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A Systematic Review of Reviews on Micro-Learning

N.G.L.S.J. Liyanage*

Faculty of Education, The Open University of Sri Lanka

Abstract

Micro-Learning (ML) is an emerging pedagogical approach gaining popularity in education, as it enhances student motivation, engagement, and knowledge retention. As an accessible and flexible technique, it enables learners with varying commitments to the material to engage in short, focused sessions by breaking content into small, manageable segments. This study conducted a systematic review of reviews (an umbrella review), examining systematic reviews, literature reviews, and meta-analyses focusing on the effectiveness, pedagogical nature, and theoretical basis of ML. This systematic review of reviews on ML was based on PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis) guidelines. Using online databases such as Google Scholar, Science Direct, Wiley Online Library, ERIC, and Semantic Scholar, 15 review articles published between 2010 and 2024 were retrieved. Findings highlight that ML is an effective technique across various educational contexts and can serve as a facilitative pedagogical technique in the teaching learning process. However, there is a notable lack of theoretical foundations in most ML studies and reviews. The findings of this review can create a roadmap to facilitate the adoption of ML. Moreover, the findings of this study could facilitate educators and instructional designers in rethinking their teaching techniques and methods, while providing future direction for researchers to engage in grounded theory research on ML.

Keywords: Micro-Learning**,** pedagogical nature, theoretical basis, effectiveness

**Contact: N.G.L.S.J. Liyanage; email: ngliy@ou.ac.lk*
ORCID: https://orcid.org/0009-0001-3887-9140

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Introduction

Micro-Learning (ML) is an innovative pedagogical strategy involving learning through small-sized, well-planned units and short-term learning activities (Senandheera et al., 2024). ML focuses on teaching large learning content in small chunks over a short period of time. These bite-sized chunks, known as micro content, provide opportunities for learners to absorb information quickly without feeling overwhelmed (Bruck et al., 2012; Hug, 2010).

Educational practices have evolved toward learner-centered approaches with advancing digital technologies (Mercan et al., 2023). Digital content delivery has transcended time and space barriers, making learning faster and more efficient through open and distance learning systems. ML exemplifies this evolution.

Although ML represents a relatively new educational paradigm, its conceptual origins trace back to the 1960s (Hug, 2010). It became widespread in the early 2000s with Web 2.0 technologies, which provided platforms for creating, sharing, and using learning content (Redondo et al., 2020). ML is now gaining popularity due to its learner-centered, cost-effective, and interactive features (Rof et al., 2024).

Leong et al. (2020) note that ML enables work-based learners to gain new knowledge or skills just in time to meet their immediate needs and achieve a specific, actionable task. While most previous studies suggest that ML suits smaller content delivery, it can also facilitate larger content by breaking complex concepts into more manageable aspects. In the 21st century's shift toward learner-centered education, ML provides opportunities for learners who need immediate application and utilization of knowledge and skills through learning that is not limited to certain places but is accessible anytime, anywhere, and through any learning tool (Abidin, 2025; Filipe et al., 2020).

Higher Education students confront challenges balancing academic responsibilities with personal and professional commitments (Li et al., 2025), limiting time and cognitive resources for traditional learning (Filipe et al., 2024). ML addresses these constraints by fitting within human cognitive capacity and reducing cognitive overload (Silva, 2025). It delivers content in small, digestible units accessible quickly in short bursts, offering targeted lessons that facilitate retention without overwhelming the learners. While ML promotes continuous engagement and self-paced skill acquisition, its flexibility and adaptability allow access via smartphones, tablets, or computers anytime and anywhere (Lee, 2021), providing seamless learning experiences for busy students with other commitments. Through repetition and periodic intervals, ML enhances knowledge retention, with learners retaining bite-sized information, better than lengthy, conventional learning formats (Shail, 2019).

