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MOBILE LEARNING ANALYSIS IN COMPUTER SCIENCE: A SYSTEMATIC REVIEW OF THE IMPACT AND FACTORS ON STUDENT LEARNING OUTCOMES

Erlangga[1*], Alya Nurfaridah [2*], Erna Piantari [3], Muhamad Dzikri Gumilang[3] , Muhammad Riza Abqari[4] , Raka Ibnu Firdaus[5]
[1,2,3,4,5]Universitas Pendidikan Indonesia, Indonesia
erlangga@upi.edu, * Coresponding Author

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ABSTRACT
Limited access and flexibility in higher education, particularly in Computer Science programs that require strong analytical and technical skills, highlight the need for more adaptive and learner-centered instructional approaches. This study aims to systematically examine the impact of Mobile Learning (M-Learning) on student learning outcomes and to identify the Critical Success Factors (CSFs) influencing its effective implementation in higher education contexts. The study employed a Systematic Literature Review (SLR) methodology following the planning, execution, and reporting stages, with literature sourced from reputable academic databases and limited to publications between 2020 and 2025. A total of ten peer-reviewed empirical studies meeting predefined inclusion and quality criteria were analyzed using thematic synthesis. The findings indicate that M-Learning has a significant positive effect on learning outcomes, particularly in terms of academic achievement, learning motivation, learner autonomy, and engagement. These effects are especially pronounced in programming-oriented and applied computer science courses, where flexibility, instant feedback, and practice-based learning are essential. Furthermore, the analysis identified key Critical Success Factors, including well-structured pedagogical design, active learning strategies, instructor facilitation, usability of mobile platforms, and the availability of reliable technological infrastructure.
Overall, this study confirms that M-Learning is a relevant and effective instructional strategy in higher education, particularly for Computer Science education. However, its successful implementation is highly dependent on pedagogical quality and institutional readiness, rather than technology alone. These findings provide practical implications for educators and policymakers in designing sustainable and effective M-Learning environments.
***Keywords**: Computer Science; Digital Learning; Higher Education; Learning Outcomes; M-Learning; Mobile Learning; Technology-Enhanced Learning*

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INTRODUCTION
The development of information and communication technology in the current digital era has brought significant changes to the world of education, especially in higher education environments. The shift in the learning paradigm from conventional methods to technology-based learning provides significant opportunities for lecturers and students to interact more flexibly and effectively [1], [2], [3]. One rapidly developing innovation is mobile learning (M-Learning), which is the process of learning that utilizes mobile devices such as smartphones or tablets to support teaching and learning activities anytime, anywhere. M-learning is considered capable of addressing the challenges of limited space, time, and the need for highly adaptive and personalized learning.

Mobile learning, or M-Learning, has become an important strategy in higher education institutions to improve access and flexibility in learning. Several international systematic reviews indicate that M-Learning often enhances engagement, timely access, and material retention [4]. However, its effectiveness in improving student learning outcomes has not always been consistent. Research during the pandemic, for example, shows that the use of M-Learning can maintain or even improve learning outcomes in certain modules, but it also creates an access gap due to differences in device availability and connectivity [5]. This indicates that the impact of M-Learning is not solely determined by its technology, but also by pedagogical factors and user readiness.

Various studies indicate that instructional design variables, content quality, faculty and student digital readiness, and technical infrastructure support significantly influence the effectiveness of M-Learning. Without a pedagogy-centered learning design, the implementation of technology does not automatically improve learning outcomes [6]. Thus, the question arises as to how M-Learning can consistently improve student learning outcomes in higher education while simultaneously minimizing access limitations. Systematic reviews are needed to examine the still diverse empirical evidence and identify key success factors.

In the context of Computer Science and Information Technology, the application of M-Learning is becoming increasingly relevant. Courses like Computer Programming require students to have strong logical analysis skills and technical proficiency. However, many students find it difficult to understand programming concepts due to the complexity of the material and the need for repeated practice. Research by Fatoni and Rosalina (2021) shows that using M-Learning-based educational games can increase student motivation and learning outcomes in Computer Programming courses, with an average improvement of 52% based on normalized gain. In line with this, [7] developed an Android-based M-Learning application that was proven to improve the programming skills of Informatics Engineering students. These results confirm the potential of M-Learning as an effective interactive learning medium in higher education.

