Behavioral Involvement, Technology Acceptance, and Failure in Mobile Learning: A Systematic Review

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As we move further into the digital age, machine learning algorithms have become increasingly popular in E-learning for their ability to predict learner failure and assess behavioral engagement, particularly in mobile learning environments. This paper reports on the systematic review conducted by the most relevant research in the literature that uses machine learning algorithms to predict failure, verify acceptance of mobile technology, and analyze behavioral engagement in mobile learning platforms. The search was performed using research papers extracted from four commonly used databases and published between 2010 and 2023; the last database access was on 15/05/2023. Guided by the PRISMA checklist, the review followed a structured approach to select, analyze, and report relevant studies. Studies were selected based on strict inclusion and exclusion criteria, focusing on peer-reviewed articles that empirically test the application of machine learning in mobile learning contexts. Of the initial 332 screened articles, 20 were eligible for inclusion. The results highlight the transformative role that machine learning is playing in revolutionizing online mobile learning experiences.

Keywords: mobile learning, behavioral involvement, student failure, prediction, machine learning, technology acceptance, systematic review

WHY IS IT IMPORTANT TO DO THIS RESEARCH?

This systematic review possesses significant importance for various reasons. Firstly, in a landscape where mobile learning is increasingly prevalent in educational settings, understanding the key factors influencing a learner's success or failure is vital for facilitating immediate and suitable interventions.

By methodically analyzing existing literature on this subject, the study offers a synopsis of the most recent research, identifies gaps in knowledge, and suggests potential paths for subsequent inquiries.

In summary, this research is indispensable in enhancing our comprehension of student engagement with mobile learning and its consequent effects on learner outcomes within the mobile learning environment.

INTRODUCTION

A systematic review is a review of a clearly formulated question that uses systematic and unambiguous methods to identify, classify, and critically appraise relevant research and to collect and analyze data from the research included in the review (Moher et al., 2009).

This systematic review explores the use of machine learning algorithms in conjunction with variables indicating behavioral involvement. The objective is to predict the failure or acceptance of mobile technology among learners using smartphones. She intends to clarify the following questions:

***RQ1:** What are the latest studies on the application of machine learning algorithms for the prediction of failure using features of learner behavioral engagement, as well as technology acceptance?*

***RQ2:** What sources and types of data are used to implement machine learning models for the prediction of failures?*

***RQ3:** What are the most influential factors of learner behavioral engagement and technology acceptance in predicting failure with machine learning algorithms?*

***RQ4:** What are the machine learning algorithms that show more performance for developing models to predict failure?*

The main objective of this study is to synthesize and examine, in a structured, rigorous and reproducible way, the most relevant studies conducted in the field of Mobile Learning to understand the impact of the use of mobile devices on the behavioral involvement of students in a distance-learning environment. Furthermore, we investigate the factors leading to success or failure of learners during their academic courses. This study is a systematic review conducted in accordance with the guidelines of "Preferred Reporting Items for Systematic Reviews and Meta- Analyses (PRISMA) Approach" (Moher et al., 2009). In the context of this systematic review, we extracted and analyzed data from peer-reviewed literature spanning the period 2010 to May 2023. This serves as a baseline for future E-learning research, especially in Mobile Learning.

The structure of this research is as follows: we begin with a Research Methodology consistent with the PRISMA guidelines. The Results & Discussion section elucidates key findings, while the Risk of Bias section acknowledges potential biases, it doesn't provide detailed explanations. The final section presents the conclusions and implications of this research.

METHODOLOGY

Data Sources

In this research, we propose a systematic review within the domain of E-learning via mobile devices, based on Machine learning algorithms. Up to May 15, 2023, we have collected research published between 2010 and 2023, sourced from databases including Scopus, Web of Science, SpringerLink, and ScienceDirect.

In our search strategy, the terms employed across these databases included "M-learning" OR "Mobile Learning", "Involvement" OR "Failure" OR "Technology Acceptance" OR "Prediction" OR "Machine Learning". We utilized a uniform approach for all research databases. Yet, we integrated additional filters for the extensive SpringerLink platform to refine the search outcomes. Table 1 delineates the queries executed for each research database.

TABLE 1
DATABASES AND SEARCH STRINGS FOR LITERATURE REVIEW

Name of the search query or database	Search String
Scopus	*TITLE-ABS-KEY ((m-learning OR "Mobile learning") AND (Involvement OR Prediction OR Failure OR "Technology Acceptance" OR "Machine learning")) AND PUBYEAR > 2009 AND (LIMIT-TO (DOCTYPE,"ar"))*
ScienceDirect	*("Mobile learning" OR "M-learning") AND ("Involvement" OR "Failure" OR "Technology Acceptance" OR "Prediction" OR "Machine learning")*
SpringerLink	*("mobile learning" OR m-learning) AND (Involvement AND Prediction AND Failure AND "Technology Acceptance" AND "Machine learning")*
Web of Science	*(ALL=(M-learning) OR ALL=("Mobile learning")) AND(ALL=(Involvement)OR ALL=(Failure) OR ALL=("Technology Acceptance") OR ALL=(Prediction) OR ALL=("Machine learning"))*

Selection Process

To carry out this work, we followed the following steps: determining the eligibility criteria and then screening the relevant articles, by three researchers, based on the titles and abstracts of the articles. The final step was a full-text examination to select the research included in this literature review. This systematic review was conducted using the "Preferred Reporting Items for Systematic Reviews and Meta- Analyses (PRISMA)" approach (Moher et al., 2009).