Despite the need to implement the ML approach in the teaching-learning process, educators remain hesitant to apply this technique. Although numerous reviews and studies on ML exist across various educational contexts, no synthesis of existing reviews specifically evaluates its effectiveness, pedagogical nature, and theoretical background. Review papers are crucial for developing new theories and for setting paths for future research. Even though several reviews exist, no study provides a comprehensive summary serving as a definitive reference for different stakeholders. To the best of the researcher's knowledge, no systematic review of existing reviews on ML has been conducted so far.

By systematically examining high-quality and published literature review articles, this review attempts to reveal the reported ML effectiveness, pedagogical nature, and theoretical understanding. Accordingly, this study aims to address the following objectives:

1. To examine the effectiveness of employing ML in the teaching-learning process.
2. To analyse how ML can be used as a facilitative pedagogical technique to enhance the quality of the teaching-learning process.
3. To examine the theoretical foundations underlying Micro-Learning

The findings from this review could help different stakeholders, such as teachers, educators, instructional designers, policymakers, and others, facilitate and adopt ML in their teaching and learning practices.

Methodology

This section outlines the systematic approach employed to identify, select, and analyze existing systematic reviews, literature reviews, and meta-analyses on ML. It describes the research design, search strategy across multiple databases, inclusion and exclusion criteria for article selection, systematic screening process following PRISMA guidelines, and the thematic data analysis approach used to synthesize findings on ML's effectiveness, pedagogical nature, and theoretical foundations.

This study employed a systematic review of reviews methodology, synthesizing evidence from published review articles on ML. This approach is also termed an 'umbrella review' or 'overview of reviews'. This methodology is particularly appropriate for several reasons. First, systematic reviews are fundamental tools for evidence-based decision-making in education, providing synthesized evidence from multiple studies to inform practice and policy (Petticrew & Roberts, 2006). Second, when multiple systematic reviews, literature reviews, and meta-analyses exist on a topic, as in the case with ML, an umbrella review allows identification of patterns, consistencies, and gaps across these reviews, offering a higher-level synthesis than would be possible from examining primary studies alone (Aromataris et al., 2015). Additionally, this approach is especially valuable for identifying research gaps and providing a comprehensive understanding across diverse contexts and disciplines.

This review was conducted according to the guidelines of PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analysis). The scope of this review is specifically limited to systematic reviews, literature reviews, and meta-analyses on ML. This inclusion ensures comprehensive coverage of high-quality review evidence while maintaining methodological rigour. This process consists of four steps: problem identification, screening, eligibility through applying the inclusion criteria, and exclusion criteria. Focusing on the effectiveness, pedagogical nature, and theoretical basis of ML, a comprehensive literature search was conducted across multiple databases such as Google Scholar, Science Direct, Wiley Online Library, ERIC, and Semantic Scholar using a combination of keywords and subject-specific terms as follows.

Search string: (Micro-Learning substring) AND (literature review substring)

Micro-Learning substring: “Micro-Learning” OR “Micro Learning” OR “Microlearning” OR “microlearning” OR “bite-sized learning”

Literature review substring: “Review” OR Systematic literature review” OR “Systematic review” OR “Literature review”

The search was conducted from November 2024 to 15th of January 2025. Peer reviewed articles which were published from 2010 to 2024 were searched to find the targeted articles. The inclusion and exclusion criteria are presented in Table I.

