2014–2023.	Context-specific analysis	Improved communication via mobile presentations	Narrow pedagogical focus
Geographical Distribution & Institutional Contributions	Kaisara & Bwalya [16]	567 articles from the Web of Science; 2002–2022	Country-level productivity and citation analysis	The U.S., China, and the UK dominate research output	Limited institutional-level analysis
	Khan & Gupta [17]	722 articles, 2010–2020	Regional, Developing-country contributions	Rising output from Asia and Africa	Uneven database coverage

Where not clearly reported in the publication abstracts, publication counts and database sources are determined through author queries and full-text inspection, where available. We encourage future bibliometric reports to clearly specify data scope, bibliographic source, and temporal coverage.

Table 2
RQs and corresponding analytical techniques.

Research Question	Unit of Analysis	Analytical Approach
RQ1: What are the bibliometric patterns in publication output and citation impact?	Growth and impact of the field over time	Descriptive and predictive performance analysis of annual publications and citation counts
RQ2: Which countries are the most productive based on publications and citations?	Country-level research productivity	Country-level performance and citation impact analysis
RQ3: Which institutions are the leading contributors to the field?	Institutional research contribution	Institutional productivity and citation analysis
RQ4: Who are the most prolific researchers based on citation impact?	Author influence and productivity	Author-level performance metrics (total citations, citation impact)
RQ5: Which publications exhibit the greatest influence based on citation metrics?	Influential scholarly works	Document-level citation analysis (highly cited publications)
RQ6: What are the leading journals regarding citation impact?	Source influence and visibility	Journal-level (source) citation and impact analysis
RQ7: What are the predominant research themes, core topics, and critical keywords of the intellectual structure?	Thematic and conceptual structure of the field	Co-word analysis and keyword co-occurrence mapping

reviews, which provide qualitative syntheses, or systematic reviews, which aggregate empirical findings based on narrow inclusion criteria, bibliometrics enabled us to capture structural, relational, and temporal patterns that would otherwise be difficult to discern. This approach revealed the intellectual structure of m-learning, dominant and emerging themes, influential actors, and evolving research frontiers over extended periods [23–25]. By doing so, the study generated insights on trends, knowledge gaps, and predictive trajectories that traditional reviews cannot fully provide. These advantages are supported by prior bibliometric studies in m-learning and related fields (e.g. [24,25],).

We conducted both performance analysis and science mapping. Performance analysis allowed us to examine publication counts, citation trends, and core journals, which allowed us to identify the most influential contributors and sources in the field [26]. On the other hand, science mapping enabled us to investigate the intellectual and thematic structure of the domain [27]. We analysed author keywords to detect recurring themes and track shifts in research priorities over time [28]. We used VOSviewer [29] version 1.6.20 to generate and visualise bibliometric networks, which enabled us to explore the conceptual development and knowledge structure underpinning m-learning research.

3.2. Data collection: SPAR-4-SLR protocol

We implemented Paul et al.'s [30] 3-stage Scientific Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR) protocol, namely assembling, arranging and assessing (Fig. 1).

3.2.1. Assembling

Assembling involved identifying and acquiring relevant publications for review. We collected bibliographic data from the WoS Core Collection. While database triangulation (e.g., WoS, Scopus, and others) can provide broader coverage in some contexts, this study exclusively used the Web of Science (WoS). This choice was driven by the study's temporal scope (1994-2024), where maintaining consistency across three decades is essential. Although Scopus includes publications from earlier periods, the database was launched in 2004, and its citation coverage is more consistently indexed from that point onward [31,32]. Accordingly, analyses spanning earlier decades should take this difference in coverage into account. As with most bibliometric studies relying on a single data source (e.g. [12,24,25],), this approach may not capture all publications indexed in alternative databases; however, this consideration does not affect the internal consistency of the longitudinal analysis. Our search period spanned from 1994 to 2024. We extracted full bibliographic record and cited references, including title, authors, affiliations, abstract, keywords, publication year, journal name, and citation count. To retrieve pertinent studies, we applied the following search strategy:

Title: "m-learning" OR "M-Learning" OR m-Learning

Title-Abstract-keywords: "higher education*" OR University

DocType: Article OR Proceedings OR Review OR Books OR Book chapters

PUBYEAR: 1993> publication <2025.

3.2.2. Arranging

The next stage focused on organising and refining the collected publications to ensure consistency and relevance. We categorised the publications based on key attributes, including publication title, journal title, country of affiliation, author name, number of publications and citations, and h-index. To refine the dataset, we applied inclusion and exclusion criteria by selecting only peer-reviewed journal articles, review articles, and conference proceedings published in English, excluding editorials, commentaries, non-English publications, preprints, monographs and retracted publications. After this filtering process, 3792 results met the final criteria for analysis.

3.2.3. Assessing

The final stage focused on analysing and presenting the findings. First, we conducted a descriptive analysis, tracking annual publication and citation trends, mapping the distribution of articles across countries, institutions, journals, and authors. Second, we ran a performance analysis to examine citation impact using metrics such as the h-index, total citations, and average citations per paper. We also evaluated journal influence through indicators like the Journal Impact Factor (JIF) and SCImago Journal Rank (SJR). Third, we conducted thematic mapping and trend analysis by identifying emerging topics through keyword evolution analysis to categorise research themes. We present the findings through a combination of descriptive analysis, tables, graphs, and visual representations, with limitations acknowledged in the article's final section.

3.3. List of indicators

- TP (Total Publications): The total count of publications indexed in the WoS database.
- TC (Total Citations): A publication's citation frequency by other works in the WoS database.
- TC/TP (Citation-to-Publication Ratio): A measure obtained by dividing the total citation count by the total number of publications.
- H-index: The maximum value h for which the journal/author has published h papers, each of which has been cited at least h times.
- TC/Year (Annual Citations): The cumulative number of times articles are cited during that year, independent of their original publication dates.
- SJR (SCImago Journal Rank): A metric that evaluates journal prestige by considering citation links, where citations from highly ranked journals contribute more to the score than those from lesser-ranked journals.
- Impact Factor (IF): A metric that reflects the average number of citations received in a given year by articles published in that journal during the two preceding years. This value is then divided by the total count of "citable" publications in the same timeframe.

4. Results

This section details our bibliometric evaluation of mobile learning in higher education. We explore temporal patterns in both publications and

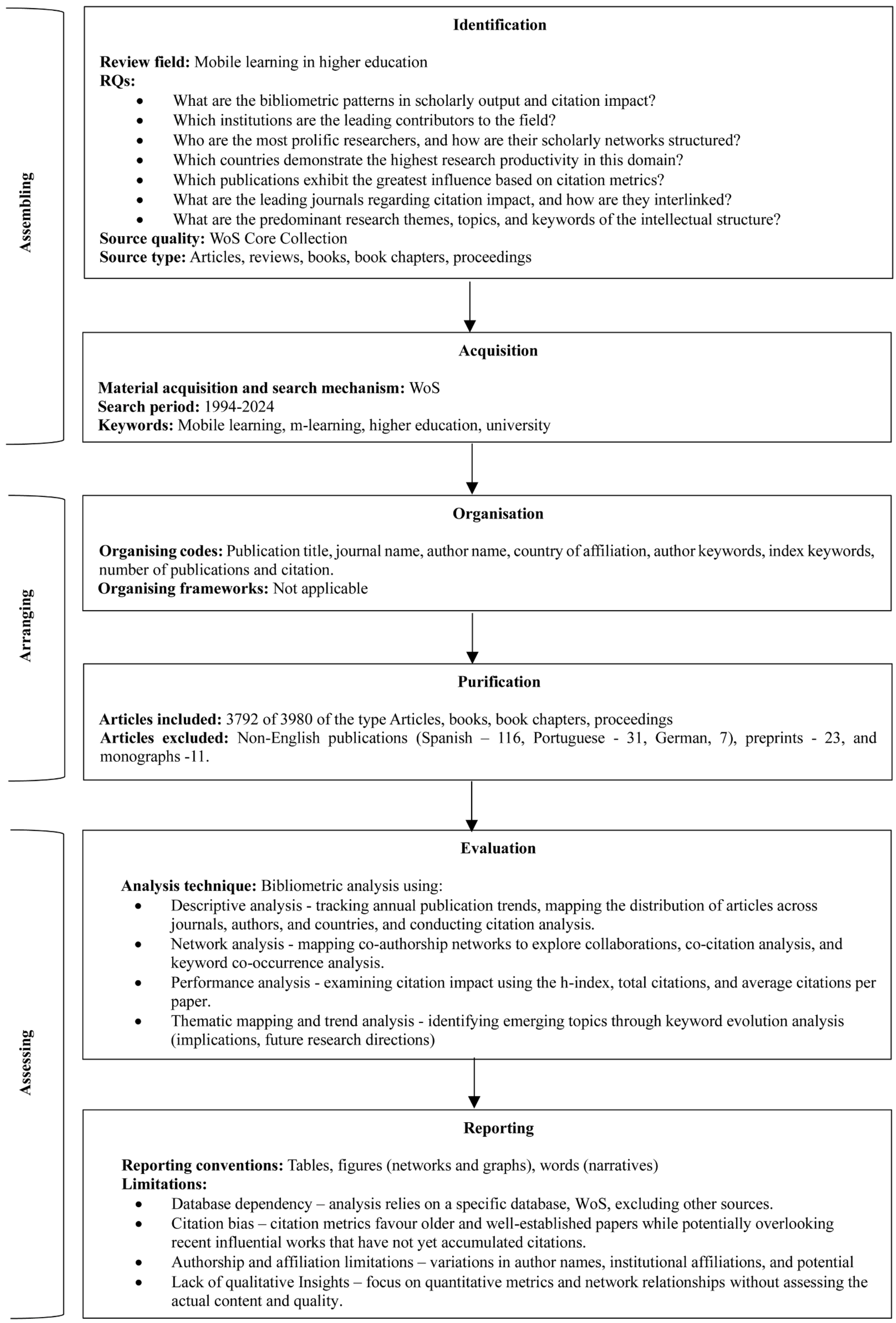

Fig. 1. Research design (SPAR-4-SLR protocol).

citations, identify leading countries, institutions, journals, articles, and researchers, and examine the distribution of research disciplines alongside the progression of key thematic areas.

