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Mapping the Mobile Shift: A Bibliometric Exploration of Mobile Learning Innovations in STEM Education

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Abstract

Given the rapid proliferation of mobile technologies and their potential to reshape science, technology, engineering, and mathematics (STEM) education, there is a pressing need to systematically examine how research in this domain has evolved over time. This study maps the intellectual structure and emerging trends of mobile learning (m-learning) in STEM education through a comprehensive bibliometric analysis. Drawing from a corpus of 1,462 journal articles indexed in Scopus, the study employed citation, co-citation, and co-word analyses using VOSviewer to uncover influential authors, dominant themes, and evolving conceptual patterns. The findings reveal three major research domains: foundational learning theories, pedagogical strategies, and user acceptance models. Four thematic clusters were identified: immersive and collaborative learning through emerging technologies, AI integration in digital pedagogy, infrastructural and accessibility challenges in developing contexts, and adoption of m-learning in higher education systems. Despite a marked growth in research output, the study highlights persistent challenges, including inequitable access to mobile technologies, insufficient teacher training, and weak alignment between mobile tools and STEM learning objectives. These limitations underscore the need for constructivist-aligned instructional designs, investment in scalable infrastructure, and institutional policy support, particularly in underserved educational settings. This study represents one of the first large-scale bibliometric investigations of m-learning in STEM education. By synthesizing a fragmented body of literature, it reveals critical research gaps and provides a roadmap for future inquiry, with particular attention to AI-driven learning design, inclusive pedagogies, and sustainable technology integration in STEM education.

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Introduction

The proliferation of mobile technologies has ushered in new possibilities for transforming Science, Technology, Engineering, and Mathematics (STEM) education. Mobile learning (m-learning), defined as the use of mobile devices to facilitate anytime, anywhere learning, has emerged as a promising modality for promoting personalized, collaborative, and contextual learning experiences (Liu et al., 2024; Crompton et al., 2017). In the context of STEM education, where inquiry, experimentation, and problem-solving are fundamental, mobile technologies hold particular promise in bridging formal and informal learning environments, enhancing learner engagement, and supporting authentic, real-world applications of STEM concepts.

Despite the rapid advancements in mobile technology and the increasing ubiquity of smartphones and tablets in educational settings, the integration of mobile learning in STEM remains inconsistent and under-theorized (Bazhenova & Shuzhebayeva, 2022). A key concern lies in the *digital divide*, where learners from different socioeconomic backgrounds experience unequal access to mobile devices and reliable internet connectivity, thereby exacerbating educational inequities (Krishnamurthi & Richter, 2013). Additionally, infrastructural limitations, lack of teacher training, and minimal institutional support hinder the widespread adoption of m-learning in STEM classrooms, particularly in resource-constrained settings (Bakri et al., 2023). Another persistent challenge is the pedagogical alignment of mobile learning tools with STEM-specific learning outcomes. Although many mobile applications foster student motivation and engagement, they often lack depth in promoting higher-order thinking skills such as critical thinking, scientific reasoning, and problem-solving, which are competencies central to STEM proficiency (Bakri et al., 2023; Sahito & Sahito, 2024). Furthermore, existing mobile learning tools tend to prioritize content delivery over experiential and interactive learning models that align with constructivist approaches.

Empirical investigations into mobile learning have produced promising findings. For instance, mobile-integrated project-based learning has been shown to enhance students' motivation, science process skills, and conceptual understanding (Bakri et al., 2023). Bano et al. (2018), in their systematic review, underscore the collaborative affordances of mobile learning but also note significant methodological gaps and limited focus on actual learning outcomes. Similarly, Liu et al. (2024) report improvements in students' science literacy through mobile learning packages but emphasize the importance of intentional pedagogical design. However, existing research tends to be fragmented, with limited efforts to synthesize knowledge across disciplines, contexts, and time. Most studies are concentrated in developed countries, raising questions about the generalizability of findings to diverse educational systems, especially those in low- and middle-income countries (Naveed et al., 2023). Moreover, scholars such as Crompton et al. (2017) and Sarrab et al. (2016) critique the dominance of behaviorist approaches and advocate for more inquiry-oriented, constructivist uses of mobile technology in STEM.

Given these limitations, a comprehensive bibliometric analysis is timely and necessary to map the intellectual landscape of mobile learning in STEM education. Bibliometric methods can reveal publication trends, key contributors, thematic clusters, and knowledge gaps, thereby guiding future research and informing practice and policy. This study, therefore, aims to provide a macro-level analysis of the mobile learning research corpus within the context of STEM education. Specifically, the study seeks to:

1. identify the most influential publications related to mobile learning in STEM education through citation analysis;
2. assess current research patterns using co-citation analysis to detect theoretical and methodological trends, and;
3. uncover emerging themes and future directions using co-word analysis.

By addressing these objectives, the study contributes to a deeper understanding of how mobile learning is shaping STEM education. It offers valuable insights for researchers, educators, curriculum developers, and policymakers seeking to leverage mobile technologies in more equitable, scalable, and pedagogically sound ways. Ultimately, the findings aim to strengthen the theoretical and practical foundations of mobile learning innovations and inform the design of future STEM interventions aligned with 21st-century learning goals.