As a strategic step, systematic literature indicates that a mobile-first approach with clear pedagogy, faculty training for mobile instructional design, providing offline and low-bandwidth options, and data-driven evaluation (pre-post tests and effect sizes) are a combination of best practices that can improve learning outcomes while reducing access barriers [8].

Recent advances in digital and mobile technologies have accelerated the adoption of technology-enhanced learning in higher education. A systematic mapping study by [9] demonstrates that AI-enabled adaptive learning systems play a crucial role in improving personalization, learner engagement, and learning efficiency. However, the study also identifies that many implementations lack pedagogical integration and clear alignment with learning outcomes, particularly in complex domains such as Computer Science. This issue is further reinforced by [10], who report that chatbot-based learning environments can enhance learner interaction and accessibility but often fail to support higher-order cognitive skills when instructional design is insufficient.

Despite the increasing use of mobile and intelligent learning technologies, the literature reveals a significant research problem: learning effectiveness is inconsistent and highly dependent on instructional design quality, learner autonomy support, and technological readiness [9]. In higher education contexts, especially in programming-oriented courses, mobile learning tools are frequently adopted as supplementary technology rather than as an integrated pedagogical strategy, limiting their impact on measurable learning outcomes.

Therefore, the purpose of this study is to systematically review recent empirical literature (2020–2025) to examine the influence of mobile and intelligent learning approaches on student learning outcomes in higher education. Additionally, this study aims to identify Critical Success Factors (CSFs) that determine effective implementation, providing evidence-based guidance for designing pedagogically sound and outcome-oriented M-Learning environments.

RESEARCH METHODS

This research uses the Systematic Literature Review (SLR) method. This method is the main approach in synthesizing scientific research, aiming not only to collect and review existing scientific evidence related to the research question but also to support the development of evidence-based practice [10]. The SLR method is implemented through three main stages: planning, conducting, and reporting, designed to produce a collection of relevant, valid, and accurate literature according to the topic being studied. The objects analyzed in this study include the feasibility, advantages, and disadvantages of mobile learning-based learning media that have been developed in various previous studies.

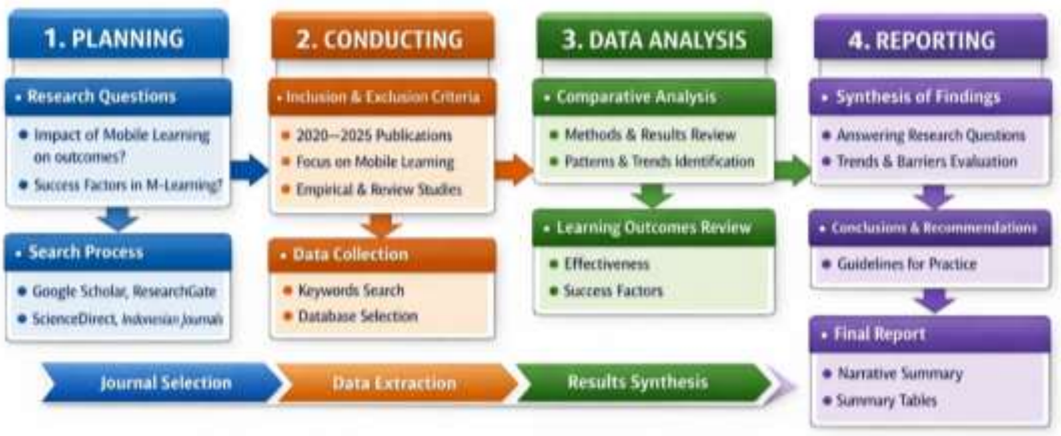

Figure 1. SLR Stages (Systematic Literature Review)

1) Planning

a) Research questions

At this stage, the researcher determines the questions that are appropriate for the research topic. The following are the research questions for this study.