4.1. RQ1: what are the bibliometric patterns in publication output and citation impact?

Using statistical computing, we performed polynomial regression analysis, with the *year* as the independent variable (x), to report and model the trends in publication and citation counts. We selected polynomial regression to model our publication and citation growth trends after observing distinct non-linear trajectories characterised by initial stagnation followed by later acceleration (Fig. 2). We excluded linear models due to their assumption of a constant growth rate, which proved inadequate for our complex data patterns [33]. We also evaluated exponential models but found their requirement for uninterrupted,

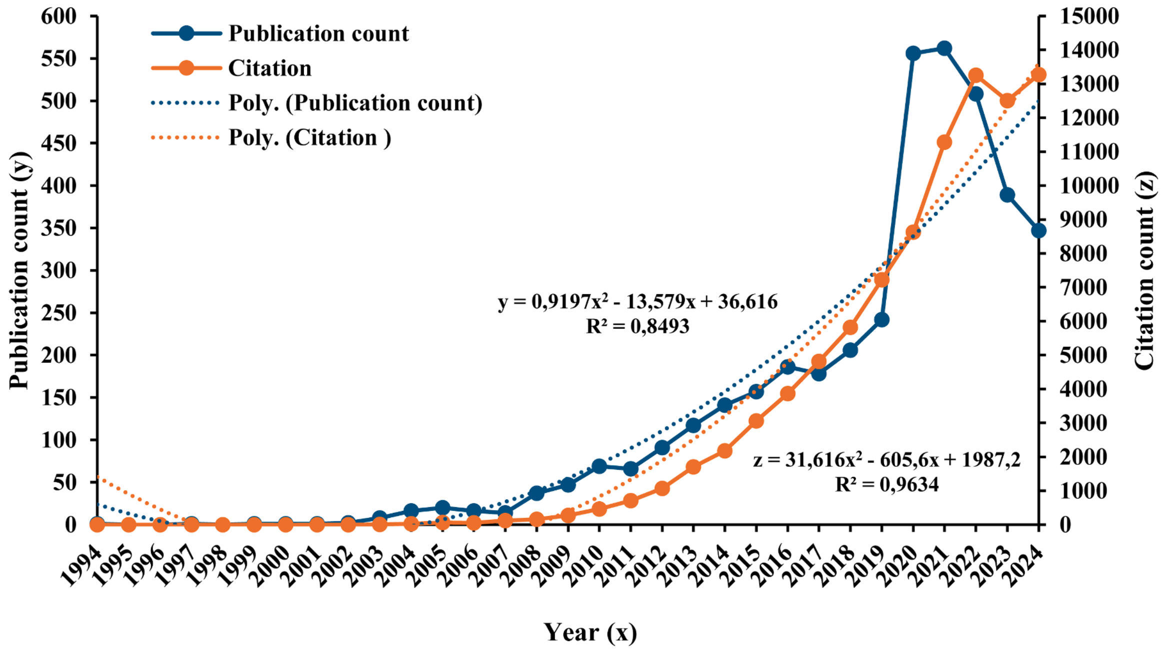

Fig. 2. Trends analysis of publications and citations.

monotonic growth [34,35] incompatible with the inflexion points and variable growth phases evident in our longitudinal dataset. Consequently, we adopted polynomial regression for its specific ability to model curvature flexibly and explicitly identify phases of acceleration and deceleration [36,37], making it the optimal choice for our long-term bibliometric analysis.

We derived second-degree polynomial regression equations using Excel's LINEST() function, which applies ordinary least squares estimation to fit models. The resulting regression equations, therefore, represent the best-fitting curve describing the temporal trend in the observed publication and citation trends. We included two polynomial regression curves with their respective R^2 values in Fig. 2. The results show a clear upward trend in publication volume, reflecting an increasing research interest. The positive coefficients of R^2 in the regression models ($R^2 = 0.8493$ and $R^2 = 0.9634$) further support this trend and validate the model's strong predictive power. The regression model allows for the accurate prediction of future publication values. For instance, the predicted future publication count can be calculated using the regression equation: $y = 0.9197x^2 - 13.579x + 36.616$, where x is the *year*. We also recorded and analysed citation counts, which reveal a sharp increase, especially from 2010 onward.

The graph shows a steady increase in publications and citations from the early 2000s, with a significant surge between 2015 and 2022, peaking around 2020–2022. This rapid growth likely corresponds to increased interest in m-learning, technological advancements, and the impact of the COVID-19 pandemic, which accelerated research in digital education. However, a noticeable decline in publications for 2024 may be due to a post-pandemic research shift, where the surge in studies during 2020–2022, driven by increased funding and interest in m-learning, has naturally subsided as priorities shift. Additionally, the drop could be attributed to delays in the publication process, with many studies from 2024 still under review and expected to be published in 2025 or later.

4.2. RQ2: which countries are the most productive based on publications and citations?

To address RQ2, we analysed the most productive countries based on both publication volume and citation impact. Research in this field spans 126 countries, with the top 50 contributors summarised in Table 3. As of 2024, the United States, China, Taiwan, Spain, and England lead in research output, with the U.S. maintaining a dominant position in recent years, 2015–2024. Fig. 4 shows a steady increase in annual publications among these countries, whereas activity before the mid-2000s was minimal, reflecting the field's early stage of development. While high publication volume is concentrated among a few nations, citations per publication (C/P) reveal a broader impact distribution. Taiwan (44.13), Greece (42.19), the Netherlands (38.00), Switzerland (36.98), and Singapore (35.30) stand out for their high average citations per publication, suggesting substantial scholarly impact despite comparatively lower output. In addition, patterns of international collaboration further shape the outlook for global research. As visualised in Fig. 3 using VOSviewer, the United States (TLS: 310), England (TLS: 170), and Malaysia (TLS: 143) emerge as central hubs in the collaborative network. In this visualisation, node size represents research output and collaboration strength. At the same time, colours indicate clusters of countries with frequent partnerships, for example, the red cluster includes England, Saudi Arabia, Turkey, and Jordan, reflecting strong regional ties.

Consistent with Table 3 and Fig. 4, the VOSviewer analysis shown in Fig. 3 reveals structured and uneven patterns of research productivity and influence. We applied full counting, setting the maximum number of authors per document to 25. To ensure analytical robustness, we imposed thresholds of at least 55 documents and 100 citations per country, which reduced the dataset from 125 to 20 of the most productive countries. We normalised the network using the association strength method and performed clustering at a resolution of 1.00 with 10 random starts and 10 iterations to ensure solution stability. The resulting network (Fig. 3) consisted of four clusters, each comprising five countries. Highly productive countries, most notably the United States, the United Kingdom, China, Australia, and several Western European nations, occupied central positions, reflecting sustained dominance in high-impact research. In contrast, Global South countries, particularly from Africa, did not meet the inclusion thresholds and were therefore absent from the core clusters, indicating persistent asymmetries in scholarly visibility and citation influence in m-learning research.

4.3. RQ3: which institutions are the leading contributors to the field?

We conducted a bibliometric publication and citation analysis of

Table 3
Most production countries/regions ranked by total number of publications.