Review of Related Literature

Mobile learning (m-learning) has emerged as a transformative approach in Science, Technology, Engineering, and Mathematics (STEM) education, offering flexible, contextualized, and personalized learning experiences. Early scholarship focused on the technological affordances of mobile devices, such as portability, connectivity, and ubiquity, that support learning across formal, non-formal, and informal settings (Mutambara & Bayaga, 2021). These features align well with STEM pedagogies that emphasize active participation, real-time feedback, and inquiry-based learning (Al Hamad et al., 2024; Bano et al., 2018). Grounded in experiential and constructivist learning theories (Kolb, 1984; Lave & Wenger, 1991), m-learning enables learners to engage in authentic, situated tasks that nurture scientific reasoning, critical thinking, and problem-solving, which are core competencies in STEM education.

A substantial body of research has explored how m-learning aligns with pedagogical goals in STEM contexts. Studies such as those by Bakri et al. (2023) and Liu et al. (2024) highlight how mobile-assisted project-based learning improves students' motivation, engagement, and cognitive gains. Nonetheless, persistent critiques point to a dominant focus on content transmission, with many applications falling short in promoting higher-order cognitive skills and scientific inquiry (Sahito & Sahito, 2024). Furthermore, there remains a paucity of longitudinal and curriculum-aligned studies that evaluate the sustained impact of mobile learning interventions on learning outcomes (Bazhenova & Shuzhebayeva, 2022).

User acceptance and behavioral intention have also garnered significant attention, particularly through the lens of the Technology Acceptance Model (TAM) and its extended versions. These models posit that learners' perceived usefulness and ease of use are critical determinants of mobile learning adoption (Davis, 1989; Venkatesh et al., 2003). Empirical studies by Mata et al. (2021) and Hamidi and Chavoshi (2018) confirm that demographic variables, such as age, gender, and academic background, substantially influence learners' attitudes toward mobile technologies. This highlights the necessity for adaptive and user-centered systems that cater to diverse levels of digital literacy, learning styles, and cultural backgrounds (Oviedo Ramirez et al., 2025).

A parallel concern is the persistent *digital divide* and infrastructural inequities that limit the scalability of mobile learning. While much of the literature originates from developed nations, emerging research from developing contexts identifies systemic barriers, including limited access to mobile devices, unreliable internet connectivity, and insufficient institutional readiness (Naveed et al., 2023; Akpan, 2024). These challenges disproportionately affect marginalized and rural learners, emphasizing the need for inclusive mobile learning policies and cost-effective technological solutions that promote equitable access to STEM education.

Recent advances in educational technologies, such as augmented reality (AR), artificial intelligence (AI), and game-based mobile applications, are expanding the scope of m-learning in STEM. Studies by Wu et al. (2013), Kamarainen et al. (2013), and Chen and Huang (2023) illustrate how these innovations enhance learner engagement, visualization of abstract concepts, and experiential learning opportunities. However, research also suggests that the effectiveness of such tools is contingent on sound pedagogical integration, teacher preparedness, and institutional capacity (Tong et al., 2023; Nurunnabi et al., 2025). Without these conditions, even the most advanced mobile technologies may fall short of their educational potential.

Despite the growing body of work, the literature on mobile learning in STEM remains fragmented, often siloed within specific disciplines or educational levels. Methodological inconsistencies and the lack of systematic synthesis have limited the ability to draw generalizable conclusions. In response, scholars have advocated for bibliometric approaches to map research landscapes, identify influential works, and uncover thematic and methodological trends (Donthu et al., 2021; Aria & Cuccurullo, 2017). Such analyses are crucial for guiding evidence-informed decisions and fostering interdisciplinary dialogue in the field.

As m-learning continues to evolve, future research must holistically address technological affordances, pedagogical alignment, and equity-driven design to fully realize its potential in STEM education. A more integrative and globally inclusive research agenda is essential to advancing mobile learning as a catalyst for innovation, access, and excellence in STEM learning environments.

Theoretical Framework

This study is anchored on complementary theoretical perspectives that explain how mobile learning (m-learning) shapes, mediates, and enhances STEM education. At its core, m-learning is grounded in constructivist and experiential learning theories, which view knowledge as actively constructed through interaction with meaningful tasks and real-world contexts (Kolb, 1984; Al Hamad et al., 2024). Mobile technologies extend this process by enabling learners to explore, collect data, visualize phenomena, and engage in inquiry beyond the classroom, thereby fostering deeper conceptual understanding and higher-order thinking. These ideas are reinforced by sociocultural theory, which emphasizes that learning is a socially mediated process where knowledge emerges through collaboration, dialogue, and participation within communities of practice (Vygotsky & Luria, 1978; Wenger, 1999). Through mobile platforms, learners co-construct knowledge, share experiences, and bridge the gap between formal and informal learning environments.

The adoption and sustained use of mobile technologies are further explained by technology acceptance models, including the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT), which highlight perceived usefulness, ease of use, social influence, and behavioral intention as critical determinants of user engagement (Davis, 1989; Ajzen, 1991; Venkatesh et al., 2003). These models reveal how individual attitudes, demographic factors, and institutional support shape the adoption of m-learning in STEM contexts. Finally, socio-technical and ecological perspectives underscore the importance of aligning technological tools with pedagogical design, infrastructure, and policy to ensure equitable access and sustainable implementation, particularly in resource-limited settings (Kukulska-Hulme & Traxler, 2007; Krishnamurthi & Richter, 2013). Together, these frameworks provide a comprehensive lens for analyzing the intellectual structure and evolution of m-learning research, guiding this study's bibliometric exploration of how theory, practice, and technology converge to transform STEM education.