Table 1

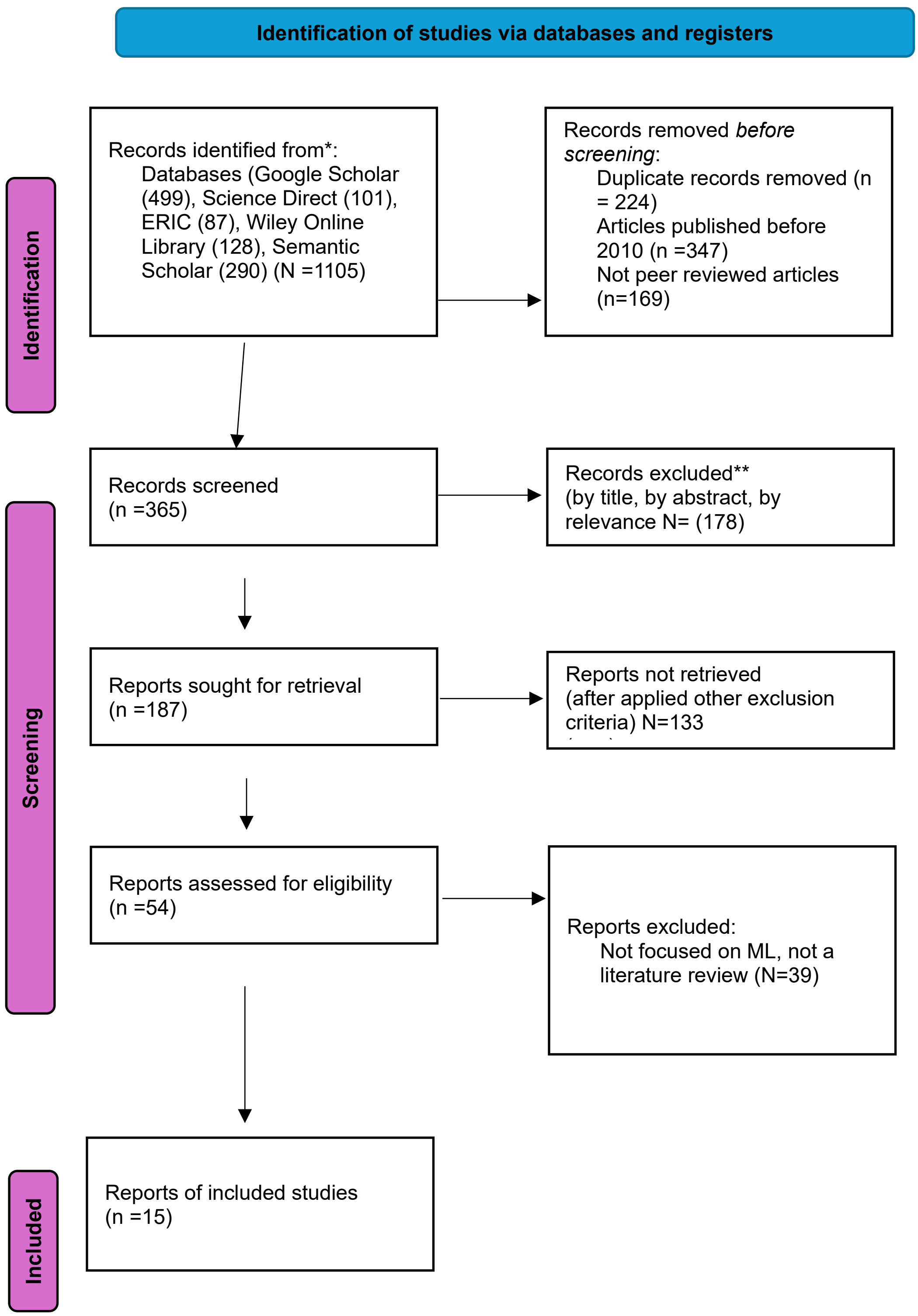
Inclusion and Exclusion Criteria for Selecting Articles

Inclusion Criteria	**Exclusion Criteria**
Journal articles	Conference proceedings, books, chapters, thesis and dissertations
Articles written in English	Articles written in other languages
Systematic review, literature review, meta analyses	Articles not followed the method of literature review
Articles only focused on ML in the teaching learning process	Articles are not done related to the teaching learning process.
Available as full texts	Available only as abstracts
Related to education discipline	Other disciplines than education

In the initial search, 1105 sources were found. Only 365 peer-reviewed articles remained after removing duplicates. After removing inaccessible papers and screening titles and abstracts, 54 papers were considered and assessed as full texts. 39 of these articles did not fulfil the inclusion criteria in the systematic review. All these filters and selection processes were done according to PRISMA guidelines, as shown in Figure 1.