1. How does the implementation of mobile learning affect student learning outcomes in the field of Computer Science and Informatics?
2. What factors influence the successful implementation of mobile learning in improving student learning outcomes?

b) Search Process

At this stage, a search for journals was conducted on Google Scholar, ResearchGate, ScienceDirect, and the Indonesian Journal of Primary Education. The search focused on scientific publications discussing the influence of mobile learning on learning outcomes, particularly at the higher education level and in technology-based learning contexts.

2) Conducting

a) Inclusion and exclusion

At this stage, the researcher establishes the criteria for the suitability of the data used as a research source.

1. 10 journals published between 2020 and 2025.
2. The journals were obtained from Google Scholar, ResearchGate, ScienceDirect, and the Indonesian Journal of Primary Education.
3. The journal focuses on the influence of mobile learning on student learning outcomes and the factors that affect its success.
4. Journal/article in the form of empirical research, development, or systematic review

b) Data Collection

This stage involves collecting relevant data for analysis.

1. Conducting searches through data sources such as Google Scholar, ResearchGate, ScienceDirect, and the Indonesian Journal of Primary Education.
2. Using the keywords: "computer science," "higher education," "mobile learning," "learning outcomes," and "systematic literature review" with a publication range of 2020–2025.

c) Data Analysis

The collected data was analyzed by examining the main findings, methods, and results of each journal to answer the predetermined research questions. The analysis was conducted descriptively-comparatively by examining the similarities in patterns, differences in results, and the context of mobile learning implementation in each study. Each article was reviewed based on the type of research, population, learning approach, and the learning outcome indicators measured, such as the effectiveness of M-Learning, factors supporting and hindering implementation, and its contribution to improving student motivation and learning outcomes. The results of this process were then summarized to gain a comprehensive understanding of the trends and influence of M-Learning on learning outcomes in the field of Computer Science and Informatics.

3) Reporting

The reporting stage is the final process in the Systematic Literature Review (SLR) method, focusing on compiling, documenting, and interpreting the research findings. At this stage, researchers systematically prepare a report based on the analyzed literature. The study results are presented in narrative form and summary tables to illustrate the relationship between mobile learning and student learning outcomes.

This stage also includes:

1. Synthesis of findings to answer research questions. Evaluation of consistency of results across studies, including identification of trends, success factors, and implementation barriers.
2. Conclusions and recommendations for research and the implementation of mobile learning in the context of higher education.
3. The reporting stage ensures that the results of the systematic review are scientifically accountable, transparent, and can be replicated by other researchers.

RESULTS AND DISCUSSION

1) Planning Result

Based on the Systematic Literature Review (SLR) of ten selected studies published between 2020 and 2025, the results indicate that Mobile Learning (M-Learning) has a generally positive impact on student learning outcomes in higher education, particularly in the fields of Computer Science and Informatics. Most reviewed studies reported improvements in academic performance, learning motivation, learner independence, and engagement, especially when M-Learning was integrated into programming, software development, and applied computing courses. The flexibility and accessibility of mobile platforms enabled students to engage in learning activities beyond traditional classroom settings, supporting self-paced and continuous learning.

2) Conducting Result

However, the findings also reveal that the effectiveness of M-Learning is not uniform across studies. Several articles emphasized that learning gains are strongly influenced by the quality of pedagogical design rather than the use of mobile technology alone. Studies that incorporated active learning strategies, such as problem-based learning, interactive tasks, and immediate feedback mechanisms, demonstrated more significant improvements in learning outcomes compared to those relying on passive content delivery. This suggests that M-Learning functions optimally when aligned with clear learning objectives and appropriate instructional strategies.

Furthermore, the analysis identified key Critical Success Factors (CSFs) affecting successful implementation, including instructor readiness, student digital literacy, usability of mobile applications, and availability of reliable technological infrastructure. Conversely, inadequate internet access, poorly designed learning materials, and limited institutional support were frequently reported as barriers. These results confirm that while M-Learning is a promising and relevant approach for Computer Science education, its success depends on a balanced integration of pedagogical, technological, and organizational factors, rather than technology-driven adoption alone.