Method

Research Design

This study employed a bibliometric research design to map the intellectual structure, conceptual evolution, and emerging trends of mobile learning (m-learning) in Science, Technology, Engineering, and Mathematics (STEM) education. Bibliometric analysis is a quantitative method that systematically analyzes bibliographic data to uncover patterns in scholarly communication, influential works, thematic developments, and research frontiers within a specific field (van Eck & Waltman, 2014).

Bibliometric Analysis Approach

Bibliometric analysis, as a form of science mapping, visualizes relationships among documents, authors, journals, and key terms. Among the five major types of bibliometric analyses, this study utilized three complementary techniques: citation analysis, co-citation analysis, and co-word analysis. Together, these approaches provided a comprehensive understanding of the field's intellectual landscape and conceptual development.

Citation Analysis

Citation analysis was conducted to assess the scholarly impact and relevance of publications based on citation frequency. This approach identifies the most influential studies and traces the historical development and foundational knowledge of the field (Donthu et al., 2021). By analyzing citation counts, the study pinpointed key works that have significantly shaped mobile learning research in STEM education.

Co-Citation Analysis

Document co-citation analysis was employed to map the intellectual structure of the field by examining the frequency with which two publications are cited together (Hota et al., 2020). Publications that are co-cited often are likely to be conceptually related, reflecting shared theoretical foundations or methodological approaches

(Donthu et al., 2021). This method allowed the identification of core research clusters and intellectual schools of thought that underpin the evolution of m-learning scholarship.

Co-Word Analysis

Co-word analysis was conducted to reveal conceptual patterns and thematic structures by analyzing the frequency and co-occurrence of keywords across publications (Aria & Cuccurullo, 2017). This technique is particularly valuable for tracking the evolution of research topics, detecting emerging areas, and predicting future research directions (Zawacki-Richter et al., 2019). Unlike citation-based methods, co-word analysis directly examines publication content, offering insights into the semantic relationships and conceptual linkages within the literature.

Data Analysis and Visualization

The dataset was analyzed using VOSviewer software, a widely used tool for constructing and visualizing bibliometric networks. The software generated visual maps of publications, authors, and keywords, allowing for the identification of research clusters, intellectual structures, and interdisciplinary intersections. These visualizations served as a foundation for interpreting the field's knowledge architecture and informing future empirical and theoretical directions.

Search Strategy and Data Collection

The data collection was conducted using the Scopus database on April 15, 2025. Scopus was selected for its extensive coverage of high-quality, peer-reviewed journals, encompassing over 89 million records across more than 330 disciplines (Singh et al., 2021). A comprehensive search strategy was applied to the "Title," "Abstract," and "Keywords" fields using the search string presented in Table 1. This ensured the retrieval of literature relevant to mobile learning in STEM education contexts.

Table 1. Search String used for the Database Search

Keyword	Justification
("mobile learning" OR "m-learning" OR "mobile-assisted learning" OR "mobile technology in education") AND ("STEM education" OR "science education" OR "technology education" OR "engineering education" OR "mathematics education")	To identify the literature on mobile learning in STEM education
("teaching" OR "learning" OR "instruction")	To identify literature on teaching or learning

Results

Descriptive Analysis

From the Scopus database search, after filtering only journal publications and time to 2025, the total number of documents was finalized to 1462 publications. The total number of citations is 19,061. The average number of citations per item is 13.04. Figure 1 presents a bar chart of the number of publications and citations since 2015. The chart reflects the immense interest of scholars and practitioners in mobile learning in STEM. The number of citations is expected to increase in the coming years, contributing to high interest in and a large untapped research area in mobile learning within STEM education.

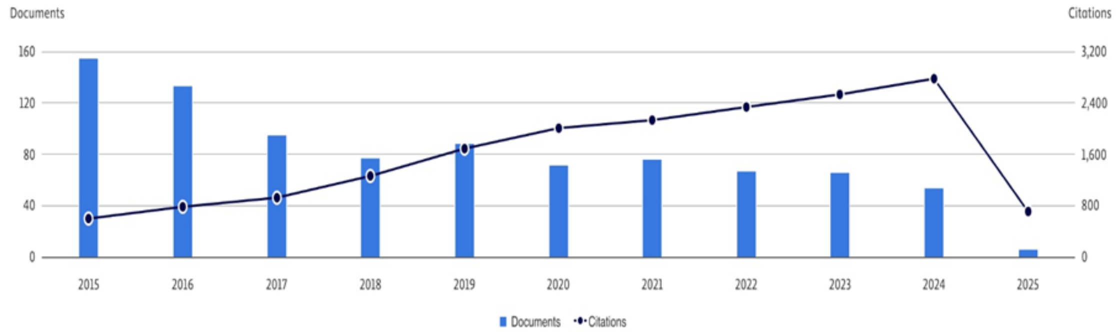

Figure 1. Number of Publications and Citations (Source: Scopus)

Citation Analysis

The highest-cited publications obtained by applying document citation analysis are presented in Table 2. The top three publications were Wu et al. (2013) (1,672 citations), Al-Emran et al. (2016) (413 citations), and Martin and Ertzberger (2013) (403 citations). The following is a discussion of the significant issues among the highest-cited publications in the citation analysis.