Three researchers (two PhD students and one research professor) from the "Engineering Sciences (SI)" laboratory team individually reported the titles and abstracts of 221 selected articles after duplicate removal and discussed discrepancies until a consensus was reached. Their collaborative efforts ensured a comprehensive and unbiased review of the available literature. Subsequently, in pairs, the reviewers scrutinized the titles and abstracts of all retained articles. In the event of disagreement, the researchers (two PhD students) would proceed to a full-text review after a brief discussion. Their iterative review process enhanced the rigor of the selection. If necessary, the third researcher (Professor) is consulted to make the final decision. The two PhD students independently examined the full-text articles to decide on their inclusion or exclusion. Similarly, in cases of disagreement, a consensus on inclusion or exclusion established through discussion, and if required, the third professor is consulted.

Rayyan software served in the selection process. This free online platform assists researchers with the methodology of systematic review and meta-analysis projects (Johnson & Phillips, 2018). This systematic review examined and evaluated abstracts and titles using this software.

Eligibility Criteria

This study focused on behavioral involvement, mobile technology acceptance, and prediction of failure in a distance-learning environment. Specifically, it aims to predict learner failure using Machine Learning algorithms that analyze learners' behaviors on smartphones, and to explore the potential for these learners to utilize such mobile technology. With this objective, we included articles that met the eligibility criteria presented in Table 1. Articles not fitting these criteria faced exclusion from our systematic review after removing duplicates in multiple research databases.

TABLE 2
LISTS OF INCLUSION AND EXCLUSION CRITERIA

Inclusion criteria	Exclusion criteria
1. A journal manuscript in English published between 2010 and 2023.	1. The subject does not pertain to the prediction of failure or the behavioral engagement of the learner.
2. Articles related to the field of Mobile Learning.	2. Articles published before 2021 without any citations.
3. Prediction of failure with machine learning algorithms.	3. Studies focusing on E-learning, but unrelated to the specific context of mobile learning.
4. Tracking learner behavior in a distance-learning platform.	4. The absence of machine learning algorithms in the study
5. To be included, a manuscript had to present a study result that is based on machine learning algorithms.	

The PRISMA methodology employs a three-step process to filter out irrelevant literature. These steps include Identification, Screening, and Inclusion, making it a valuable instrument in conducting Systematic Literature Reviews (Billion & Mauritsius, 2023). Refer to Figure 1 for a visual representation of the PRISMA diagram.

FIGURE 1
PRISMA 2020 FLOW DIAGRAM
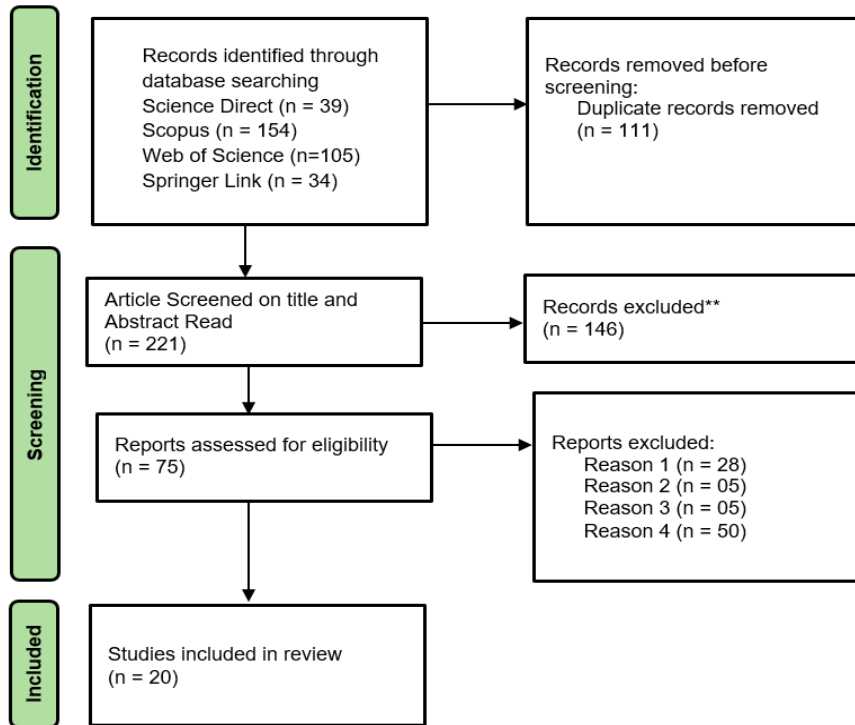
Data Collection Process

To gather data from each study included in the selection, the two review authors (two doctoral students) utilized a data extraction form similar to the one used by Lumley in 2009 (Lumley et al., 2009), to extract information from the eligible studies. The team compared the extracted data and resolved any discrepancies through discussion. Then, we entered the extracted data into Review Manager 5 software, reviewing their accuracy again. When data or information related to any elements of the extraction form were unclear, we consulted the authors of those studies to provide more details. For each included study, the researchers noted the following aspects:

Study References
- Article title;
- Authors' names;
- Title of the journal;
- Year of publication;
- Keywords;
- Source research database.