		Total					1994-2004			2005–2014			2015–2024		
R	Country	TP	TP %	TC	C/P	TLS	TP	TP %	TC	TP	TP %	TC	TP	TP %	TC
1	USA	653	13.90	19,815	30.34	310	5	20.83	98	134	20.52	8551	513	13.07	11,039
2	China	491	10.45	9279	18.90	252	-	-	-	30	4.59	1523	454	11.57	7595
3	Taiwan	423	9.00	18,665	44.13	123	3	12.50	411	113	17.30	9826	301	7.67	8259
4	Spain	352	7.49	6470	18.38	139	-	-	-	46	7.04	1307	300	7.64	5035
5	England	215	4.58	6938	32.27	170	5	20.83	222	56	8.58	3618	150	3.82	3035
6	Malaysia	182	3.87	4336	23.82	143	-	-	-	10	1.53	617	170	4.33	3659
7	Australia	180	3.83	4905	27.25	129	2	8.33	2	34	5.21	1600	143	3.64	3253
8	Saudi Arabia	140	2.98	2776	19.83	118	-	-	-	-	-	-	132	3.36	2414
9	Turkey	125	2.66	3446	27.57	35	-	-	-	19	2.91	930	106	2.70	2494
10	Canada	120	2.55	2505	20.88	88	-	-	-	29	4.44	1286	87	2.22	1203
11	South Korea	109	2.32	3498	32.09	54	3	12.50	10	26	3.98	1562	80	2.04	1896
12	Germany	104	2.21	2348	22.58	59	4	16.67	43	15	2.30	417	83	2.11	1852
13	India	86	1.83	1575	18.31	51	-	-	-	-	-	-	78	1.99	1437
14	South Africa	82	1.75	1265	15.43	47	-	-	-	-	-	-	71	1.81	860
15	Brazil	81	1.72	245	3.02	24	-	-	-	9	1.38	380	76	1.94	233
16	Iran	74	1.57	1243	16.80	29	-	-	-	-	-	-	70	1.78	1086
17	Indonesia	69	1.47	352	5.10	32	-	-	-	-	-	-	67	1.71	349
18	Mexico	60	1.28	680	11.33	26	-	-	-	23	3.52	1151	54	1.38	465
19	Colombia	57	1.21	489	8.58	41	-	-	-	6	0.92	212	56	1.43	458
20	Greece	57	1.21	2405	42.19	20	-	-	-	-	-	-	42	1.07	1468
21	Pakistan	57	1.21	1043	18.30	76	-	-	-	-	-	-	55	1.40	1002
22	Singapore	57	1.21	2012	35.30	40	-	-	-	12	1.84	778	34	0.87	856
23	Japan	51	1.09	1324	25.96	39	-	-	-	-	-	-	36	0.92	522
24	Portugal	50	1.06	808	16.16	31	2	8.33	113	7	1.07	448	44	1.12	697
25	Netherlands	49	1.04	1862	38.00	57	-	-	-	19	2.91	930	38	0.97	1268
26	Jordan	44	0.94	1315	29.89	54	-	-	-	14	2.14	787	43	1.10	1297
27	Turkiye	44	0.94	258	5.86	10	-	-	-	11	1.68	210	44	1.12	236
28	Finland	43	0.92	1226	28.51	33	-	-	-	11	1.68	578	33	0.84	641
29	Italy	43	0.92	623	14.49	25	-	-	-	5	0.77	106	31	0.79	398
30	Russia	42	0.89	126	3.00	13	-	-	-	10	1.53	499	42	1.07	124
31	Switzerland	42	0.89	1553	36.98	35	-	-	-	-	-	-	32	0.82	1043
32	Ukraine	39	0.83	93	2.38	2	-	-	-	-	-	-	39	0.99	93
33	New Zealand	38	0.81	1235	32.50	27	-	-	-	-	-	-	25	0.64	510
34	UAE	35	0.74	996	28.46	47	-	-	-	-	-	-	32	0.82	899
35	Ecuador	34	0.72	375	11.03	24	-	-	-	-	-	-	30	0.76	365
36	Scotland	32	0.68	1016	31.75	35	-	-	-	-	-	-	29	0.74	856
37	France	31	0.66	1011	32.61	42	-	-	-	-	-	-	29	0.74	778
38	Chile	30	0.64	507	16.90	21	-	-	-	-	-	-	25	0.64	305
39	Thailand	30	0.64	390	13.00	17	-	-	-	-	-	-	29	0.74	281
40	Sweden	27	0.57	603	22.33	21	-	-	-	-	-	-	21	0.54	396
41	Ireland	24	0.51	616	25.67	31	-	-	-	-	-	-	18	0.46	354
42	Norway	24	0.51	616	25.67	21	-	-	-	-	-	-	19	0.48	516
43	Cyprus	23	0.49	883	38.39	19	-	-	-	-	-	-	19	0.48	316
44	Egypt	23	0.49	366	15.91	20	-	-	-	-	-	-	23	0.59	363
45	Ghana	23	0.49	353	15.35	20	-	-	-	-	-	-	22	0.56	342
46	Israel	23	0.49	435	18.91	10	-	-	-	5	0.77	94	21	0.54	396
47	Nigeria	21	0.45	294	14.00	21	-	-	-	-	-	-	21	0.54	293
48	Croatia	20	0.43	537	26.85	14	-	-	-	5	0.77	201	16	0.41	419
49	Oman	20	0.43	653	32.65	20	-	-	-	-	-	-	20	0.51	651
50	Peru	20	0.43	103	5.15	11	-	-	-	-	-	-	19	0.48	65

Abbreviations: R: rank; TP: total publications; TP %: percentage of publications; TC: total citations; C/P: citations per publications; TLS: total link strength.

3503 contributing institutions. Table 4 lists the top 25, led by the National Taiwan University of Science and Technology, National Taiwan Normal University, and National Cheng Kung University. Notable institutions beyond Taiwan include Nanyang Technological University (Singapore) and the University of Granada (Spain), with Western representation from the University of Michigan and Stanford University. Fig. 6 shows a steady rise in publications among the top five institutions since 2004.

To analyse institutional productivity, we mapped the network using VOSviewer from an initial corpus of 3503 institutions. To focus on the most productive and influential hubs, we raised the criteria to a minimum of 10 documents and 100 citations, resulting in 81 core institutions. The resulting visualisation (Fig. 5) reveals a decentralised, multi-polar network structure. National Taiwan University of Science and Technology emerges as a primary connective hub, with Nanyang Technological University and the University of Hong Kong forming other significant nodes. We observe that the network organises into distinct yet interlinked regional clusters, including a prominent Taiwanese group, a Southeast Asian cluster anchored by the University of Malaya and University of Sains Malaysia, and a separate Australian-Spanish collaboration group. This structure indicates a globally distributed field where leadership and scholarly exchange are shared across several high-productivity institutions in Asia-Pacific and Europe, rather than centralised around a single dominant entity.Table 4. Top institutions ranked by total number of publications and citations

4.4. RQ4: who are the most prolific researchers based on citation impact?

Recognising prolific authors is a longstanding tradition in bibliometric research [31]. In this study, the ranking of productive authors was based on their TP, TC and h-index (Table 5). The analysis shows Taiwan as the leading country in author representation. Notably, Hwang, Gwo-Jen, from the National Taiwan University of Science and Technology, ranks first, followed by Huang, Yueh-Min, from the

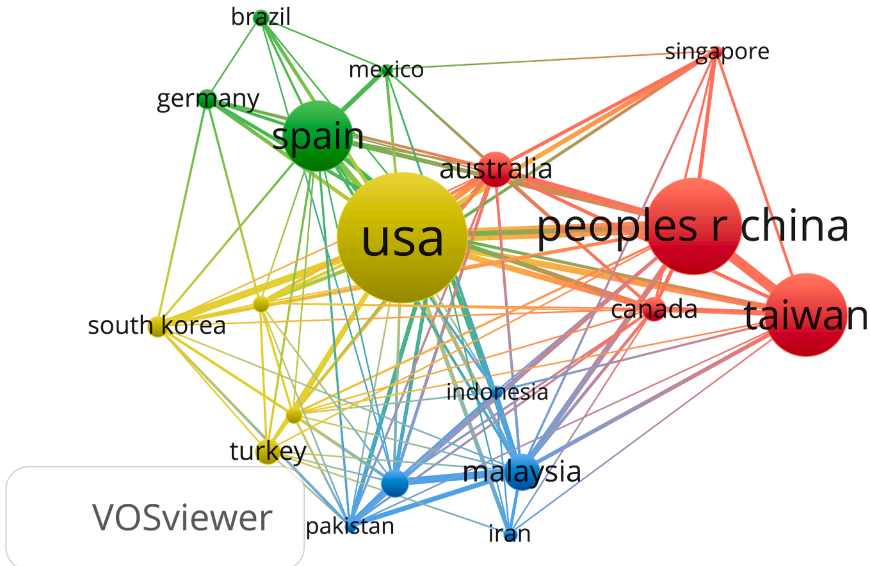

Fig. 3. Country productivity visualisation.

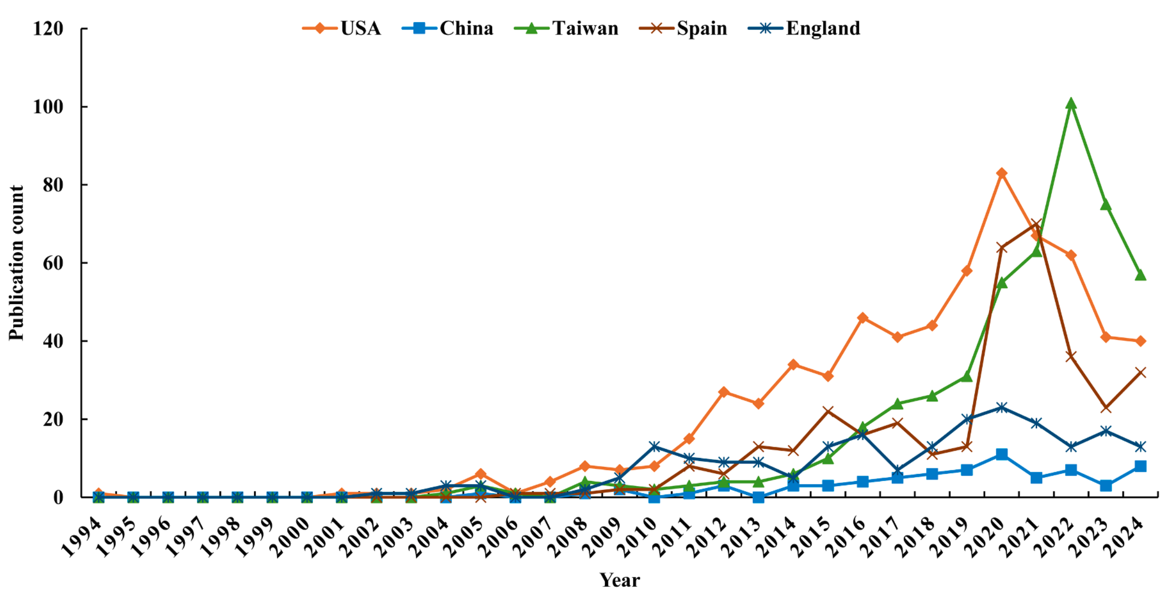

Fig. 4. Publication trends of the top five countries.

National Cheng Kung University. Among non-Taiwanese scholars, Looi, Chee-Kit from Nanyang Technological University (Singapore) and other researchers from Jordan, Hong Kong, Australia, and Spain demonstrate a broadening international research base in m-learning.

We mapped the author co-citation network using VOSviewer, analysing 10,881 contributing authors in the field. Applying thresholds of 5 minimum documents and 100 minimum citations per author, we identified 103 qualifying authors, with 33 forming the connected network (Fig. 7). The visualisation reveals a centralised scholarly structure. Hwang, Gwo-Jen, emerges as the dominant hub, his work anchoring the network and connecting distinct collaborative clusters. We observe that his central position bridges a cohesive Taiwanese research group with international clusters featuring scholars like Kinshuk. This structure leads us to interpret the field as maturing around a key authority, where Hwang's influence actively integrates disparate research streams and drives cross-regional collaboration among the field's core contributors.