Table 2. Top 10 Highest Co-cited Documents

No.	Authors	Title	Citations
1	Wu, H. K., Lee, S. W., Chang, H., & Liang, J. (2013)	Current status, opportunities and challenges of augmented reality in education	1672
2	Al-Emran, M., Elsherif, H. M., & Shaalan, K. (2016)	Investigating attitudes towards the use of mobile learning in higher education	413
3	Martin, F., & Ertzberger, J. (2013)	Here and now mobile learning: An experimental study on the use of mobile technology	403
4	Panigrahi, R., Srivastava, P. R., & Sharma, D. (2018)	Online learning: Adoption, continuance, and learning outcome—A review of literature	384
5	Kamarainen, A. M., Metcalf, S., Grotzer, T., Browne, A., et al. (2013)	EcoMOBILE: Integrating augmented reality and probeware with environmental education field trips	382
6	Arici, F., Yildirim, P., Caliklar, S., & Yilmaz, R. M. (2019)	Research trends in the use of augmented reality in science education: Content and bibliometric mapping analysis	302
7	Briz-Ponce, L., Pereira, A.,	Learning with mobile technologies – Students’	289

No.	Authors	Title	Citations
	Carvalho, L., Juanes-Méndez, J., et al. (2017)	behavior	
8	Hamidi, H., & Chavoshi, A. (2018)	Analysis of the essential factors for the adoption of mobile learning in higher education	283
9	Zydney, J., & Warner, Z. (2016)	Mobile apps for science learning: Review of research	281
10	Bower, M., & Sturman, D. (2015)	What are the educational affordances of wearable technologies?	204

Technological Integration and Innovation in STEM Learning

Several top-cited studies, such as those of Wu et al. (2013), Kamarainen et al. (2013), Arici et al. (2019), Bower and Sturman (2015) emphasize the role of emerging technologies, such as augmented reality (AR), wearable technologies, and mobile apps, in enhancing science and environmental education. The balance between technological and pedagogical usability is a key issue. While these innovations offer immersive, interactive learning opportunities, challenges persist in terms of scalability, cost-effectiveness, and teacher readiness for technology integration. Wu et al. (2013), for instance, detail the potential and limitations of AR, making it clear that technical infrastructure and instructional design must co-evolve for effective STEM education.

Learner Engagement, Behavior, and Attitudinal Dynamics

Learners' attitudes, behaviors, and adoption patterns of mobile learning in higher education were explored in the publications of Al-Emran et al. (2016), Briz-Ponce et al. (2017), and Hamidi and Chavoshi (2018). These publications collectively emphasize that the effectiveness of mobile learning does not only involve technological availability but also includes user perception, motivation, and digital literacy. A notable concern is found on the variability of acceptance across contexts and cultures. This raises the urgency of integrating an adaptive and inclusive mobile learning strategies. Gender, academic discipline, and prior technological experience also play a role, pointing to the importance of demographic-sensitive design in mobile learning tools.

Learning Effectiveness and Outcome Evaluation

The studies of Martin and Ertzberger (2013), Panigrahi et al. (2018), and Zydney and Warner (2016) highlight the effectiveness of mobile learning on educational outcomes. These studies critically assessed the impact of mobile learning on cognitive gains, engagement, and knowledge retention. A key issue identified is the inconsistency in evaluation methods, which complicates the synthesis of evidence on mobile learning efficacy. Moreover, many studies rely on short-term interventions, leaving a gap in the understanding of their long-term impacts. There is also a tension between novelty effects and sustained pedagogical value, prompting calls for longitudinal and cross-disciplinary research.

Co-citation Analysis

Of the 34,845 cited references derived from the database, 55 met the minimum threshold of five cited references. The threshold was tested several times until robust and evenly distributed clusters were obtained. The threshold must be an appropriate level, neither too high nor too low, which can result in oversimplified or overly complicated visualization. The highest co-cited publications are Davis et al. (1989) (23 citations), Davis (1989) (19 citations), and Venkatesh et al. (2003) and Crompton (2013) (18 citations). Table 3 presents the top 10 most co-cited documents and their total link strengths based on co-citation analysis. The total link strength refers to the total strength of a document in relation to its connections with other documents (Van Eck & Waltman, 2014).

Table 3. Top 10 Documents with the Highest Co-citation and Total Link Strength

No.	Authors and Year	Title	Citation	Total Link Strength
1	Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989)	User Acceptance of Computer Technology: A Comparison of Two Theoretical Models	23	69
2	Davis, F. D. (1989)	Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology	19	69
3	Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003)	User Acceptance of Information Technology: Toward a Unified View	18	55
4	Ajzen, I. (1991)	The Theory of Planned Behavior	10	45
5	Fornell, C., & Larcker, D. F. (1981)	Evaluating Structural Equation Models with Unobservable Variables and Measurement Error	15	41
6	Crompton, H. (2013)	A Historical Overview of Mobile Learning: Toward Learner-Centered Education	18	39
7	Venkatesh, V. (2000)	Determinants of Perceived Ease of Use: Integrating Control, Intrinsic Motivation, and Emotion into the Technology Acceptance Model	9	37
8	Crompton, H., & Burke, D. (2018)	The Use of Mobile Learning in Higher Education: A Systematic Review	13	33
9	Wang, Y. S., Wu, M. C., & Wang, H. Y. (2009)	Determinants and Age-Gender Differences in Mobile Learning Acceptance	12	33
10	Cheon, J., Lee, S., Crooks, S. M., & Song, J. (2012)	Mobile Learning Readiness in Higher Education Based on the Theory of Planned Behavior	13	32

Source: Author interpretation based on VOSviewer analysis

Based on network visualization, the co-citation analysis produced five distinct clusters. Figure 2 shows the network structure of the co-citation analysis. Each cluster was labelled and characterized based on representative publications according to the authors' inductive interpretation and understanding of the five clusters.