Overview of Search Metrics
- Scimago ranking;
- CiteScore;
- Number of citations.

Methods and Results
- The machine learning algorithm used;
- Feature selection/filtering;
- Machine learning model performance;
- Behavioral features used for failure prediction;
- Description of search result;
- Inclusion and exclusion criteria;

Study Selection

In this preliminary systematic review, we employ the PRISMA Flow diagram to delineate our search and selection methodology. This approach will guide subsequent investigations within this research domain and facilitate the inclusion of studies from diverse sources. Figure 2 delineates the procedural steps for incorporating a search into our systematic review.

FIGURE 2
PRISMA FLOW DIAGRAM OF THE SEARCH AND SELECTION PROCESS
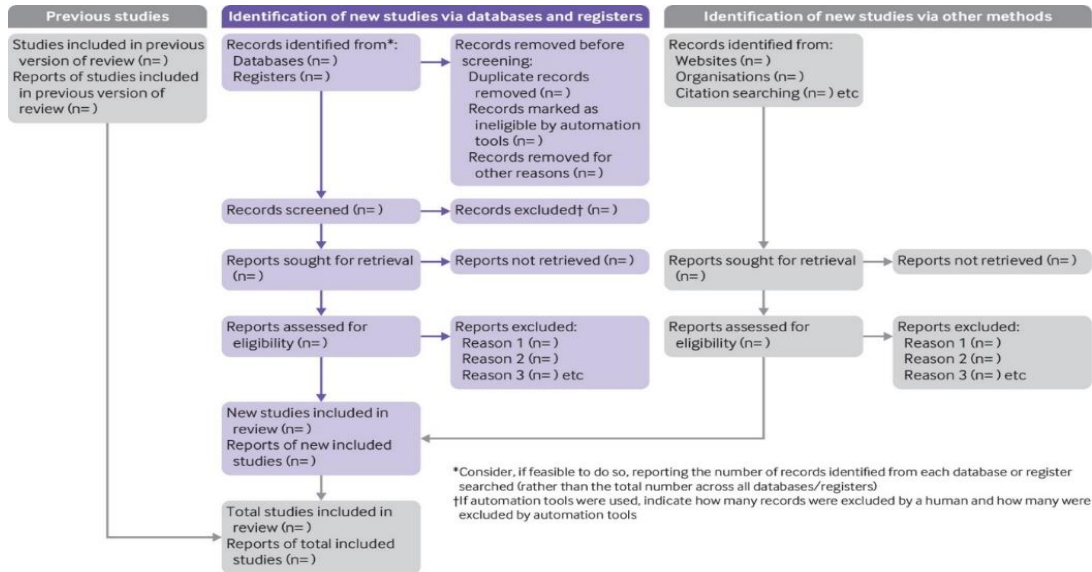
RESULTS & DISCUSSION

The intersection of machine learning algorithms and mobile learning platforms has significantly transformed teaching methods. Using detailed databases such as Scopus and Web of Science, Springer Link and Science Direct, we started a rigorous systematic review. After careful screening based on specific inclusion and exclusion criteria, we identified certain research articles as particularly important.

The search flow and process appear in Figure 4. Initially, we selected 332 articles from four databases. Most articles came from the Scopus and Web of Science research databases, as illustrated in Figure 3.

As shown in Figure 1, after removing 111 duplicates, we subjected the articles to screening based on inclusion and exclusion criteria. This preliminary screening yielded 75 articles for full-text evaluation. During the final eligibility check, 55 articles were excluded for various reasons: 28 were unrelated to the prediction of failure or the behavioral engagement of the learner; five, published before 2021, lacked citations; another five focused on E-learning but not specifically on mobile learning. Notably, 50 of the articles lacked the use of machine learning algorithms.