Figure 1

PRISMA 2020 flow diagram for identifying, screening, and including studies in this review



Data Analysis

Selected reviews were analyzed thematically according to the three research objectives: effectiveness, pedagogical nature, and theoretical foundations. Data extraction focused on study characteristics (author, year, country, discipline, methodology) and on key findings for each objective. A narrative synthesis approach was employed to synthesize findings across reviews, identifying common themes, patterns, and gaps in literature. Key themes were identified in each review regarding effectiveness, pedagogical nature, and theoretical foundations. Then, the themes were compared and contrasted across all included reviews to identify patterns and consistencies. Related codes were grouped into overarching themes aligned with the three research objectives, and then, the findings were synthesized narratively to explain the effectiveness, pedagogical nature, and theoretical foundations of ML.

Results and Discussion

This section presents and discusses the findings of the systematic review of reviews on ML. The results are organized according to the review objectives, focusing on effectiveness, pedagogical nature, and theoretical foundations.

Effectiveness of Employing ML in the Teaching and Learning Process

Table 2

Effectiveness of employing ML in the teaching-learning process

Author(s)/year and country	**Discipline**	**Methodology**	**Findings**
Denojean-Mairet et al. 2024 USA	General Education	Systematic Literature Review (SLR)	Integration of ML and social media enhances learner engagement, satisfaction, reach, and effectiveness. Focus on leveraging social media for extended reach and engagement in ML.
Moore et al. 2024 USA	Adult Learning	SLR	Mobile-based ML is being effectively implemented in various instructional contexts and the included studies focus on its effectiveness and design principles. Further exploration of mobile-based ML's potential in adult education is needed and provided recommendations for practices.
Suvandy et al. 2024 Thailand	Higher Education	Systematic Review & Meta-analysis	ML via the metaverse improves digital literacy, empathy, and satisfaction in students. ML in digital and metaverse contexts is effective and easy to remember.
Prasittichok & Smithsarakarn 2024 Thailand	English as a Foreign Language (EFL)	SLR & Meta-analysis	ML enhances English language learning, especially speaking skills, with technology-integrated approaches. Diversified and technology-integrated methods (e.g., videos, mobile apps) hold promise for EFL instruction.

Fitria 2022 Indonisia	General Education	Review	ML is effective for quick learning, adaptable to diverse formats like video, gamification, and social media. ML is a convenient and efficient approach that can be incorporated into everyday routines.
Caroline et al. 2023 Indonisia	English for Specific Purposes (ESP)	Systematic Literature Review	ML facilitates self-paced learning, digital material engagement, and student empowerment in ESP. Continued integration of multimedia and ML can enhance ESP material design.

Table 2 shows that the studies reviewed demonstrate a strong, positive impact of ML on various aspects of teaching and learning in general education. These insights suggest that ML can be effectively adapted for use in teacher education. According to Monib et al. (2024), ML serves as a powerful approach for enhancing learning outcomes. Its benefits extend beyond academic performance, positively influencing learners' self-concept, self-direction, and motivation to learn. Holistic improvement is crucial to fostering an environment where students feel empowered and engaged in their educational journeys.

In their literature review, Denojean-Mairet et al. (2024) highlighted key trends, impacts, and challenges associated with the integration of ML and social media. Their findings reveal that this integration significantly enhances learner engagement, satisfaction, reach, and effectiveness. This is particularly important because it makes learning more accessible in a dynamic, user-friendly way. Such an approach not only caters to diverse learning preferences but also encourages a more interactive and collaborative learning experience.