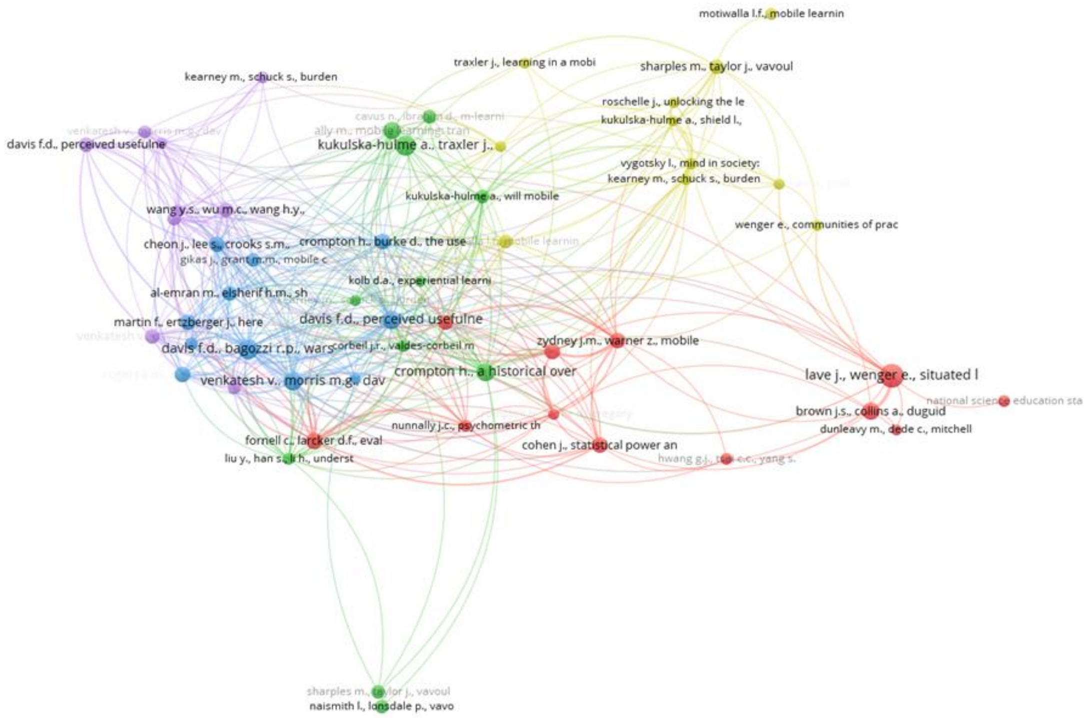

Figure 2. Co-citation Analysis of Mobile Learning in STEM Education

Cluster 1(red): This cluster is labeled "Foundations and Impact of Mobile Learning in STEM Education." This cluster established the pedagogical and empirical foundations of mobile learning in STEM. The key works of Bano et al. (2018) and Crompton et al. (2017) showed how mobile technologies enhance student engagement and understanding, particularly when grounded in situated learning theory and context-aware strategies. Innovations like augmented reality and educational standards support this pedagogical shift, backed by rigorous methodological foundations.

Cluster 2 (green): This cluster is labeled "Theoretical Foundations and Early Pedagogies of Mobile Learning". Focusing on foundational theories and early applications, this cluster emphasizes mobile learning's shift toward learner-centered and flexible education. Studies draw on experiential and constructivist learning theories (Kolb, 1984; Sharples et al., 2010) and document early successes, particularly in language education using mobile tools. Frameworks by Naismith et al. (2004) and Liu et al. (2010) provide critical insights into adoption and integration.

Cluster 3 (Blue): This cluster presents the idea of "User Acceptance and Adoption of Mobile Learning in Higher Education". This cluster examines the factors influencing mobile learning adoption. This cluster is guided by models such as TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003). Studies have highlighted that perceived ease of use and usefulness significantly shape adoption behaviors (Al-Emran et al., 2016). Students appreciate flexibility, but integration challenges persist, underscoring the need for designs aligned with user needs.

Cluster 4 (Yellow): This cluster is labeled "Theoretical and Social Dimensions of Mobile Learning". This cluster emphasizes sociocultural perspectives that view mobile learning not just as a method for content delivery but as a collaborative and identity-forming process. Referring to the studies of Vygotsky and Luria (1978) and Wenger (1999), this cluster highlights the importance of interaction, community, and social context in the learning experience. Scholars within this cluster advocate for a shift toward more situated, participatory, and socially grounded forms of learning where mobile technologies support the development of learners' identities and foster meaningful engagement within learning communities.

Cluster 5 (Violet): This cluster centers on "Technology Acceptance and Behavioral Intentions in Mobile Learning." Focusing on psychological and contextual drivers of mobile learning, this cluster builds on behavioral theories (Ajzen, 1991; Davis, 1989). Research shows that motivation, demographics, and perceived utility shape adoption. Effective implementation requires both thoughtful design and deep understanding of learner behavior.