4.5. RQ5: which publications exhibit the greatest influence based on citation metrics?

Table 6 presents the most cited publications on m-learning in higher education. The articles highlight key themes: student adoption, behavioural intention, pedagogical frameworks, and technology integration. The most cited article, *Mobile Computing Devices in Higher Education: Student Perspectives on Learning with Cellphones, Smartphones & Social Media* by Gikas and Grant, has 678 citations, underscoring the role of mobile devices and social media in learning. Many studies adopt established models such as TAM, UTAUT, and Self-Determination Theory, while others explore gamification, augmented reality (AR), and mobile-based assessments to enhance engagement. Research has shifted from adoption-focused studies to long-term impacts on learning outcomes. While older publications maintain high citation-per-publication (C/P) rates (e.g., Wang et al. [38], C/P: 39.53), newer studies, such as Bond et al. [39] (C/P: 56.5), suggest increasing research influence. However, TC may underestimate the impact of recent publications, as

Table 4
Top institutions ranked by total number of publications and citations.

R	Institution	Country	TP	TC	C/P	ARWU 2023	QS 2024
1	National Taiwan University of Science and Technology	Taiwan	83	5567	67	401–500	387
2	National Taiwan Normal University	Taiwan	55	3641	66	701–800	431
3	National Cheng Kung University	Taiwan	41	1776	43	301–400	228
4	National Central University	Taiwan	40	2616	65	601–700	611–620
5	Nanyang Technological University	Singapore	39	1626	42	37	26
6	University of Granada	Spain	36	651	18	201–300	476
7	University of Hong Kong	Hong Kong	35	1057	30	88	26
8	University of Malaya	Malaysia	33	542	16	401–500	65
9	National University of Tainan	Taiwan	32	2503	78	-	-
10	Near East University	Cyprus	31	912	29	901–1000	514
11	King Faisal University	Saudi Arabia	26	919	35	901–1000	581–590
12	University of Technology Malaysia	Malaysia	26	881	34	801–900	188
13	Education University of Hong Kong	Hong Kong	26	597	23	601–700	272
14	University of Science Malaysia	Malaysia	25	644	26	601–700	278
15	King Saud University	Saudi Arabia	24	724	30	101–150	203
16	Beijing Normal University	China	23	422	18	151–200	275
17	Athabasca University	Canada	20	692	35	-	-
18	University of Salamanca	Spain	19	925	49	401–500	534
19	University Kebangsaan Malaysia	Malaysia	19	138	7	601–700	159
20	King Abdulaziz University	Saudi Arabia	18	226	13	101–150	106
21	Open University	UK	18	988	55	201–300	329
22	Fiji National University	Fiji	18	236	13	-	-
23	National Chung Hsing University	Taiwan	16	251	16	901–1000	661–670
24	University of Valencia	Spain	16	239	15	201–300	485
25	University of Michigan	United States	15	571	38	24	25

Abbreviations in Table 3 except ARWU: The 2023 Academic Ranking of World Universities; QS: World University Rankings 2024.

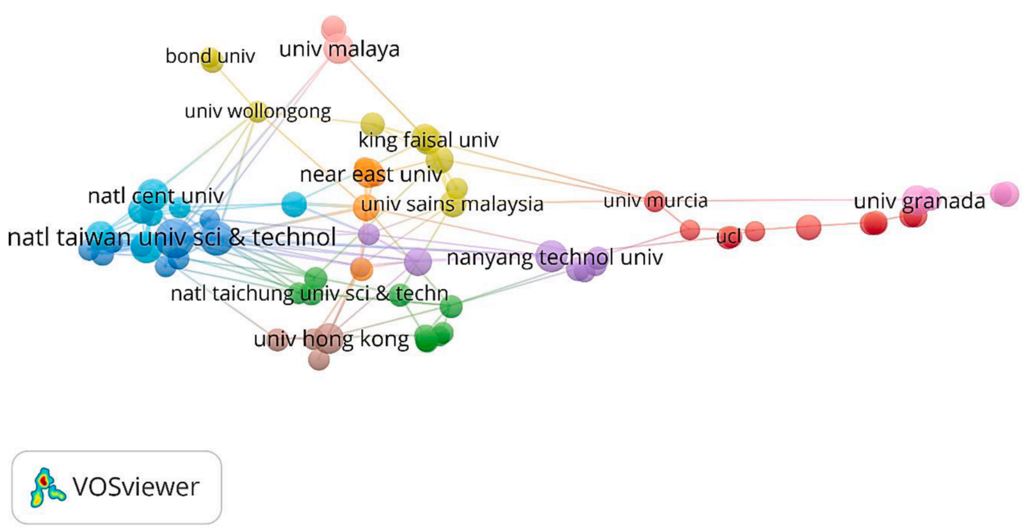

Fig. 5. Institution productivity visualisation.

seen in Hoi [40] (C/P: 20.67).

4.6. RQ6: what are the leading journals regarding citation impact?

To address RQ6, we analysed 136 journals, ranking the top 20 based on publication output and citation impact (Table 7). *Computers & Education* (IF: 8.9, Q1) leads the field, followed by *Education and Information Technologies* (IF: 4.8, Q1) and *Interactive Learning Environments* (IF: 3.7, Q1). Noteworthy high-impact journals such as *Computers in Human Behaviour* (IF: 9.0, Q1) and the *British Journal of Educational Technology* (IF: 6.7, Q1) emphasise human-computer interaction. Meanwhile, empirical and review studies dominate *Educational Technology & Society* and the *Journal of Computer-Assisted Learning*. However, C/P rates and H-index values reveal a significant limitation, older journals tend to accumulate higher citations and H-indices, while recent publications need more time to gain impact. This suggests that traditional citation-based metrics may overlook emerging research. As a result, alternative measures, such as download counts and engagement tracking, are needed to capture the evolving influence of newer studies more accurately. Based on our VOSviewer analysis (Fig. 8), we analysed 1083 journals, applying thresholds of a minimum of 15 documents and 100 citations. From the 41 journals meeting these criteria, *Computers & Education* occupies a definitive central position. This structural centrality indicates that the journal is not merely influential but serves as the essential conduit for knowledge synthesis and discourse across the fragmented landscape of digital education research.

4.7. RQ7: what are the predominant research themes, core topics, and critical keywords?

4.7.1. Research keywords and analysis of their evolution

Table 8 presents the top 20 keywords ranked by frequency from 1994 to 2024. Notably, the keyword “mobile learning” leads with 1500 occurrences and a co-occurrence value of 3125, reflecting its central role in

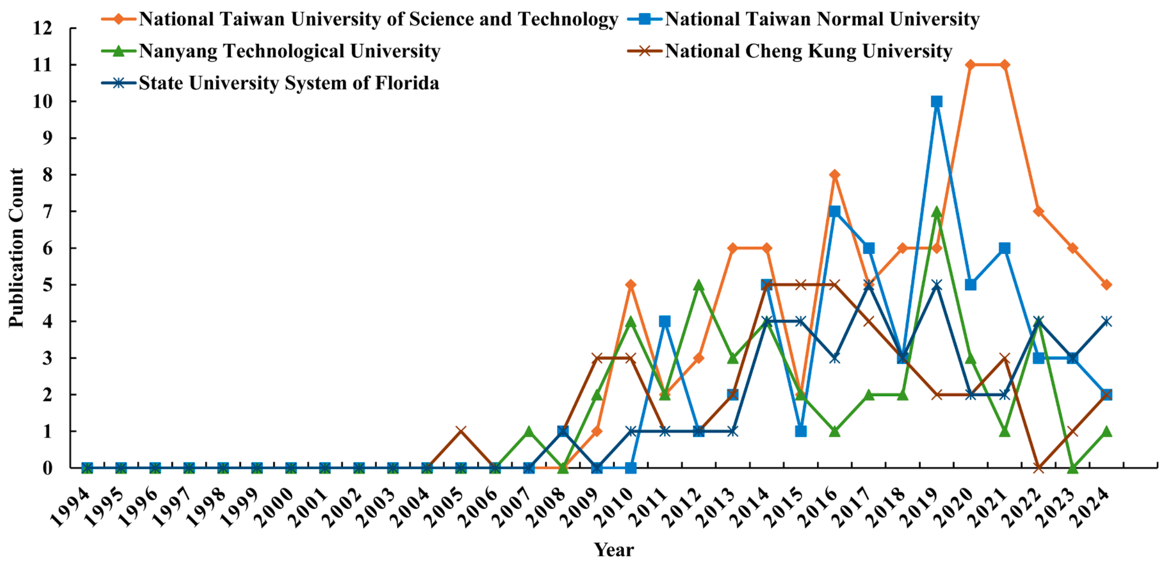

Fig. 6. The top five most productive institutions.

Table 5
The top twenty most prolific authors in m-learning research.