ML's adaptability and effectiveness across various educational settings, including adult learning and English as a foreign language (EFL) (Moore et al., 2024; Prasittichock and Smithsarakarn, 2024). Prasittichok and Smithsarakarn (2024) specifically show that ML effectively improves language skills, particularly speaking abilities. This evidence highlights the potential of ML to enhance specific learning outcomes, making it a valuable tool in language education.

Additionally, some studies emphasize the positive impact of multimedia formats on ML content delivery. Fitria (2022) emphasizes the importance of incorporating diverse formats such as video, gamification, and mobile applications, which make ML an engaging and flexible educational approach. Supporting this notion, Suvandy et al. (2024) explored the use of ML in the metaverse and found that it significantly improved students' digital literacy and overall satisfaction. The technological aspect of ML caters to contemporary learners' preferences and facilitates personalised learning experiences, enabling them to engage with content at their own pace and convenience.

In summary, there is consistent agreement among the reviews that delivering content in short, focused units reduces cognitive overload and supports efficient knowledge acquisition, especially when supported by digital and mobile technologies. As education continues to evolve, the integration of ML can play a critical role in enhancing educational practices and outcomes, making learning more accessible and enjoyable for learners of all backgrounds.

ML as a Facilitating Pedagogical Technique to Enhance the Quality of the Teaching Learning Process

Table 3

ML as a facilitating pedagogical technique to enhance the quality of teacher education

Author(s)	**Discipline**	**Methodology**	**Findings**
Sankaranarayanan et al. 2023 USA	Higher Education, Corporate Training, K-12 Teacher Professional Development	Bibliometric analysis of ML usage	Key findings from this study is that ML as an instructional strategy or intervention is widely used across different contexts and disciplines, such as higher education, cooperate learning, MOOCs and k-12 schools. Further studies should explore ML's application in K-12 schools.
Alias & Razak 2023 Malaysia	Higher education Instructional Design	SLR	Effective ML design focuses on content development and instructional flow. Curriculum designers and instructors should enhance ML strategies by focusing on content and instructional flow.
Sozmen 2022 Turkey	General school education	A Review	Many Studies show that ML facilitated learning by dividing into smaller pieces encourages students to study. A wide range of activities might be used in this technique, and it can be easily integrated into daily routine; it allows on-demand learning for

			the students. On the other hand, the success of ML techniques is closely related to the personal characteristics of learners; teachers' prone to use digital technology and the external factors such as access to learning materials.
Fitria 2022 Indonesia	General Education	SLR	This systematic review highlighted the benefits of ML, including its accessibility, ability to deliver content in a short time, and its flexibility in accommodating different learning styles. Moreover, studies synthesised that ML can be used as a pedagogical technique; even though its limitations, it requires careful implementation.

ML has emerged as a revolutionary pedagogical tool in various educational contexts, enabling educators to improve their teaching practices through concise, focused content delivery. Studies such as Sankanarayanan et al. (2023) reveal that ML fosters higher learner motivation and engagement, especially in the context of K-12 and higher education professional development. By breaking complex concepts into manageable units, ML not only accommodates educators' varying time constraints but also enables more flexible interaction with course material. This adaptability is crucial in today's fast-paced educational environments where teachers must continuously update their skills and knowledge to meet evolving educational demands.

Similarly, in order to maximize the effectiveness of ML strategies in teaching-learning process, their design and implementation are essential. As highlighted by Alias and Razak (2023), effective ML design depends on proper content development and instructional flow. The insights from these reviews are crucial for instructors as they design ML activities that are pedagogically sound. ML can assist educators as instructional designers by focusing on specific skills and content areas, and it also enables teachers to enhance their teaching practices in a targeted and efficient manner. Such pedagogical facilitation supports teachers' professional growth and enriches their students' learning experiences.