These five clusters collectively reveal that mobile learning in STEM education is a multidimensional field shaped by theoretical foundations, pedagogical innovations, user acceptance models, sociocultural perspectives, and behavioral intentions, all of which converge to support effective, learner-centered, and context-aware technology integration.

Table 4 summarizes the co-citation analysis by presenting its clusters, cluster labels, number of articles, and representative publications.

Table 4. Co-citation clusters on Mobile Learning in STEM Education

Cluster	Cluster Label	Number of Articles	Representative Publications
1 (Red)	Foundations and Impact of Mobile Learning in STEM Education	12	Lave & Wenger (1991); Brown, Collins & Duguid (1989); Dunleavy et al. (2009); Zydney & Warner (2016); Cohen (1992)
2 (Green)	Theoretical Foundations and Early Pedagogies of Mobile Learning	11	Ally (2009); Crompton (2013); Kukulska-Hulme & Traxler (2007); Kolb (1984); Naismith et al. (2004)
3 (Blue)	User Acceptance and Adoption of Mobile Learning in Higher Education	11	Davis (1989); Venkatesh et al. (2003); Cheon et al. (2012); Al-Emran et al. (2016); Gikas & Grant (2013)
4 (Yellow)	Theoretical and Social Dimensions of Mobile Learning	10	Vygotsky & Luria (1978); Wenger (1999); Sharples et al. (2010); Roschelle (2003); Kukulska-Hulme & Shield (2008)
5 (Violet)	Technology Acceptance and Behavioral Intentions in Mobile Learning	9	Ajzen (1991); Davis (1989); Venkatesh & Davis (2000); Wang et al. (2009); Liu et al. (2010)

Co-word Analysis

A co-word analysis was applied to the same database. Of the 6,750 keywords, 61 met a minimum of nine occurrences, resulting in four clusters. Keywords with the highest co-occurrence were engineering education (1190), e-learning (828), and mobile learning (947). Table 5 summarizes the top 15 co-occurring keywords with their number of occurrences and total link strengths.

Table 5. Top 15 Keywords in the Co-occurrence of Keywords Analysis

Ranking	Keyword	Occurrences	Total Link Strength
1	engineering education	1190	6485
2	e-learning	828	4863
3	mobile learning	947	4789
4	students	549	3443
5	teaching	338	2298
6	education	324	2201
7	learning systems	341	2054
8	mobile devices	277	1783
9	computer-aided instruction	256	1666
10	m-learning	287	1663
11	mobile technology	241	1560
12	telecommunication equipment	172	1182
13	education computing	160	1056
14	mobile telecommunication systems	117	750
15	curricula	114	726

Figure 3 presents a network map of the co-word analysis. The map produced four clusters that were classified and labeled based on the author's inductive interpretation of the occurring words. All clusters were closely related and partially integrated.

Cluster 1 (red): With 22 keywords, this cluster is labeled as "Technological Ecologies for Immersive and Collaborative STEM Learning". This cluster highlights the technological ecosystem driving mobile learning in STEM education. Core concepts like mobile learning, ubiquitous learning, and mobile learning environments underscore the shift toward flexible, anytime-anywhere access (Zhang & Yu, 2022). Augmented reality, virtual reality, and game-based learning introduce immersive, interactive experiences that enhance engagement in science and engineering education (Chen et al., 2023). Supporting these innovations are cloud computing and learning systems, which enable scalable, real-time delivery of content. Collaborative learning and computer-aided instruction promote social constructivism, while human-computer interaction and user interfaces emphasize the need for learner-friendly design (Lee et al., 2024). This cluster reflects an interdisciplinary shift toward experiential and adaptive learning environments, integrating pedagogy with emerging technologies (Tong et al., 2023).