R	Author(s)	Institution	Country	TP	TC	H
1	Hwang, Gwo-Jen	National Taiwan University of Science and Technology	Taiwan	78	4375	92
2	Huang, Yueh-Min	National Cheng Kung University	Taiwan	26	1027	65
3	Looi, Chee-Kit	Nanyang Technological University	Singapore	22	866	45
4	Hwang, Wu-Yuin	National Central University	Taiwan	16	586	36
5	Almaayah, Mohammed Amin	University of Jordan	Jordan	16	760	10
6	Chiu, Dickson K. W.	University of Hong Kong	Hong Kong	15	504	27
7	Kumar, Bimal Aklesh	University of the South Pacific	Fiji	15	741	15
8	GARCÃ-A-PEÃ‘ALVO, Francisco JosÃ©	University of Salamanca	Spain	14	678	40
9	Kearney, Matthew	University of Technology Sydney	Australia	13	510	30
10	Lai, Chiu-Lin	National Taipei University of Education	Taiwan	12	646	25
11	Ho, Kai Wing Kevin	Lingnan University	Hong Kong	12	407	20
12	So, Hyo-Jeong	Ewha Womans University	South Korea	12	739	35
13	LujÃ¡n-Mora, Sergio	University of Alicante	Spain	11	216	22
14	Shadiev, Rustam	Nanjing Normal University	China	11	445	18
15	Seow, Peter	Singapore University of Social Sciences	Singapore	11	762	12
16	Lo, Patrick	University of Tsukuba	Japan	11	450	28
17	Wong, Lung-Hsiang	National Institute of Education	Singapore	11	705	33
18	Al-Rahmi, Waleed	Universiti Teknologi Malaysia	Malaysia	11	299	14
19	Tu, Yun-Fang	National Taiwan Normal University	Taiwan	11	122	16
20	OOI, Keng-Boon	Monash University Malaysia	Malaysia	10	120	24

Abbreviations in Table 3, except H: *h*-index.

the literature. Other frequently occurring keywords include “m-learning” (310 occurrences), “higher education” (231 occurrences), and “mobile devices” (164 occurrences). The temporal analysis in Table 8 reveals that most keywords have increased in frequency over time. In particular, keywords such as “e-learning” and “education” have experienced dramatic growth. The VOSviewer visualisations (Figs. 9) demonstrate the occurrences and evolution of author keywords for the periods 1994 to 2004, 2005 to 2014, 2015 to 2024, and 1994 to 2024, respectively.

4.7.2. Research theme analysis

To explore RQ7, main research themes, topics, and keywords in m-learning (Table 8), we conducted a co-word analysis using VOSviewer. This method helps identify the progress made by prior research and the future directions being explored in the field. Keywords in an article reflect its core focus, and their co-occurrence and frequency point to prevalent themes [41]. VOSviewer allowed us to visualise clusters of highly similar keywords, with a threshold of 15 occurrences per keyword for cluster formation [29]. We found that the evolution of m-learning research from 1994 to 2024 shows a shift from technology-driven exploration to pedagogy-centred approaches. In the early phase (1994–2004), research was focused on foundational concepts like ‘Wireless,’ “Handheld,” and “Mobile,” with low occurrences, reflecting the early stages of mobile learning. From 2005 to 2014, as mobile technologies became more accessible, the focus shifted to structured research on “Mobile Learning” (Oc: 240, Co: 232) and “M-Learning” (Oc: 54, Co: 68), with growing attention on mobile-assisted pedagogy and “Mobile Devices” (Oc: 30, Co: 31). In the latest phase (2015–2024), mobile learning research surged, driven by global events like COVID-19, with keywords like “Gamification” (Oc: 50, Co: 127) and “Augmented Reality” (Oc: 97, Co: 253) marking a shift towards engagement and interactivity. Research now emphasises learner-centred approaches, with an increasing focus on “Higher Education” (Oc: 210, Co: 559) and “Self-Efficacy” (Oc: 36, Co: 100). This trajectory highlights the transition from technical feasibility to pedagogical effectiveness, accessibility, and human-centred learning innovations.

From 10,149 extracted keywords, 146 met the minimum threshold of 30 occurrences. Applying VOSviewer’s default relevance filter (60 % most relevant terms) yielded 87 keywords for the overlay analysis. The temporal mapping (Fig. 9) reveals a clear theoretical evolution. Early studies (1994-2005) centred on technology-oriented terms such as ICT, information technology, and instruction, reflecting an implementation-

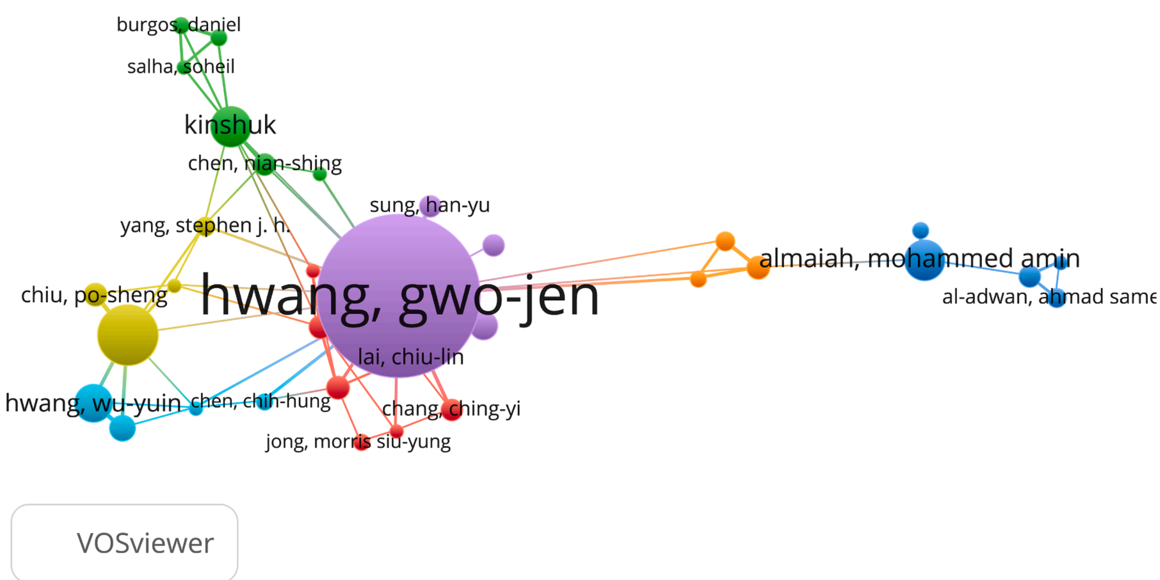

Fig. 7. Network citation visualisation of authors.

focused research logic. During the consolidation phase (2006–2014), pedagogical and institutional constructs, including higher education, teachers, design, and framework, gained prominence. In the most recent period (2015–2024), mobile learning and m-learning persist as dominant conceptual anchors, while surrounding keywords converge around acceptance- and outcome-oriented constructs (e.g., adoption, intention, satisfaction), signalling a shift toward explanatory and predictive scholarship.

5. Discussion

5.1. Publication output and citation impact

The results of our analysis reveal a marked and sustained growth in publications on m-learning in higher education, particularly over the past decade. This upward trend mirrors the findings of prior research especially Wang and Hasim [9], who similarly observed a surge in research focused on technology-enhanced learning. While these earlier studies attributed the increase primarily to advancements in smartphone technology, our analysis suggests that the experiences of the COVID-19 contagion and institutional adoption of digital learning strategies have been equally influential. Notably, the rising citation impact of m-learning research in recent years further highlights its growing academic recognition and influence. This is in line with Gulzar et al. [12], who also emphasised the increasing scholarly impact of mobile technologies in education.

5.2. Country-level research productivity

Further analysis of regional contributions highlights the continued dominance of countries such as the United States and China in shaping the m-learning research area. Nonetheless, there is a clear and growing contribution from scholars in Taiwan, Singapore, and Hong Kong. These developments suggest that while the field has traditionally been concentrated in specific geographical areas, it is now being enriched by a more diverse range of voices and institutions. Geographically, our findings confirm that developed countries continue to lead in m-learning research output, with strong contributions from institutions in North America, Europe, and Asia. Despite these promising findings, research on m-learning remains relatively scarce in some regions, especially across much of Africa. Previous studies have largely overlooked these geographical disparities, an oversight to which our study makes a crucial contribution. These disparities are not merely a matter of limited academic output but reflect deeper structural and contextual challenges. Firstly, limited infrastructure, such as unreliable internet access, inconsistent electricity supply, and inadequate access to mobile devices, continues to hinder both the implementation and study of m-learning in many low-resource settings [42]. Secondly, constrained research funding further suppresses the development of robust research ecosystems. Compounding these challenges are systemic issues such as reduced access to scholarly networks and international collaborations, which restrict the global visibility of locally relevant research. Together, these factors have contributed to a fragmented and uneven global research field.

5.3. Author influence and influential scholarly works

In examining the intellectual structure of the field, our analysis identified key authors and seminal works that have significantly shaped the trajectory of m-learning research. Notably, Hwang, Gwo-Jen, ranks as the most prolific author, followed by Huang, Yueh-Min. Among non-Taiwanese scholars, Looi, Chee-Kit from Nanyang Technological University (Singapore), along with other researchers from Jordan, Hong Kong, Australia, and Spain, reflect a broadening international research base in m-learning. While earlier studies, such as those by Panackal et al. [14], primarily focused on technological innovations, our findings indicate a recent and notable shift toward pedagogical frameworks and teaching strategies. This evolution is reflected in the expanding body of literature that explores m-learning's role in active learning, personalised education, and student engagement. Guo et al. [7] likewise highlighted the transformative pedagogical potential of mobile technologies, reinforcing our observation that the field is maturing. Rather than emphasising tools and devices alone, our findings reveal that contemporary research increasingly prioritises effectively integrating these technologies into teaching and learning practices.

An important consideration emerging from this study concerns the distinctive epistemic contribution and affordances of mobile learning in relation to other digital learning modes. Unlike conventional web-based platforms or desktop-oriented e-learning, mobile learning enables knowledge construction that is contextually situated, personalised, and temporally immediate, thereby supporting learning in authentic settings beyond the formal classroom. Prior scholarship consistently highlights these affordances, including mobility [2], expanded access [43], immediacy of interaction and feedback [44], situativity [45], ubiquity

Table 6
Top twenty most cited publications.