FIGURE 3
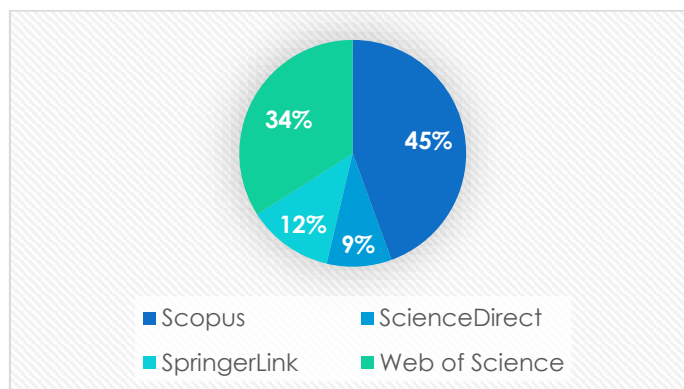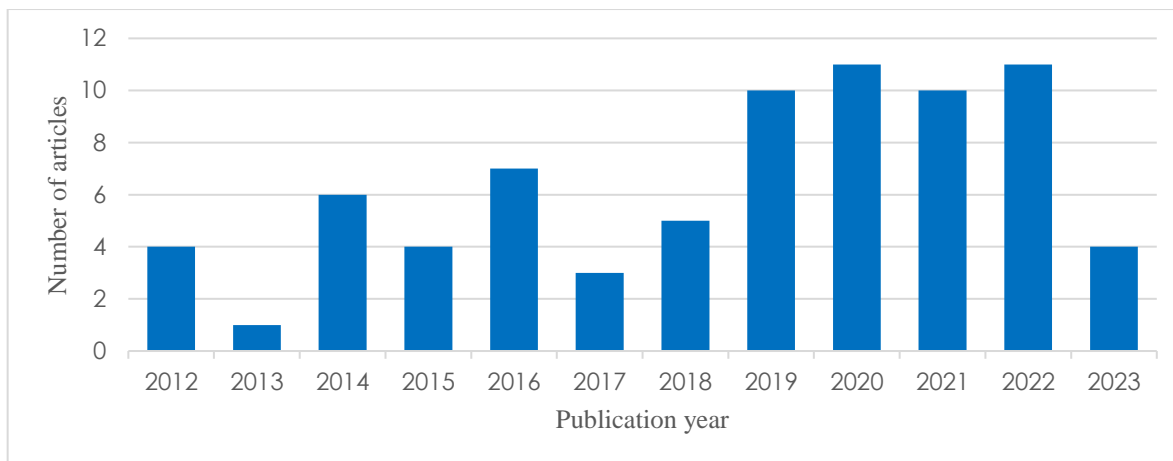**PERCENTAGE OF ARTICLES ACROSS VARIOUS DATABASES**

FIGURE 4
**NUMBER OF ARTICLES INCORPORATED INTO THE SYSTEMATIC REVIEW BY
PUBLICATION YEAR**

Within our eligibility criteria, we scoped our search to encompass the past 13 years. Notably, a substantial chunk of this research emerged between 2019 and 2022. In Figure 4, we have visually represented 75 articles published from 2012 to 2023. We can observe that the number of articles selected for full-text screening has increased significantly since 2019. This trend signifies the escalating interest in the subject over the latter years.

When examining the 20 articles sourced from the four databases based on the first author's affiliation, it is evident that a majority of the research about mobile learning, technology adoption, and failure prediction using machine learning algorithms originates from Asian countries. Research from other databases is not included in this summary. Figure 5 provides a global overview of research in this domain, with countries in dark blue signifying those with the highest volume of research in this area.

FIGURE 5
**GEOGRAPHIC COLORED MAPPING: 20 SELECTED RESEARCH ARTICLES MENTIONED
IN OUR GLOBAL REVIEW ANALYSIS**
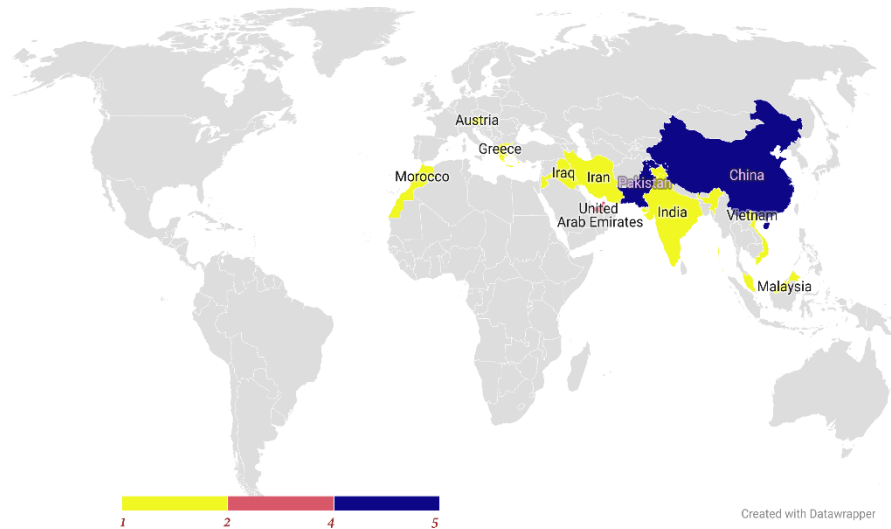
We used a Boxplot, generated after excluding outliers, to visualize the 20 research articles based on their Scimago Rank and CiteScore (as shown in Figure 6). Among them, 10 articles were ranked in Q1, 03 in Q2, and 07 in Q3, with no articles in Q4. The Boxplot highlights a notable concentration of journals in Q1 ranking, and most articles have a CiteScore higher than 2.0, indicating the valuable findings from our selected articles.