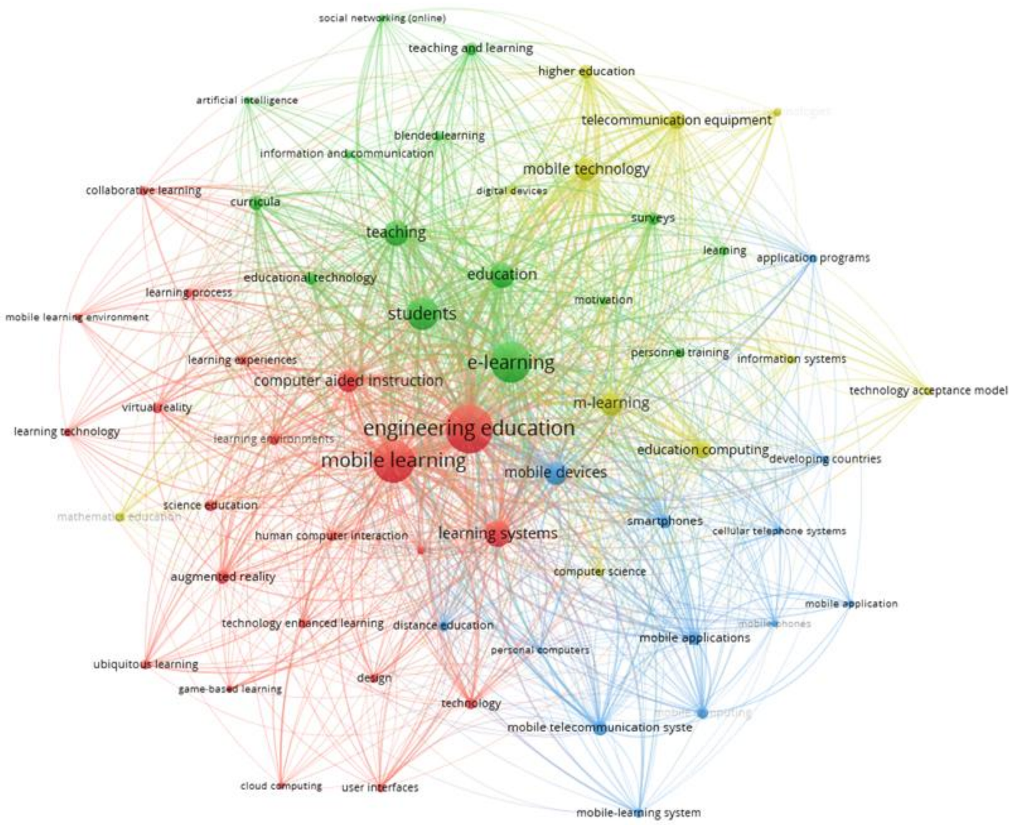

Figure 3. Co-word Analysis of Mobile Learning in STEM Education

Cluster 2 (green): This cluster consists of 15 words labeled “Digital Pedagogies and AI Integration in Modern Education”. This cluster centers on the integration of digital technologies and AI into teaching and learning. Artificial intelligence, educational technology, and information and communication technology (ICT) reflect a growing focus on automating instruction, personalizing learning, and supporting data-driven decision-making in classrooms (Ali et al., 2023). Blended learning and e-learning represent flexible instructional models combining face-to-face and online approaches. Emphasis on teaching, curricula, and personnel training points to the restructuring of academic programs and professional development to align with technological advancements (Khan et al., 2023). Students, motivation, and social networking suggest increasing attention to learner engagement and interaction within digital platforms (Rodríguez-Arce et al., 2023). Through surveys, researchers assess the effectiveness of these innovations; while learning and education remain foundational threads. Collectively, this cluster reflects the pedagogical and systemic transformation of education through AI and digital tools.

Cluster 3 (blue): This cluster comprises 13 keywords labeled “Mobile Infrastructure and Accessibility in Emerging Educational Contexts”. This cluster focuses on the technological infrastructure and accessibility that support mobile learning, especially in developing countries. Central terms like mobile devices, mobile phones, smartphones, and personal computers highlight the hardware backbone enabling mobile education (Akpan, 2024). Mobile computing, mobile telecommunications, and cellular telephone systems reflect the connectivity required to support learning at a distance, particularly where traditional infrastructure is lacking. The presence of distance education and mobile-learning systems signals the growing use of mobile platforms to reach remote or underserved learners (Hwang et al., 2014). Meanwhile, mobile applications and application programs emphasize software development tailored for educational content delivery on these platforms. This cluster underscores mobile learning's role in expanding educational equity through scalable, low-cost digital solutions that address geographic and economic barriers.

Cluster 4 (yellow): The fourth cluster is labeled "Technology Adoption and Mobile Integration in Higher and STEM Education". This cluster highlights the adoption of mobile and digital technologies within higher education and STEM fields, particularly computer science and mathematics education. Central terms like mobile technologies, mobile technology, and M-learning emphasize the shift toward portable, on-demand learning tools (Nurunnabi et al., 2025). Digital devices, telecommunication equipment, and information systems form the technological foundation for delivering educational content, especially in computing disciplines. Technology acceptance suggests the use of models like TAM and UTAUT to understand faculty and student readiness for these tools (Chen et al., 2023). Meanwhile, education computing refers to the application of digital tools in instructional design and curriculum development. The cluster reflects a growing effort to embed mobile learning seamlessly into academic environments, improving accessibility, interactivity, and discipline-specific engagement in higher education contexts.

Together, the co-word clusters reveal a multidimensional landscape of mobile learning in STEM education, encompassing immersive technologies and collaborative environments (Cluster 1), digital pedagogy and AI integration (Cluster 2), mobile infrastructure and accessibility in developing contexts (Cluster 3), and the adoption of mobile technologies in higher and STEM education through the lens of technology acceptance (Cluster 4).

Table 6 summarizes the co-word analysis represented by the cluster label, number of keywords, and representative keywords.

Table 6. Co-word Analysis on Mobile Learning in STEM Education

Cluster No and Color	Cluster Label	Number of Keywords	Representative Keywords
1 (Red)	Technological Ecologies for Immersive and Collaborative STEM Learning	22	engineering education, computer-aided instruction, mobile learning, learning systems
2 (Green)	Digital Pedagogies and AI Integration in Modern Education	15	e-learning, students, education, teaching
3 (Blue)	Mobile Infrastructure and Accessibility in Emerging Educational Contexts	13	mobile devices, smartphones, mobile applications, mobile telecommunication systems
4 (Yellow)	Technology Adoption and Mobile Integration in Higher and STEM Education	11	mobile technology, m-learning, education computing, telecommunication equipment, higher education

Discussion

The bibliometric findings reveal a sustained emphasis on theoretical frameworks and pedagogical foundations that shape mobile learning in STEM education. Citation and co-citation analyses demonstrate that the most influential publications underscore the transformative potential of mobile technologies, particularly in facilitating immersive, situated, and collaborative learning experiences. These studies affirm the role of mobile learning in enhancing STEM engagement, especially when underpinned by constructivist, experiential, and context-aware pedagogies (Lave & Wenger, 1991; Kolb, 1984). The use of augmented reality (AR), game-based learning, and mobile simulations highlights a growing shift toward active, student-centered instruction, particularly in science and engineering fields.