R	TC	Title	Authors	Year	C/Y
1	678	Mobile computing devices in higher education: Student perspectives on learning with cellphones, smartphones & social media	Gikas, Joanne; Grant, Michael M.	2013	52.15
2	672	Investigating the determinants and age and gender differences in the acceptance of mobile learning	Wang, Yi-Shun; Wu, Ming-Cheng; Wang, Hsiu-Yuan	2009	39.53
3	570	An investigation of mobile learning readiness in higher education based on the theory of planned behaviour	Cheon, Jongpil; Lee, Sangno; Crooks, Steven M.; Song, Jaeki	2012	40.71
4	565	Opportunities and Challenges for Smartphone Applications in Supporting Health Behavior Change: Qualitative Study	Dennison, Laura; Morrison, Leanne; Conway, Gemma; Yardley, Lucy	2013	43.46
5	513	Review of trends from mobile learning studies: A meta-analysis	Wu, Wen-Hsiung; Wu, Yen-Chun Jim; Chen, Chun-Yu; Kao, Hao-Yun; Lin, Che-Hung; Huang, Sih-Han	2012	36.64
6	457	A formative assessment-based mobile learning approach to improving the learning attitudes and achievements of students	Hwang, Gwo-Jen; Chang, Hsun-Fang	2011	30.47
7	455	Factors Determining the Behavioral Intention to Use Mobile Learning: An Application and Extension of the UTAUT Model	Chao, Cheng-Min	2019	65
8	453	Mobile learning: A framework and evaluation	Motiwalla, Luvai F.	2007	23.84
9	449	University students' behavioural intention to use mobile learning: Evaluating the technology acceptance model	Park, Sung Youl; Nam, Min-Woo; Cha, Seung-Bong	2012	32.07
10	408	The effectiveness of m-learning in the form of podcast revision lectures in higher education	Evans, Chris	2008	22.67
11	360	A Pedagogical Framework for Mobile Learning: Categorizing Educational Applications of Mobile Technologies into Four Types	Park, Yeonjeong	2011	24
12	339	Mapping research in student engagement and educational technology in higher education: a systematic evidence map	Bond, Melissa; Buntins, Katja; Bedenlier, Svenja; Zawacki-Richter, Olaf; Kerres, Michael	2020	56.5
13	320	Predicting the drivers of behavioural intention to use mobile learning: A hybrid SEM-Neural Networks approach	Tan, Garry Wei-Han; Ooi, Keng-Boon; Leong, Lai-Ying; Lin, Binshan	2014	26.67
14	317	An Augmented Reality-based Mobile Learning System to Improve Students' Learning Achievements and Motivations in Natural Science Inquiry Activities	Chiang, Tosti H. C.; Yang, Stephen J. H.; Hwang, Gwo-Jen	2014	26.42
15	310	Here and now mobile learning: An experimental study on the use of mobile technology	Martin, Florence; Ertzberger, Jeffrey	2013	23.85
16	309	Factors driving the adoption of m-learning: An empirical study	Liu, Yong; Li, Hongxiu; Carlsson, Christer	2010	19.31
17	303	A mobile gamification learning system for improving learning motivation and achievements	Su, C—H.; Cheng, C—H.	2015	27.55
18	292	The use of mobile learning in higher education: A systematic review	Crompton, Helen; Burke, Diane	2018	36.5
19	275	Investigating attitudes towards the use of mobile learning in higher education	Al-Emran, Mostafa; Elsherif, Hatem M.; Shaalan, Khaled	2016	27.5
20	235	Mobile-Based Assessment: Integrating acceptance and motivational factors into a combined model of Self-Determination Theory and Technology Acceptance	Nikou, Stavros A.; Economides, Anastasios A.	2017	26.11

Abbreviations in Table 1, except C/Y: citations per year.

across time and space [46], convenience for learners' everyday practices [47], and contextual responsiveness [48]. Taken together, these affordances position m-learning not merely as a delivery channel for digital content, but as a distinct pedagogical ecology that reshapes how, where, and when knowledge is constructed, thereby offering epistemic value that extends beyond other forms of digital learning

5.4. Journal-level citation and impact analysis

Furthermore, we also identified several high-impact journals consistently serving as key platforms for disseminating m-learning research in higher education. Journals such as *Computers & Education, Education and Information Technologies and the Interactive Learning Environments* emerged as the most productive and influential outlets, contributing not only to technological discourse but also to pedagogical and theoretical advancements in the field. This pattern supports the observations of Gulzar et al. [12], who recognised these journals' role in shaping the educational technology research agenda. Moreover, the growing presence of interdisciplinary journals that address digital learning and educational innovation indicates that m-learning research is expanding beyond traditional education-focused publications, further broadening its academic reach.

5.5. Thematic and conceptual structure of the field

The keyword analysis revealed prominent research themes across three distinct timeframes over the past 30 years: 1994 - 2004, 2005 - 2014, and 2015 - 2024. This temporal breakdown is crucial in providing insights into the research focus in each period. The thematic evolution through the analysis of keyword occurrences of the field reveals a

Table 7
The top twenty journals with the most publications and citations.

R	Journal	All publications of the journal (1994–2024)							1994–2004		2005–2014		2015–2024	
		TP	TC	C/P	TLS	H	IF (Q) 2023	5-Year IF	TP	TC	TP	TC	TP	TC
1	Computers & Education	147	15,504	105.47	2989	232	8.9 (1)	9.3	-	-	64	9529	84	6105
2	Education and Information Technologies	118	2564	21.73	1424	76	4.8 (1)	4.8	-	-	-	-	122	2563
3	Interactive Learning Environments	95	2176	22.91	788	68	3.7 (1)	4.5	-	-	-	-	92	1959
4	Educational Technology & Society	87	4184	48.09	1027	111	4.6 (1)	4.7	1	27	55	3178	34	1015
5	Sustainability	84	1419	16.89	764	162	3.3 (1)	-	-	-	-	-	86	1452
6	British Journal of Educational Technology	75	4778	63.71	1229	119	6.7 (1)	7.2	-	-	23	2903	53	1849
7	Computers in Human Behaviour	63	4417	70.11	930	251	9.0 (1)	9.5	-	-	15	1305	50	3517
8	Journal of Computer Assisted Learning	65	3616	55.63	981	114	5.1 (1)	5.4	5	656	19	2043	45	1091
9	International Review of Research in Open and Distributed Learning	45	1891	42.02	597	90	3.2 (2)	3.2	-	-	17	1163	29	721
10	Computer-Assisted Language Learning	40	1551	38.78	374	75	6.0 (1)	6.8	-	-	9	558	33	1055
11	International Journal of Mobile Learning and Organisation	46	297	6.46	255	29	0.6 (2)	1.2	-	-	-	-	46	300
12	Ieee Access	37	884	23.89	419	242	3.4 (1)	3.7	-	-	-	-	38	925
13	Computer Applications in Engineering Education	34	484	14.24	120	42	2.0 (1)	2.2	-	-	5	114	30	370
14	Education Sciences	40	351	8.78	227	53	0.7 (2)	2.6	-	-	-	-	42	369
15	Journal of Universal Computer Science	37	449	12.14	111	58	0.7 (3)	0.9	-	-	12	216	25	230
16	Australasian Journal of Educational Technology	37	1459	39.43	340	68	4.1 (1)	3.9	-	-	15	999	23	495
17	Educational Technology Research and Development	36	1369	38.03	538	109	3.3 (1)	4.8	-	-	5	207	32	1194
18	International Journal of Emerging Technologies in Learning	34	420	12.35	118	46	2.3 (2)	3.2	-	-	-	-	35	426
19	International Journal of Engineering Education	31	261	8.42	60	61	0.7 (3)	0.8	-	-	15	100	18	246
20	International Journal of Mobile and Blended Learning	31	92	2.97	214	21	0.9 (3)	0.9	-	-	-	-	33	92

Abbreviation in Table 1 except Q: quartile ranking; IF: impact factor.

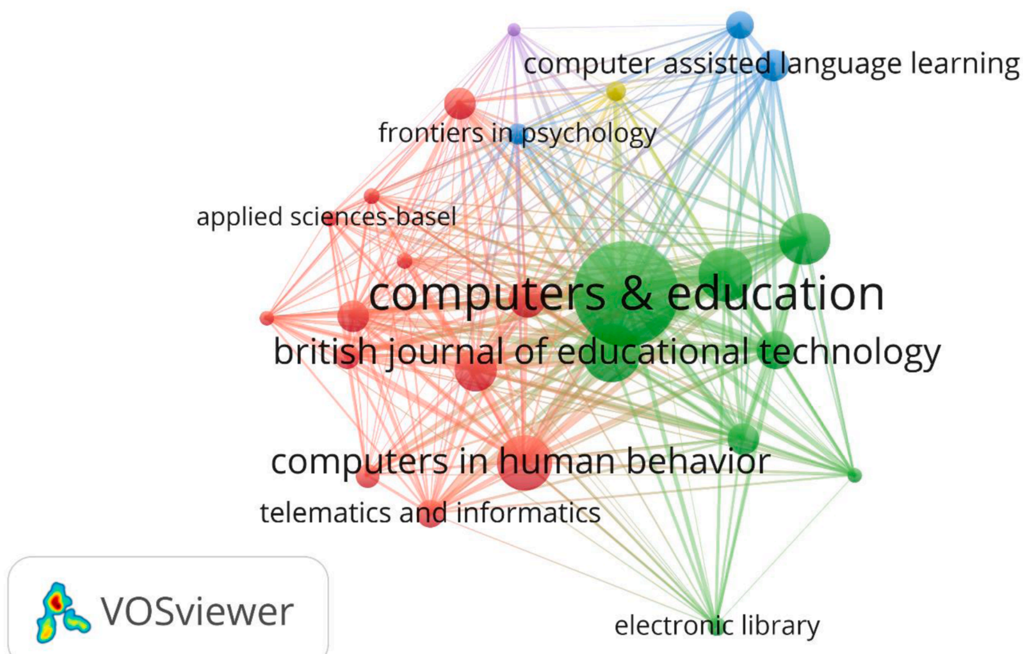

Fig. 8. Journal citation network visualisation.

distinct transition from initial explorations of device usability toward more complex discussions involving learning analytics, AI, and adaptive learning environments. This finding adds to the trends identified by Panackal et al. [14] and Guo et al. [7], who observed a move towards blended and collaborative learning, mobile technology adoption, and student engagement. In addition, our findings go a step further by demonstrating that m-learning research is becoming increasingly interdisciplinary. Such convergence of disciplines points to a more holistic understanding of how m-learning can be effectively embedded in diverse educational contexts.