To reinforce these valuable ideas from researchers, Sozmen (2022) emphasizes ML's ability to break content into smaller, more manageable units, encouraging self-directed learning, especially for teachers undergoing professional development. In this review, the researcher mentions that ML is one of the innovative teaching techniques that utilises digital technologies. The autonomy that comes from ML is particularly beneficial for them to select when and how they engage with the content. The innovative use of digital technologies in ML further enhances this self-directed approach, making learning more accessible and engaging.

In a systematic review, Fitria (2022) emphasized that the qualities of accessibility, time efficiency, and flexibility in ML cater to diverse learning styles, making it an attractive pedagogical tool for learners across teacher education and general education. However, this study also emphasises the importance of quality and careful implementation for successful ML interventions. The emphasis on quality and careful implementation remains paramount, as poorly designed ML interventions can hinder rather than facilitate learning. Therefore, educators and instructional designers must prioritize these elements to get the full potential of ML as a pedagogical tool.

Overall, ML emerges as a highly adaptable and flexible pedagogical tool with significant potential for facilitating learning in teacher education. By focusing on concise content delivery, thoughtful design, and learner autonomy, ML enhances the professional development of educators and supports the overall quality of the teaching-learning process.

Theoretical Foundations behind Micro-Learning

It is very important to identify the theoretical frameworks of ML. By critically analysing existing theories, researchers can effectively contribute to the development of new or refined theoretical frameworks. Moreover, it demonstrates the importance of employing ML into practice.

Cognitive Load Theory

The importance of applying Cognitive Load Theory (CLT) into ML research is emphasised by Balasundaram et al. (2023). They pointed out CLT as a well-established and highly regarded framework in the learning sciences, focusing on the critical role cognitive load plays in the learning process. According to CLT, ML modules can successfully reduce unnecessary cognitive load by deconstructing complex content into smaller, more manageable segments, thereby facilitating more efficient learning (Mayer & Moreno, 2010).

Table 4

Theoretical foundations in micro-learning research

Theory	**Key Principles**	**Application for Micro-Learning**	**Studies**
Cognitive Load Theory	Managing intrinsic, extraneous, and germane cognitive load	Breaking content into small chunks reduces cognitive overload and improves learning efficiency, enhancing retention and recall, boosting engagement, flexibility and accessibility	Balasundaram et al. (2023), Samala et al. (2023), Monib et al. (2024)
Forgetting Curve	Information retention decreases over time without reinforcement	Spaced repetition and bite-sized chunks combat forgetting through regular exposure	Alias & Razak (2023)
Blooms' Taxonomy	Specific objectives, bite size content, optimal timeframe, interactive and engaging content, personalisation, delivery medium and mode	Each micro-module targets one clear action-oriented learning goal, information is chunked into small, digestible units enabling quick consumption and recall, short sessions	Monib et al. (2024)

Samala et al. (2023) state in their review, by designing tasks that focus on the content and minimising unnecessary cognitive load, students can concentrate more effectively on the material. Moreover, the study demonstrated CLT principles can improve learning outcomes in higher education and online environments as well.

Forgetting Curve

In order to comprehend the significance of ML in the teaching-learning process, Alias and Razak (2023) demonstrate that the Forgetting Curve is one of the influential theories behind ML. This theory was introduced by Ebbinghaus in 1885 (Murre & Dros, 2015). The Forgetting Curve highlights that people tend to forget information over time. Moreover, the rate of forgetting is greatest in the first few days after the information is consumed. ML addresses this issue by delivering content in small doses or bite-sized chunks, over time, ensuring learners have continuous exposure to the information and reducing the rate of forgetting.