Clusters from the co-citation analysis, notably “Foundations and Impact of Mobile Learning” and “Theoretical and Social Dimensions of Mobile Learning,” further reveal that successful m-learning strategies rely on the integration of social learning theories and communities of practice. Scholars such as Sharples et al. (2010) and Wenger (1999) emphasize mobile learning as a socially constructed process, in which learners co-create meaning through interaction and collaboration. Moreover, the co-word analysis indicates a strong thematic convergence around the keywords “engineering education,” “learning systems,” and “collaborative learning,” reflecting a broader technological ecology in which mobile tools are embedded within adaptive, real-time learning environments. These ecosystems, driven by mobile interfaces, cloud platforms, and human-computer interaction, create opportunities for personalized and scalable instruction. However, studies also warn of implementation gaps, such as insufficient pedagogical design and teacher readiness, which hinder the full realization of mobile learning’s potential.

The second major theme centers on behavioral, psychological, and infrastructural factors that mediate the adoption and effectiveness of mobile learning in STEM education. Co-citation clusters such as “User Acceptance and Adoption of Mobile Learning” and “Technology Acceptance and Behavioral Intentions” highlight the centrality of theoretical models, namely the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT), in explaining user adoption. Influential works by Davis (1989), Venkatesh et al. (2003), and Ajzen (1991) reveal that perceived usefulness, ease of use, and behavioral intention significantly shape learners’ and educators’ willingness to integrate mobile tools into instructional practice.

Citation analysis supports this by emphasizing attitudinal and motivational dynamics, particularly in higher education contexts. These studies indicate that m-learning adoption is not homogenous across demographics; rather, it is affected by factors such as gender, age, digital literacy, and academic discipline. The role of institutional support, including faculty development and technical infrastructure, is also a key factor in determining sustained use.

The co-word cluster on “Mobile Infrastructure and Accessibility in Emerging Educational Contexts” deepens this insight by underscoring the disparities in access and connectivity, particularly in developing countries. Keywords such as "mobile devices," "telecommunication systems," and "distance education" reflect systemic challenges that limit the equitable diffusion of mobile learning. Scholars highlight how inadequate infrastructure, high device costs, and inconsistent internet access exacerbate the digital divide, ultimately impacting STEM learning outcomes.

Consequently, effective m-learning integration demands more than technological provision. It necessitates behaviorally informed strategies, cross-sector collaboration, and policies that bridge infrastructural inequities. Institutions must not only invest in technology but also in localized, inclusive approaches that consider the behavioral patterns and access reality of their learners.

Conclusion and Recommendations

This bibliometric analysis provides a comprehensive overview of the intellectual, conceptual, and thematic landscape of mobile learning in STEM education. By employing citation, co-citation, and co-word analyses on 1,462 Scopus-indexed publications, the study identified foundational theories, key adoption models, and emerging trends that shape this evolving field. The findings confirm that mobile learning has advanced beyond early experimental implementations to become an increasingly pedagogically integrated and technologically sophisticated approach in STEM contexts. Influential studies highlight the role of mobile technologies in enhancing collaboration, engagement, and personalized learning, while also drawing attention to concerns related to infrastructure, user acceptance, and pedagogical alignment.

The thematic clusters revealed through co-citation analysis reflect the multidimensional nature of the discourse, from theoretical underpinnings rooted in constructivist and sociocultural learning to practical frameworks informed by behavioral theories such as TAM, UTAUT, and TPB. Similarly, the co-word clusters highlight the intersection of mobile learning with immersive technologies, digital pedagogy, infrastructure development, and the integration of higher education. These insights underscore the field's growing interdisciplinarity and the need for responsive, context-aware learning models in STEM education.

Despite these contributions, the study is subject to several limitations. First, it relies exclusively on the Scopus database, which, while comprehensive, may omit relevant literature indexed in Web of Science, ERIC, or other academic repositories. This database restriction could result in partial coverage, especially in emerging regions and non-English contexts. Second, bibliometric indicators emphasize publication frequency and citation counts, which may not always correspond with instructional effectiveness or real-world impact. Third, the study's methodological scope does not include qualitative content analysis, which could provide deeper insight into pedagogical strategies and learner outcomes.

Thus, future research should address these gaps through multi-database analyses, longitudinal designs, and cross-cultural comparisons. Attention should be given to evaluating the long-term cognitive and behavioral outcomes of mobile learning in STEM disciplines. Additionally, as the field moves toward AI-enhanced, adaptive, and immersive learning environments, scholars must explore how emerging technologies interact with mobile platforms to support equity, inclusion, and academic achievement.

From a practical perspective, the findings underscore the need for educators, curriculum designers, and policymakers to develop pedagogical frameworks that integrate mobile technologies with next-generation tools, such as AI, augmented reality (AR), and learning analytics, to create more personalized, inclusive, and data-informed STEM learning experiences. Institutions should also invest in professional development and infrastructure to support the sustainable adoption of these technologies. Ultimately, strengthening empirical evidence, expanding global perspectives, and refining theoretical models will be critical in shaping the next phase of mobile learning scholarship and practice in STEM education—one that is adaptive, future-oriented, and responsive to the rapidly evolving digital landscape.

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