6. Conclusion and implications

This study makes distinct contributions that differentiate it from prior bibliometric analyses of mobile learning. Spanning a 30-year period, it offers a comprehensive longitudinal view of the field's evolution, while its broad geographical coverage illuminates global patterns of knowledge production, collaboration, and scholarly influence. The inclusion of polynomial regression for trend prediction further enables the analysis to move beyond descriptive reporting by providing insight into emerging research directions. The findings show that m-learning

Table 8
Temporal evolution of author keywords.

	1994-2024			1994-2004			2005–2014			2015–2024		
R	Keywords	Oc	Co	Keywords	Oc	Co	Keywords	Oc	Co	Keywords	Oc	Co
1	Mobile Learning	1500	3125	Wireless	4	28	Mobile learning	240	232	Mobile learning	1262	2552
2	M-Learning	310	714	Mobile	3	22	M-learning	54	68	Higher education	210	559
3	Higher Education	231	646	School	3	20	E-learning	35	66	M-learning	204	451
4	Mobile Devices	164	395	Collaborative learning	2	7	Mobile devices	30	31	Mobile devices	128	295
5	E-Learning	151	423	Handheld	2	15	Mobile technology	24	25	Mobile technology	117	211
6	Mobile Technology	150	294	It-use	2	15	Ubiquitous learning	22	43	Education	105	348
7	Education	118	404	Mobile learning	2	7	Teaching/learning strategies	19	42	Augmented reality	97	253
8	Augmented Reality	113	308	Primary	2	13	Higher education	14	22	E-learning	96	262
9	Educational Technology	78	236	Quantitative	2	14	Interactive learning environments	13	27	Educational technology	67	187
10	Smartphone	72	166	Ad hoc classroom	1	6	Informal learning	11	21	Covid-19	66	172
11	Social media	71	182	Audio-based learning	1	3	Mobile phones	11	17	Technology acceptance model	60	154
12	Covid-19	68	182	Augmented reality	1	3	Mobile technologies	11	12	Social media	59	149
13	Technology Acceptance Model	68	179	Cell phone	1	7	Cell phone	11	23	Mobile applications	57	157
14	Mobile Applications	65	178	Case study	1	9	Smartphone	10	11	Gamification	50	127
15	Ubiquitous Learning	59	146	Cellular radio networks	1	5	Education	9	13	Smartphone	49	102
16	Collaborative Learning	58	150	Change	1	9	Language learning	9	16	Blended learning	47	126
17	Gamification	55	151	Collaboration	1	7	Learning	9	14	N NOnline learning	47	121
18	Learning	55	164	Computer uses in education	1	1	Mobile phone	9	13	Collaborative learning	46	119
19	Smartphones	55	157	Constructivism	1	3	Pedagogical issues	9	20	Technology	46	119
20	Technology	55	143	Constructivist	1	7	Academic libraries	8	13	Learning	43	122
21	Blended Learning	54	148	Mobile agents	1	5	Applications in subject areas	8	16	Mobile application	43	101
22	E-learning	53	141	Intranet	1	9	Augmented reality	8	14	Motivation	43	108
23	Medical Education	52	136	Distributed transaction processing	1	4	Collaborative learning	8	14	Smartphones	42	109
24	Motivation	51	136	E-learning	1	4	Distance learning	8	12	Game-based learning	39	82
25	Online Learning	51	139	E-schoolbag	1	6	Educational technology	8	16	University students	39	100
26	Mobile Application	49	118	Extended transaction models	1	4	Elementary education	8	22	Medical education	36	88
27	Game-Based Learning	48	108	Formative	1	7	Medical education	8	15	Self-efficacy	36	100
28	Teaching/ Learning Strategies	45	133	Handheld learning device	1	4	Mobile	8	12	Teaching	36	123
29	Teaching	44	163	Handhelds	1	7	Mobile computing	8	13	Distance education	34	87
30	Distance Education	43	121	Interactive learning	1	4	Mobile device	8	11	Technology acceptance	34	111

Abbreviations: R = Rank; Oc = Author keyword occurrences; Co = Author keyword co-occurrences links.

has evolved from a largely descriptive, technology-centric domain into one that raises substantive theoretical questions in learning. Beyond mapping publication output, geographic contributions, and influential journals, the study identifies a sustained thematic shift toward personalisation, immediacy, immersive technologies, and data-driven pedagogies. These trajectories indicate that mobile learning research is increasingly focused on how learning unfolds across contexts rather than merely where it is delivered. Importantly, the longitudinal patterns challenge core assumptions of traditional learning science, particularly those concerning fixed instructional settings, bounded timeframes, and linear learning processes, and foreground mobility, contextuality, and real-time adaptation as integral epistemic conditions. These patterns challenge assumptions of fixed instructional settings, bounded timeframes, and linear processes. To translate insights into practice, institutions should ensure equitable access to devices, integrate m-learning into curricula with context-aware, adaptive pedagogies, and support faculty in using mobility for just-in-time scaffolding, collaboration, and immersive learning experiences.

Limitations and future directions

This study is not without limitations. One notable constraint is the potential omission of relevant articles that do not explicitly reference mobile learning in their titles, abstracts, or keywords. Such omissions

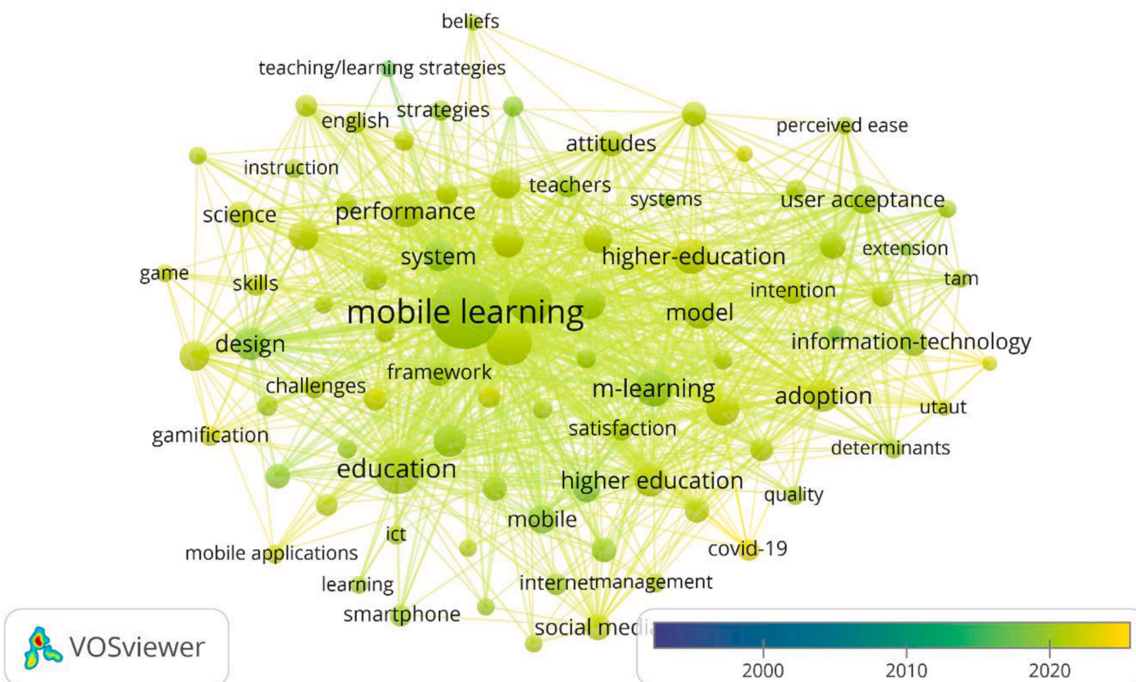

Fig. 9. Occurrence of author keywords (1994-2024).

may have introduced discrepancies in the statistical analyses, potentially limiting the completeness of the dataset. Additionally, the study's exclusive reliance on bibliometric data from the Web of Science database poses another limitation. This reliance may inadvertently narrow the scope of the findings and exclude valuable perspectives and emerging trends in other databases. Future research should consider expanding the data sources to include platforms such as Scopus and Google Scholar, which could provide a more comprehensive and inclusive overview. Another important limitation of this study is language bias, as our analysis included only publications in English. This may have excluded relevant research published in languages other than English, potentially underrepresenting contributions from non-English-speaking regions and influencing the observed geographic and thematic trends. Future studies should consider multilingual bibliometric analyses to capture a more globally representative picture of mobile learning research.

CRediT authorship contribution statement

Thuthukile Jita: Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Brian Shambare:** Writing – review & editing, Software, Methodology, Investigation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] Harari YN. Why technology favors tyranny. Atlantic 2018;322(3):64–73.

[2] He M, Ariffin SA, Wong YS, Rahmatullah B, Azizan UH, Fathil NS, Chandra YU, Kurniawan Y, Stamper J. The contribution of cultural factors to mobile learning acceptance in Chinese higher education. J Adv Res Appl Sci Eng Technol 2025;52 (2):74–88. https://doi.org/10.37934/araset.52.2.7488.

[3] Martínez-González JL. Assessing agricultural adaptation to changing climatic conditions during the English agricultural revolution (1645–1740). Cliometrica (Berl) 2025;19(1):163–93. https://doi.org/10.1007/s11698-024-00285-4.

[4] De Vries J. The industrial revolution and the industrious revolution. J Econ Hist 1994;54(2):249–70. https://doi.org/10.1017/S0022050700014467.

[5] StatCounter. (2025). Global mobile vs desktop internet traffic by region. Retrieved from https://gs.statcounter.com/platform-market-share/desktop-mobile-tablet/.