In addition, the theory emphasizes that the human brain has limited capacity to process and retain information, and that it is more effective to present information in small, manageable units (Wang et al., 2020). This concept is referred to as the "spacing effect" (Sisti et al., 2007), which states that information is more easily retained when spaced over time rather than presented all at once. The concept of ML involves breaking down learning into smaller and more manageable units (Samala et al., 2023). In this review, the researcher highlights that forgetting can be influenced by factors such as attention, psychological stress, and distractions, including hunger and environmental factors. To counteract forgetting, Ebbinghaus' research suggests reviewing materials within short time periods, for example, within 24 hours, and using spaced repetition for effective retention. ML, with its chunk-sized, focused units, aligns well with these principles and helps combat the Forgetting Curve. The key to improving retention is not just the delivery of content, but also the quality of engagement and strategic repetition over time (Shail, 2019).

Blooms' Taxonomy

Bloom's Taxonomy provides a framework for categorizing learning outcomes produced by ML across three domains. In the cognitive domain (knowledge and intellectual skills), ML modules deliver small, focused content chunks that improve knowledge acquisition, retention, recall, and application without cognitive overload (Anderson & Krathwohl, 2001). In the affective domain (attitudes, motivation, and values), short, engaging ML sessions foster positive perceptions, motivation, satisfaction, and self-efficacy, with learners reporting higher enjoyment and confidence when content is concise and relevant to their needs. In the psychomotor/behavioural domain (skills and performance), ML supports skill development and behavioural outcomes such as presentation skills, task performance, collaboration, and higher completion rates, encouraging learners to practice and demonstrate behaviours more frequently due to the short, actionable nature of modules (Alias & Razak, 2023). Systematic reviews demonstrate that ML positively impacts all three domains, improving knowledge and recall (cognitive), boosting motivation and satisfaction (affective), and enhancing practical skills and engagement (psychomotor).

Most researchers have not discussed the theoretical framework behind ML. According to the best of the reviewer's knowledge, there is a noticeable gap in the discussion of the theoretical frameworks underlying ML (Monib et al., 2024). The importance of theoretical discussion of ML is to guide instructional design, improve learning outcomes, and enhance researchers' and practitioners' understanding of how different learners interact with ML content.

Examining the theoretical underpinnings of ML was the third objective of this review. Theoretical frameworks are essential to comprehending ML and its efficacy in educational settings. Cognitive Load Theory (CLT) and the Forgetting Curve are crucial for understanding ML and its effectiveness in educational contexts.

ML is highly effective, achieving educational outcomes and enhancing learner engagement by aligning with the Cognitive Load Theory and emphasizing content delivery in small, manageable chunks to avoid cognitive overload (Sweller, 2011). ML's concise, learner-centred design improves teaching and learning across higher education, teacher education, and professional development by promoting active engagement, flexibility, and immediate application of knowledge. ML demonstrates potential to enhance engagement across both educational and professional learning settings (Leong et al., 2020). It further supports professional learning and practice-based development (Kohnke, 2023). Additional pedagogical characteristics include supporting flipped classroom models (Zhang & West, 2019), addressing diverse learning needs and contexts (Lee, 2021), and demonstrating cost-effectiveness, motivation enhancement, and accessibility across various educational applications. This study examined what selected systematic reviews, literature reviews and meta-analyses reveal ML's effectiveness and pedagogical nature to encourage ML application in teaching-learning processes.

Implications for practice

Based on the findings, several implications emerge for educational practitioners:

1. For Educators: Consider integrating ML modules to accommodate students' diverse time constraints and learning preferences, particularly in blended learning environments.
2. For Instructional Designers: Focus on content development and instructional flow when designing ML interventions, ensuring alignment with the CLT principles.
3. For Administrators: Support infrastructure development for mobile-based learning and provide professional development opportunities for faculty to design effective ML experiences.
4. For Policy Makers: Recognize ML as a legitimate pedagogical approach in educational frameworks and support research initiatives exploring its long-term effectiveness

Recommendations

Based on the synthesis of reviewed papers, the following recommendations are proposed to enhance ML practices and to strengthen pedagogical frameworks.

1. The reviewed systematic and literature reviews reveal a critical gap in theoretical grounding in ML design. Future ML studies and interventions should explicitly integrate well-established theories such as Cognitive Load theory, Forgetting Curve, and Bloom's Taxonomy. Clear theoretical grounding would enhance the pedagogical coherence and effectiveness of ML initiatives.