FIGURE 6
CITESCORE OF JOURNAL ARTICLES
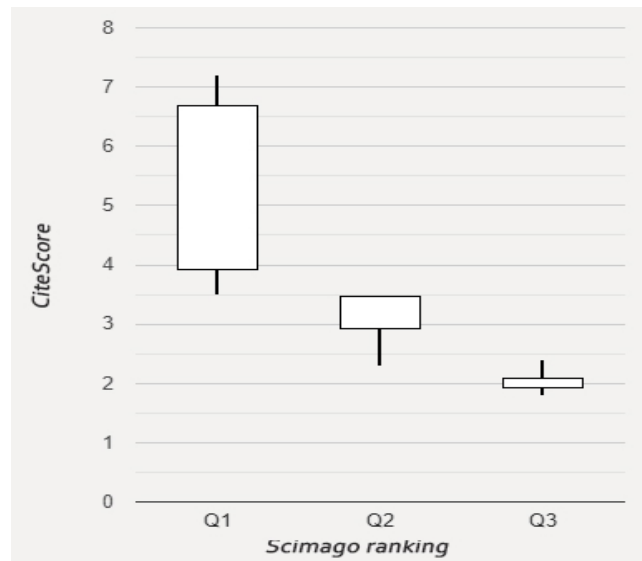
For a more detailed overview of contributions in the field of our systematic review, we have compiled a table of key articles (see Table 3). Structured for optimal clarity and ease of reference, the table comprises five distinct columns: the title of the article, the respective authors accompanied by the year of publication, the specific machine learning algorithms used, a quantification of the algorithm's performance via its overall accuracy, and the main contributions of the study. This structured format is intended to provide researchers with a concise yet comprehensive summary of the studies selected in the systematic review.

TABLE 3
SELECTED PAPERS

Ref.	Authors, Year	Machine learning algorithms	Algorithm performance (Overall accuracy)	Main contributions
(Tan et al., 2014)	Tan GW,Ooi KB,Leong LY,Lin B (2014)	Artificial Neural Networks (ANN).	N/A	This study aims to examine the determinants influencing the adoption of M-learning in Malaysia utilizing a hybrid SEM-ANN approach (J et al., 2009).
(Padhy et al., 2018)	Padhy N,Satapathy SC,Mohanty JR,Panigrahi R (2018)	Logistic regression & Decision tree & Naive Bayes & Linear regression & Logistic regression	93.41%	This paper explores the following issues: the recognition of class and UML diagrams, the identification of reusability metrics, the prediction of software reusability,

		& Polynomial regression.		and the estimation of reusability prediction using mobile apps.
(Adnan et al., 2019)	Adnan M,Habib A,Ashraf J,Mussadiq S (2019)	DBSCAN	N/A	This study introduces a cloud-aided machine learning system (CSMLS) tailored for learners aiming to master applied computer programming by leveraging their context. Using the unsupervised DBSCAN algorithm, the system extracts and analyzes students' contextual data from mobile devices. Integral to the system is a rule-driven inference engine on a cloud backend, offering timely, adaptive learning aid based on students' context-specific traits. An evaluation involving 150 students over an academic term affirmed the system's efficacy in discerning contextual insights, guiding judicious learning choices, and enhancing programming proficiency.
(Adnan, Habib, Ashraf, Shah, et al., 2020)	Adnan M,Habib A,Ashraf J,Shah B,Ali G (2020)	The machine learning algorithms used in the study include Random Forest (RF), Logistic Regression (LR), Decision Tree (DT), Support Vector Machines (SVM), and Naive Bayes (NB).	between 85.96% and 89.47%	The study presents an advanced M-learning model leveraging both machine and deep learning techniques. It dynamically investigates learning attributes, their significance, and interrelation to offer tailored content and advice for M-learners. Using a five-tier classification, learners are grouped based on performance, with specific feature weights aiding in custom support. Analysis revealed both behavioral and contextual aspects influencing M-learner performance. Notably, the model surpassed five standard ML benchmarks, with deep ANN and RF models emerging as top performers.
(Moslehi & Haeri, 2020)	Moslehi F,Haeri A (2020)	GA, PSO, ANN	This varies from one dataset to another, but remains below 60%.	In the investigation, the efficacy of the proposed hybrid algorithm is juxtaposed with three hybrid filter-wrapper methodologies, two intrinsic wrapper algorithms, two standalone filter processes, and a pair of conventional wrapper feature selection mechanisms. Empirical results underscore the