[6] Statista. (2025). Number of smartphone mobile network subscriptions worldwide from 2016 to 2028 (in billions). Retrieved from https://www.statista.com/statistics/330695/number-of-smartphone-users-worldwide/.

[7] Guo PP, Jeyaraj JJ, Razali A. A systematic review of collaborative mobile-assisted language learning (C-MALL) practices using bibliometric, content, and scientometric analyses. Humanit Soc Sci Commun 2024;(1):11. https://doi.org/10.1057/s41599-024-03940-3.

[8] Irwanto I, Saputro AD, Widiyanti W, Laksana SD. Global trends on mobile learning in higher education: a bibliometric analysis (2002–2022). Int J Inf Educ Technol 2023;13(2):373–83. https://doi.org/10.18178/ijiet.2023.13.2.1816.

[9] Wang X, Hasim Z. A bibliometric analysis on trends and patterns in self-regulated language learning in mobile-assisted learning environments. Int J Comput-Assist Lang Learn Teach 2024;14(1). https://doi.org/10.4018/IJCALLT.345401.

[10] Sweileh WM. Global research activity on e-learning in health sciences education: a bibliometric analysis. Med Sci Educ 2021;31(2):765–75. https://doi.org/10.1007/s40670-021-01254-6.

[11] Goksu I. Bibliometric mapping of mobile learning. Telemat Inform 2021;56. https://doi.org/10.1016/j.tele.2020.101491.

[12] Gulzar A, Ahmed S, Khan MA, Siddique N. Bibliometric analysis of mobile learning research from 1984 to 2020. Int J Mob Learn Organ 2022;16(4):429–46. https://doi.org/10.1504/ijmlo.2022.125963.

[13] Sobral SR. Mobile learning in higher education: a bibliometric review. Int J Interact Mob Technol 2020;14(11):153–70. https://doi.org/10.3991/ijim.v14i11.13973.

[14] Panackal N, Sharma A, Rautela S. A bibliometric analysis of the intellectual landscape of mobile technology and higher education research. Int J Interact Mob Technol 2023;17(22):4–25. https://doi.org/10.3991/IJIM.V17I22.43031.

[15] Rachman D, Khatimah K, Kusuma IPI, Roni M. Bibliometric analysis of oral presentations with mobile technology in tertiary education. Scr J 2024;9(1):79–95. https://doi.org/10.24903/sj.v9i1.1578.

[16] Kaisara G, Bwalya KJ. Mobile learning in higher education: insights from a bibliometric analysis of the body of knowledge. Int J Learn Teach Educ Res 2023; 22(6):152–74. https://doi.org/10.26803/ijlter.22.6.9.

[17] Khan FM, Gupta Y. A bibliometric analysis of mobile learning in the education sector. Interact Technol Smart Educ 2022;19(3):338–59. https://doi.org/10.1108/ITSE-03-2021-0048.

[18] Pritchard A, Wittig GR. *Bibliometrics*. Watford: AllM Books; 1981.

[19] Donthu N, Kumar S, Mukherjee D, Pandey N, Lim WM. How to conduct a bibliometric analysis: an overview and guidelines. J Bus Res 2021;133:285–96. https://doi.org/10.1016/j.jbusres.2021.04.070.
[20] Zupic I, Čater T. Bibliometric methods in management and organisation. Organ Res Methods 2015;18(3):429–72. https://doi.org/10.1177/1094428114562629.
[21] Camuñas-García D, Cáceres-Reche MP, Cambil-Hernández MD. Mobile game-based learning in cultural heritage education: a bibliometric analysis. Educ Train 2023;65 (2):324–39. https://doi.org/10.1108/ET-06-2022-0247.
[22] Ellegaard O, Wallin JA. The bibliometric analysis of scholarly production: how great is the impact? Scientometrics 2015;105(3):1809–31. https://doi.org/10.1007/s11192-015-1645-z.
[23] Chen X, Zou D, Xie H, Wang FL. Past, present, and future of smart learning: a topic-based bibliometric analysis. Int J Educ Technol High Educ 2021;18(1). https://doi.org/10.1186/s41239-020-00239-6.
[24] Fan CW, Lin J, Reynolds BL. A bibliometric analysis of trending mobile teaching and learning research from the social sciences. Sustainability 2023;15(7):6143. https://doi.org/10.3390/su15076143.
[25] Wang X, Gao Y, Sun F, Wang Q. Unveiling the tapestry of teacher belief research: tracing the present and forging the future through bibliometric analysis. Curr Psychol 2024;43(17):15659–72. https://doi.org/10.1007/s12144-023-05546-5.
[26] Broadus R. Toward a definition of bibliometrics. Scientometrics 1987;12(5–6): 373–9. https://doi.org/10.1007/bf02016680.
[27] Ninkov A, Frank JR, Maggio LA. Bibliometrics: methods for studying academic publishing. Perspect Med Edu 2022;11(3):173–6. https://doi.org/10.1007/s40037-021-00695-4.
[28] Balili C, Segev A, Lee U. Tracking and predicting the evolution of research topics in scientific literature. In: *IEEE International Conference on Big Data*. IEEE; 2017. p. 1694–7. https://doi.org/10.1109/BigData.2017.8258108; 2017.
[29] Van Eck N, Waltman L. Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics 2010;84(2):523–38. https://doi.org/10.1007/s11192-009-0146-3.
[30] Paul J, Lim WM, O'Cass A, Hao AW, Bresciani S. Scientific procedures and rationales for systematic literature reviews (SPAR-4-SLR). Inter J Consum Stud 2021;45(4):1–16. https://doi.org/10.1111/ijcs.12695.
[31] Martín-Martín A, Orduna-Malea E, Thelwall M, López-Cózar ED. Google Scholar, Web of Science, and Scopus: a systematic comparison of citations in 252 subject categories. J Inf 2018;12(4):1160–77. https://doi.org/10.1016/j.joi.2018.09.002.
[32] Ortega JL, Delgado-Quirós L. The indexation of retracted literature in seven principal scholarly databases: a coverage comparison of dimensions, OpenAlex, PubMed, Scilit, Scopus, The Lens and Web of Science. Scientometrics 2024;129(7): 3769–85. https://doi.org/10.1007/s11192-024-05034-y.
[33] Haustein S, Larivière V. The use of bibliometrics for assessing research: Possibilities, limitations and adverse effects. In: *Incentives and Performance: Governance of Research Organizations*. Cham: Springer International Publishing; 2014. p. 121–39. https://doi.org/10.1007/978-3-319-09785-5_8.
[34] Davison AC. Statistical models, 11. Cambridge university press; 2003.
[35] Gemeay AM, Moakofi T, Balogun OS, Ozkan E, Hossain MM. Analysing real data by a new heavy-tailed statistical model. Mod J Stat 2025;1(1):1–24. https://doi.org/10.64389/mjs.2025.01108.
[36] Price DJDS. Little science, big science. Columbia university press; 1963. https://doi.org/10.7312/pric91844-005.
[37] Bornmann L, Haunschild R, Mutz R. Growth rates of modern science: a latent piecewise growth curve approach to model publication numbers from established and new literature databases. Human Soc Sci Commun 2021;8(1):224. https://doi.org/10.1057/s41599-021-00903-w.
[38] Wang YS, Wu MC, Wang HY. Investigating the determinants and age and gender differences in the acceptance of mobile learning. British J Edu Technol 2009;40(1): 92–118. https://doi.org/10.1111/j.1467-8535.2007.00809.x.
[39] Bond M, Buntins K, Bedenlier S, Zawacki-Richter O, Kerres M. Mapping research in student engagement and educational technology in higher education: A systematic evidence map. Inter J Edu Technol High Edu 2020;17(1):1–30. https://doi.org/10.1186/s41239-019-0176-8.
[40] Hoi VN. Understanding higher education learners' acceptance and use of mobile devices for language learning: A Rasch-based path modeling approach. Comput Edu 2020;146:103761. https://doi.org/10.1016/j.compedu.2019.103761.
[41] Zong B, Sun Y, Li L. Advances, hotspots, and trends in outdoor education research: A bibliometric analysis. Sustainability 2024;16(22):10034. https://www.mdpi.com/2071-1050/16/22/10034#.
[42] Shambare B, Jita T. A new era of learning: exploring science teachers' perceptions of virtual lab in rural schools. Educ Inf Technol 2025:1–21. https://doi.org/10.1007/s10639-025-13412-z.
[43] Lee H-J, Hu J. Adoption of mobile technology in higher education: an introduction. Handbook of mobile teaching and learning. 2nd ed. 2019. https://doi.org/10.1007/978-981-13-2766-7_4.
[44] Crompton H, Burke D. The use of mobile learning in higher education: a systematic review. Comput Educ 2018;123:53–64. https://doi.org/10.1016/j.compedu.2018.04.007.
[45] Chang C-Y, Lai C-L, Hwang G-J. Trends and research issues of mobile learning studies in nursing education: a review of academic publications from 1971 to 2016. Comput Educ 2018;116:28–48. https://doi.org/10.1016/j.compedu.2017.09.001.
[46] Zhang Y. Exploring blended learning models enhanced by mobile interactive technology in higher education. Int J Interact Mob Technol 2024;18(23):15–29. https://doi.org/10.3991/ijim.v18i23.52881.
[47] Nagasundram U, Mahmud MM, Mustamam NI, Yaacob Y, Ahmad R, A'Seri MSM. From connectivity to dependency: smartphones in higher education mobile learning (M-learning). In: Proceedings of the 2024 the 16th International Conference on Education Technology and Computers. 2024. ICETC; 2025. p. 407–12. https://doi.org/10.1145/3702163.3702447.
[48] Aznar-Diaz I, Romero-Rodriguez J-M, Navas-Parejo MR, Gomez-Garcia G. Analysis of good teaching practices with mobile devices at the university: design and validation of the APMU scale. Rev Iberoam Tecnol Aprendiz 2021;16(1):2–10. https://doi.org/10.1109/RITA.2021.3052482.