2. Reviews consistently emphasize that effectiveness depends on careful design. Standardized design principles should be developed, with particular attention to appropriate content chunking (e.g., short learning units of 4-7 minutes), planned spacing and repetition to support retention, effective use of multimedia without increasing cognitive overload, and clear alignment between learning objectives, activities, and assessment.
3. Although ML has shown effectiveness across diverse educational settings, the findings suggest that its success is context-dependent. Institutions should adapt ML approaches to specific subject areas, learner characteristics, and institutional conditions, rather than adopting one-size-fits-all approaches.
4. Given ML's reliance on digital platforms, develop comprehensive frameworks for integrating ML with existing learning management systems, social media platforms, and emerging technologies (e.g., metaverse) while ensuring accessibility across devices and contexts.
5. The review highlights an overreliance on a narrow range of theories, particularly CLT and the Forgetting Curve. Future research should develop more comprehensive pedagogical frameworks that integrate cognitive, motivational, affective, and social dimensions of learning, drawing on perspectives such as Constructivism, Self-Determination Theory, and Social Learning Theory.
6. There is a need for pedagogical models specifically designed for ML. Such a model should address instructional sequencing, the balance between guided instruction and learner autonomy, the use of interactive elements such as quizzes, simulations, and gamification, and mechanisms for connecting ML activities to broader learning outcomes.

7. Future studies should develop sound frameworks for assessing both immediate learning outcomes and long-term retention, skill transfer, and behavioural change resulting from ML interventions.

Conclusion

This umbrella review synthesizes evidence from existing reviews on ML to evaluate its effectiveness, pedagogical applications, and theoretical underpinnings. Overall, ML is demonstrated as an effective instructional approach across higher education, teacher education, and professional development contexts. Its effectiveness is consistently associated with concise content delivery and alignment with learner's time and cognitive constraints.

Pedagogically, the findings suggest that ML serves as an effective teaching and learning technique when guided by intentional instructional design. Reviews consistently position ML as a learner-centred pedagogical approach. However, the synthesis indicates that ML is most effective as a supplementary approach rather than a substitute for comprehensive instructional methods, particularly for complex learning objectives that demand sustained engagement and deeper cognitive processing. The findings highlight that the effectiveness of ML is contingent upon purposeful instructional design and curricular integration.

A significant contribution of this review is the identification of an ongoing theoretical limitation within ML research. Although frequently cited, theoretical frameworks are applied inconsistently and lack analytical integration across reviewed literature.

As the first comprehensive synthesis of review-level evidence on ML, this study consolidates previously fragmented findings and elucidates both the strengths and limitations of the current research landscape. Future research must move beyond effectiveness claims toward theory-driven, systematic, and longitudinal investigation. These efforts are necessary to advance ML research from establishing efficacy to understanding the conditions and mechanisms that optimize its support for learning.

Limitations

This review has several limitations. First, the research was limited to five databases and English-language publications, potentially excluding relevant studies in other languages or databases. Second, focusing only on systematic reviews, literature reviews and meta-analyses, while providing high-level assessment and synthesis, may miss important primary studies. Third, the quality assessment of the included reviews, while following PRISMA guidelines, relied on the quality of the original systematic reviews. Finally, the rapid evolution of digital technologies and ML practices means some recent developments may not be fully captured in the included reviews.

Author bio:

N.G.L.S.J. Liyanage is currently serving as a Lecturer (Probationary) in the Department of Secondary and Tertiary Education, Faculty of Education at the Open University of Sri Lanka. She obtained Bachelor of Education Honors and M.Ed. in Educational Management and Leadership from the University of Colombo. Her research focuses on Adolescent Psychology, Educational Technology, Teacher Education and their applications in open and distance learning environments.

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