				superior accuracy of the introduced method in classification and its heightened capability to eliminate non-essential and inappropriate features compared to alternate techniques.
(Adnan, Habib, Ashraf, Mussadiq , et al., 2020)	Adnan M,Habib A,Ashraf J,Mussadiq S,Raza AA (2020)	ANN algorithm, Random forest	between 60.74% and 96.30%	This research aims to craft a potent m-learning model using Deep Learning (DL) techniques to simulate the m-learners' learning journey. The study spotlights essential learning attributes, like study duration, setting, frequency, content variety, and gauges their effect on learner outcomes. It delves into how optimal feature weights influence performance across varied learner environments. Using DL, learners are categorized based on feature distinctions, their significance, and interconnectedness, achieving high precision. The approach effectively guides m-learners to enhance their performance and make knowledge-driven choices throughout their learning trajectory.
(Alshurid eh et al., n.d.)	Alshurideh M,Al Kurdi B,Salloum SA,Arpaci I,Al-Emran M (2020)	Decision tree, random forest, and neural network algorithms.	the random forest 91.8%	This study uses Partial Least Squares Structural Equation Modeling (PLS-SEM), a statistical technique that measures the relationships between latent variables, while the second approach uses machine learning algorithms, specifically decision tree, random forest, and neural network algorithms.
(Adnan et al., 2021)	Adnan M,AlSaeed DH,Al-Baity HH,Rehman A (2020)	ANN (Artificial Neural Network), multiclass benchmark machine learning algorithms,	Achieving accuracy rates of 90.77%, 87.69%, 83.85%, and 80.00% across four M-learning models.	This study utilized the M-learning model based on the artificial neural network (ANN) algorithm to predict learners' performance and categorize them into five performance groups. Additionally, the random forest (RF) algorithm was employed to assess the significance of each feature in the development of the M-learning model.
(Akour et al., 2021)	Akour I,Alshurideh M,Al Kurdi B,Al	J48 classifier, BayesNet,Logistic,	J48 classifier (89.37% accuracy)	This study investigates the use of mobile learning platforms for instructional purposes in higher

	Ali A,Salloum S (2021)	LWLd,AdaBoostM 1,OneR	best performing predicting algorithm	education institutions in the United Arab Emirates. The research utilized machine learning algorithms, which were applied using various methodologies (Akour et al., 2021).
(Alhumai d et al., 2021)	Alhumaid K,Habes M,Salloum SA (2021)	The article mentions the use of a new hybrid analysis approach that combines SEM (Structural Equation Modeling) and deep learning-based artificial neural networks (ANN) to evaluate the proposed model	between 48.7%% and 81%	This study evaluates the influence of fear on mobile learning (ML) adoption among students and teachers during the COVID-19 crisis. Utilizing a combined approach of structural equation modeling (SEM) and deep learning-based artificial neural networks (ANN), the model's effectiveness is assessed. Key determinants for ML usage, such as attitude and perceived usefulness, are identified. Notably, perceived fear and expectation confirmation emerged as pivotal predictors for ML intention. The research underscores ML's potential in pandemic-era education but recognizes fears like academic concerns as potential barriers. These findings guide higher education policymakers in strategic planning (Alhumaid et al., 2021).
(Matzavel a & Alepis, 2021)	Matzavela V,Alepis E (2021)	Decision tree	N/A	This study uses decision tree algorithm in creating a predictive model for student knowledge level and academic performance, which can be used to improve personalization in learning. The development of an adaptive dynamic testing system for assessing student academic performance, which is constantly compared with the decision tree's predictive model. The identification of important features that can be used to improve the accuracy of the predictive model, such as the student's grade level, gender, and previous academic performance. The demonstration of the effectiveness of the decision tree algorithm in predicting student knowledge level and academic performance, which can be used to

				provide targeted interventions and support for students who are struggling. The potential of the proposed approach to be used in other educational settings and contexts to improve student learning outcomes.
(Daoudi et al., 2022)	Daoudi M,Lebkiri N,Ouali Y,Oumaira I (2022)	K-means	N/A	This study utilizes a K-means prediction model to analyze students' involvement in mobile learning at Ibn Tofail University in Morocco. The analysis is based on data extracted from three MOODLE platforms.
(Pishtari et al., 2022)	Pishtari G,Prieto LP,Rodríguez-Triana,MJ,Martinez-Maldonado R (2022)	supervised machine learning (SML)	SML can reliably classify designs with accuracy >0.86 and Cohen's kappa > 0.69	This research delves into using Supervised Machine Learning (SML) for automated categorization of m-learning textual content based on pedagogical parameters. It examines the balance between model performance and interpretability, using a dataset from Avastusrada and Smartzoos tools. Different models and feature extraction methods are evaluated. The study accentuates the optimized EstBERT and Logistic Regression algorithms via a case study. Results show SML's potential in accurate design classification, minimizing manual pedagogical coding.
(Zhao, 2022)	Zhao J(2022)	RLT (Machine learning training technique)	98.78%	In this study, a Chinese university developed a mobile language learning environment utilizing intelligent reinforcement learning technology within a wireless setting. Through the application of reinforcement learning technology (RLT) with a reward-penalty system, communication between students and teachers was substantially enhanced. Cloud computing was integrated to refine the learning infrastructure across multiple educational institutions. Impressively, this innovative mechanism achieved a 98.78% accuracy, surpassing traditional Q-learning methods. This underscores the imperative to revamp