3) Reporting Result

This research analyzes ten scientific articles published between 2020 and 2025, all of which were selected based on their relevance to the research topic of mobile learning in the context of computer science education, specifically addressing its impact on student learning outcomes and the factors influencing its effectiveness. The analysis was conducted qualitatively through a literature review approach, examining the findings, methodologies, and implementation contexts of each study. This literature synthesis is expected to provide a comprehensive overview of the trends, challenges, and contributions of mobile learning to improving the quality of education in the field of computer science. The detailed results from the literature obtained are as follows:

Table 1. Articles on Mobile Learning from Computer Science.

Year	Author	Method	Title	Research Finding
2025	[11]	Quantitative (meta-analysis)	*Mobile Learning Significantly Enhances Student Learning Gains: A Meta-Analysis and Research Synthesis*	M-learning shows a significant improvement in students' understanding and retention of concepts
2022	[12]	Structural Equation Modeling (SEM)	*University students' use of mobile technology in self-directed language learning: Using the integrative model of behavior*	Subjective attitudes and norms significantly influence students' intention to use mobile

Year	Author	Method	Title	Research Finding
			prediction	technology
2021	[13]	Eksperimen	*Mobile learning to support computational thinking in initial teacher education: A case study*	Application-based mobile learning enhances problem-solving skills
2024	[14]	Qualitative (conceptual framework)	*Leveraging AI-powered mobile learning: A pedagogically informed framework*	Personalization and adaptive factors improve learning outcomes
2024	[15]	SEM + Neural Network	*What drives the adoption of mobile learning services among college students: An application of SEM-neural network modeling*	Perceived ease of use and usefulness significantly influence behavior
2023	[16]	Survey (TAM)	*Factors influencing students' adoption and use of mobile learning management systems (m-LMSs): A quantitative study of Saudi Arabia*	Digital readiness and institutional support affect learning outcomes
2024	[17]	Survey	*Adoption and continued usage of mobile learning of virtual platforms in Iraqi higher education an unstable environment*	Student trust and satisfaction influence usage retention
2021	[18]	*Systematic review*	*Features, barriers, and influencing factors of mobile learning in higher education: A systematic review*	Main factors: infrastructure, digital literacy, interface design
2024	[19]	*Systematic review*	*M-Learning in education during COVID-19: A systematic review of sentiment, challenges, and opportunities*	Adapting M-Learning strengthens learning independence and flexibility
2021	[20]	Eksperimen	*Augmented Reality and programming education: A systematic review*	Increasing motivation & understanding of abstract concepts

Based on a review of ten articles from 2020 to 2025, M-Learning shows a significant impact on improving student learning outcomes, particularly in the context of computer science education.

Through meta-analysis, found that the use of M-Learning consistently improves learning gains, both in concept understanding and knowledge retention. This finding is supported by who in their meta-analysis of mobile technology use by students found that self-regulated learning facilitated by mobile devices was positively correlated with academic performance [11].

In the context of computer education emphasize that M-Learning plays an important role in supporting the development of computational thinking and problem-solving skills. Through mobile application-based learning, students can practice programming concepts and algorithms independently, thereby enhancing their computational thinking skills. This finding reinforces that integrating m-learning not only strengthens theoretical understanding but also practical competence in the field of computer science [12].

During the COVID-19 pandemic, the implementation of M-Learning has also proven capable of maintaining the effectiveness of distance learning. Systematic review found that students showed increased learning independence and time flexibility when using M-Learning, which positively impacted overall learning outcomes. Thus, in general, M-Learning can be considered a learning solution that is adaptable to various modern learning conditions [13].