				conventional educational techniques in sync with advancing technology, especially in Chinese language pedagogy.
(Zhang & He, 2022)	Zhang LZ,He J (2022)	hybrib fuzzy k-means	78,75%	"This research introduces a hybrid hierarchical k-means clustering technique aimed at enhancing unsupervised machine learning clustering for student performance analysis. The findings suggest that the proposed method outperforms the standard k-means algorithm in terms of performance" (Zhang & He, 2022).
(Xu, 2022)	Xu C (2022)	Pearson similarity and Euclidean distance correction method	The article highlights an improved user collaborative filtering technique, which significantly reduces MAE and RMSE, enhancing system accuracy.	This study propose a user collaborative filtering recommendation technique for mobile learning, which takes into account the narrative of data and the project confidence level during the matrix prefilling process.Introducing an information entropy model to measure the project confidence level, which can help to improve the accuracy of the matrix prefilling process.Combining the traditional cosine similarity and the project confidence level to calculate the user similarity matrix, which can help to budget equalization and expand the original matrix.Demonstrating through the comparison of prediction results before and after using the proposed technique, that the proposed technique can significantly reduce MAE and RMSE, and thus enhance the reliability and consistency of the mobile English system platform.
(Asghar et al., 2022)	Asghar M,Bajwa IS,Ramzan S,Afreen H,Abdullah S (2022)	Naive Bayes, SVM, KNN COMPARISON, Decision Tree, Random Forest.	90%	In this article, we introduce a unique method involving both quantitative and qualitative analysis of a mobile application. A criterion is established according to user needs and perceptions, focusing on a collection of crucial features
(Sultan et al., 2022)	Sultan LR,Abdulateef	Fast Learning Network (FLN)	91.6%	This study revealed that the introduced model outperformed the

	SK,Shtayt BA (2022)			artificial neural network, k-nearest neighbors, and multilayer perceptron algorithms. The model achieved prediction accuracies of 91.6% and 92.85% for student satisfaction coefficients in M-learning. The findings highlight the importance of diverse evaluations, instructor feedback, and high-quality technology in driving student satisfaction. Moreover, FLN surpassed ANN, KNN, and MLP in accuracy and various other metrics.
(Liao, 2022)	Liao, Li (2023)	The research introduces a machine learning algorithm designed for decision-making between two exclusive options, x and y, using enhanced data (Dx, Dy).	N/A	The article introduces AI-EVTR, a mobile language app system for enhancing English learning with a focus on language characteristics and grammatical norms. It highlights the significant improvement in English learning achieved through various mobile applications. The study explores the role of trust factors in determining service trustworthiness, influenced by the framework and machine learning. Additionally, a mathematical tool is introduced, leading to improved learning efficiency with a high convergence speed of 97.24%.
(Awwad, 2023)	Ayyal Awwad, A.M. (2023)	In this research, we use a machine learning algorithm to determine learner attributes.	N/A	The introduced system encompasses elements proficient in identifying contextual shifts and modifying the application's reactions and actions accordingly. This structure employs a machine-learning algorithm to anticipate learners' traits and adheres to Universal Design for Learning (UDL) tenets to provide an enhanced user experience with geographically sensitive content and activities.

We have conducted a systematic review of 20 research articles selected from the field of mobile learning, spanning the years 2009 to 2023. Four specific research questions guided this review, and the results have been presented to provide a comprehensive overview of the current state of knowledge in this area.

RQ1: What Are the Latest Studies on the Application of Machine Learning Algorithms for the Prediction of Failure Using Features of Learner Behavioral Engagement, as Well as Technology Acceptance?

Recent studies are increasingly exploring the application of machine learning algorithms to predict failure through both behavioral engagement features of learners and technology acceptance. In the study (Liao, 2022), AI-EVTR, a mobile application for English learning, was not only designed to focus on engagement but also considered user acceptance, showing marked improvement in predicting failure or success. Additionally, in (Adnan et al., 2021), a mobile learning model based on an artificial neural network that both assessed learner's performance and evaluated technology acceptance, offering an integrative approach to prediction was examined. In the manuscript (Zhao, 2022), a mobile learning environment for Chinese language teaching that utilized intelligent reinforcement learning technology and incorporated elements of behavioral engagement and technology adaptation was developed. Collectively, these studies represent a burgeoning interest in multifaceted approaches that consider various aspects of learners' interactions and acceptance of technology in predicting learning outcomes.

RQ2: What Sources of Data Are Used to Implement Machine Learning Models for the Prediction of Failure?

In studies on mobile learning, the sources and quantities of data used vary. In paper (Daoudi et al., 2022), a K-means prediction model based on data from three MOODLE platforms at Ibn Tofail University in Morocco was employed. In (Adnan et al., 2019), data from 150 students were used to evaluate a cloud-based learning system. Other researchers have utilized tools like Avastusrada and Smartzoos for mobile learning designs or mobile devices to extract contextual information from students. These methods illustrate the diversity of data sources in research on mobile learning.

RQ3: What Are the Most Influential Factors of Learner Behavioral Engagement and Technology Acceptance in Predicting Failure with Machine Learning Algorithms?

The research question has been explored in various studies. In this work (Liao, 2022), an AI-powered English learning mobile app's importance of trust factors that determine service reliability, influenced by machine learning, achieving 97.24% convergence speed was demonstrated. In (Adnan, Habib, Ashraf, Shah, et al., 2020), the role of behavioral and contextual features in influencing learning performance, showcasing robust modeling through deep ANN and RF models was emphasized. In the following manuscript (Akour et al., 2021), machine learning algorithms were employed to predict intentions to use mobile learning platforms, with the J48 classifier showing superior performance. In the paper (Alhumaid et al., 2021), key predictors such as attitude, ease of use, usefulness, satisfaction, and more were identified in influencing mobile learning acceptance. In the study by (Sultan et al., 2022), diversity in evaluation, teacher attitude and response, and quality of technology were found to be key determinants of student satisfaction in M-learning, with an accuracy of 91.6%. These studies collectively highlight the multifaceted factors influencing the engagement and acceptance of learning technologies, with machine learning algorithms playing a pivotal role in predicting and enhancing educational outcomes.