Analysis of the literature shows that the success of M-Learning is influenced by various factors, including technological, psychological, pedagogical, and institutional aspects. Technologically, infrastructure and application quality are the main factors determining the effectiveness of learning. Internet connection stability, ease of interface navigation, and the availability of interactive features are important elements in determining a positive learning experience. Meanwhile, from a psychological and pedagogical perspective, perceived ease of use and perceived usefulness have been proven to influence students' intention to adopt M-Learning. Which used the Technology Acceptance Model (TAM) approach. Both confirmed that digital readiness, intrinsic motivation, and faculty support have a strong influence on improving learning outcomes through mobile platforms [14].

Institutional factors also play an important role. Support from the university, both in terms of policy and technology training, encourages the continued use of M-Learning. Without such systemic support, the use of M-Learning tends to decline over time [15].

Additionally, the latest technological innovations such as the integration of artificial intelligence (AI) and augmented reality (AR) also enhance the effectiveness of learning. AI-powered mobile learning conceptual framework that enables the personalization of learning experiences to meet students' needs. Meanwhile, Theodoropoulos and Lepouras showed that using mobile device-based AR can increase motivation and understanding of abstract concepts in computer programming [16].

In the field of computer science, M-Learning offers significant opportunities for enhancing students' cognitive competence and practical skills. Connolly showed that mobile-based learning not only supports theory but also strengthens students' analytical abilities through activities such as debugging, simulations, and algorithmic exercises. Additionally, the integration of M-Learning with adaptive technologies (AI, AR, and game-based learning) fosters the creation of more interactive and contextual learning environments [17]. From a pedagogical perspective, the implementation of M-Learning aligns with the principles of student-centered learning, which emphasizes student independence and responsibility in the learning process. This model is considered effective in building self-regulated learning, which contributes to improved academic outcomes [18].

A review of publications between 2020 and 2025 indicates a shift in the focus of M-Learning research from mere technology adoption toward exploring sustainability and personalization of learning. In the 2020–2021 period, research focused heavily on the effectiveness of M-Learning on learning outcomes, such as the study by Connolly, which emphasized the impact of mobile learning on improving computational thinking, and the research by Lai, which identified that the use of mobile technology is significantly influenced by students' self-regulation abilities and directly contributes to improved learning performance. Meanwhile, from 2023 to 2025, research directions will focus more on the integration of intelligent technologies (AI, AR), adaptive models, and data-driven learning analytics approaches [19]. This trend shift indicates the evolution of M-Learning as an integral part of smart education, supporting competency-based learning in the digital age.

Overall, the results of this systematic review indicate that mobile learning has a consistent positive impact on improving student learning outcomes, including in the field of computer science. The most influential factors include ease of technology use, institutional support, learning motivation, and content personalization. Going forward, the development of M-Learning in computer education needs to be directed toward the design of interactive learning media, based on adaptive intelligence, and capable of supporting project-based independent learning. This aligns with the needs of 21st-century competency development, such as critical thinking, problem-solving, and digital literacy [21], [22], [23], [24].

CONCLUSION

The implementation of M-Learning in Computer Science education has been proven to have a significant and positive impact on student learning outcomes, as evidenced by a large effect size (g=0.90) that confirms its superiority over static learning methods such as traditional e-learning. This positive impact is empirically evident in the improvement of programming skills and higher-order thinking abilities (HOTS), facilitated by active methods such as educational games (resulting in an N-gain of 0.52) and rich interactions that allow students to analyze and create. The successful implementation of M-Learning is highly dependent on Critical Success Factors (CSFs), which are multidimensional, with pedagogical factors playing the most critical role. The quality of the "Learning Approach" is the main determinant of success with the highest estimated impact (0.687), surpassing user perception factors. Additionally, technological factors such as user-friendly application design and support for learning processes that allow students to learn anytime, anywhere, and in any way thru information and technology (ubiquitous learning) are crucial for sustainable adoption. However, the implementation of M-Learning faces critical infrastructure challenges, including unstable internet connections and hardware limitations, which were exacerbated after 2020. Therefore, optimizing M-Learning in Computer Science requires a focus on strengthening pedagogies that support active learning and mitigating infrastructure barriers so that curriculum integration can proceed smoothly and sustainably.

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