RQ4: What Are the Machine Learning Algorithms That Show More Performance for Developing Models to Predict Failure?

Several studies have shed light on the various machine-learning algorithms used in predicting failure across different contexts. As stated in Ref. (Adnan, Habib, Ashraf, Shah, et al., 2020), deep ANN and RF models were utilized to improve M-learners' performance, demonstrating the best performance over five baseline models. In the manuscript (Zhao, 2022), intelligent reinforcement learning technology was leveraged, achieving an accuracy rate of 98.78% when compared to traditional Q-learning mechanisms. As stated in (Akour et al., 2021), the J48 classifier outperformed others in predicting people's intention to use mobile learning platforms during the COVID-19 pandemic. Moreover, in (Pishtari et al., 2022), SML was applied to classify m-learning designs, with EstBERT and Logistic Regression emerging as the best-performing and most interpretable algorithms. In (Sultan et al., 2022), the superior performance of the fast

learning network, with an accuracy of 91.6% in predicting student satisfaction in M-learning, was demonstrated. The study (Zhang & He, 2022) emphasized the improved performance of a hybrid hierarchical -means clustering algorithm over the traditional -means. The result of this research question illustrates the diversity and effectiveness of machine learning techniques in developing predictive models across various domains.

Recent studies in the field of Mobile Learning are increasingly exploring machine learning algorithms to predict failure in learning, focusing on both engagement and technology acceptance (Tan et al., 2014), (Padhy et al., 2018), and (Adnan et al., 2019). Diverse sources of data, such as MOODLE platforms and student data are used to implement these predictive models (Adnan, Habib, Ashraf, Shah, et al., 2020), (Moslehi & Haeri, 2020). Key influential factors like trust, attitude, and quality of technology have been identified as crucial in leveraging machine learning algorithms (Tan et al., 2014), (Adnan, Habib, Ashraf, Mussadiq, et al., 2020), and (Akour et al., 2021). Several effective algorithms, including deep ANN, RF models, and J48 classifiers, have demonstrated superior performance across different learning contexts (Adnan, Habib, Ashraf, Mussadiq, et al., 2020), (Adnan et al., 2019), (Alshurideh et al., n.d.), (Akour et al., 2021), (Alhumaid et al., 2021), and (Matzavela & Alepis, 2021). The collective findings indicate a rich and multifaceted approach to predicting learning outcomes through machine learning.

RISK OF BIAS IN STUDIES

In the execution of this research, rigorous methodologies were employed to minimize potential risks of bias. Following the PRISMA 2020 approach, a structured, systematic review was undertaken to critically evaluate the existing literature on machine learning applications in mobile e-learning platforms. The systematic methodology, rooted in the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-analysis) checklist, guaranteed a transparent, replicable, and systematic process in article selection. Searches were methodically conducted across reputable databases, with precise keywords guiding the inclusion and exclusion of articles. From a preliminary list of 332 articles, only 20 met the stringent inclusion criteria, and these were extensively reviewed. The thorough nature of this review process and the structured guideline adherence substantially mitigates the risk of bias in our research outcomes. As a result, this research does not detail the risk of bias. However, the authors acknowledge this constraint.

CONCLUSION

The combination of machine learning algorithms and mobile learning platforms constitutes a turning point in educational methodologies. Our systematic review, drawing on reputable databases such as Scopus, Web of Science, Springer Link, and Science Direct, highlighted several key research articles in this interdisciplinary field.

From a vast pool of 332 articles, we have meticulously refined our selection to include only the most impactful, following rigorous criteria. The selected articles not only trace the evolution of academic interest in this field, but also highlight the growing enthusiasm at the confluence of machine learning and mobile learning platforms.

In our review, we addressed several key research questions. First, we explored recent studies on the application of machine learning algorithms to predict learning outcomes, focusing on learner engagement and technology acceptance. Secondly, we examined the various data sources used in these studies. Third, we investigated the key factors influencing learner engagement and technology acceptance in the context of machine learning algorithms. Finally, we evaluated the different machine learning algorithms' performance in prediction models. Through these questions, our study has provided an understanding of the current state and potential trajectory of machine learning in mobile learning.

Our study offers a panoramic view of the dynamic interaction between machine learning and mobile learning. It highlights researchers' innovative paths, paving the way for a more predictive and optimized educational future.

TABLE SUMMARIZING THE REVIEWED RESEARCH ARTICLES

The summary of our 20 selected articles, encompassing all relevant information, is available at the link below. Additionally, we have included details about the 55 excluded articles and the reasons for their exclusion.
https://github.com/mohameddaoudi86/SR/blob/main/Summary%20table%20of%20selected%20articles.pdf

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