Machine Learning for Student Performance Prediction in Online Learning, MOOCS, and Learning Management Systems: A Systematic Literature Review

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ABSTRACT

The rapid expansion of online learning in higher education has generated large volumes of learner interaction data through Learning Management Systems (LMSs), Massive Open Online Courses (MOOCs), and related digital platforms. These data provide new opportunities for machine learning to predict academic performance, identify at-risk learners, and support timely intervention.

This study presents a systematic literature review of machine learning approaches used for student performance prediction in online learning environments, with specific focus on MOOCs, LMS data, and digital learning traces. Guided by the PRISMA 2020 framework, the review synthesizes evidence from peer-reviewed studies and addresses five questions: the most common machine learning algorithms, the types of online learning data and predictive features employed, the major prediction targets, the evaluation methods used, and the main research gaps in the field.

The literature indicates that classification-based models dominate the field, with Random Forest, Support Vector Machine, Decision Tree, Artificial Neural Network, and Naïve Bayes among the most frequently used approaches. LMS logs, MOOC clickstreams, assessment records, historical grades, and demographic variables are the most common predictive inputs, while final grades, pass/fail outcomes, dropout, and retention are the main targets.

The review also identifies persistent weaknesses, including limited explainability, weak cross-institutional validation, inconsistent reporting of feature importance, and relatively few studies that evaluate the effect of interventions after prediction. The manuscript concludes with a conceptual framework and a future research agenda to support robust, ethical, and actionable machine learning in online higher education.

Keywords - Online learning; MOOCs; learning management systems; machine learning; student performance prediction; educational data mining; learning analytics; higher education

INTRODUCTION

Online learning has become a central mode of delivery in higher education. Universities increasingly rely on LMS platforms such as Moodle, Blackboard, Canvas, and Sakai to manage content delivery, communication, assessment, and learner interaction. At the same time, MOOCs have expanded access to higher education and professional learning, while creating large clickstream and behavioral datasets that can be used to understand patterns of student success and failure. Although online learning environments generate abundant data, institutions still struggle to identify at-risk learners early enough for effective intervention. Online courses often report lower retention and completion rates than conventional face-to-face formats. Many existing predictive studies are fragmented by platform, context, and target outcome, and many emphasize prediction accuracy more than operational value or educational impact. This manuscript aims to systematically review machine learning-based student performance prediction in online learning environments, with attention to MOOCs, LMS data, and higher-education digital learning settings. The objectives are to identify the dominant machine learning algorithms, examine the online data sources and predictive features employed, analyze the most frequent prediction targets and evaluation methods, synthesize practical implications, and propose a conceptual framework and future research agenda. This review narrows the scope from general student performance prediction to digitally mediated learning environments where data richness and modeling opportunities are especially strong. It is relevant to researchers in educational data mining and learning analytics, institutions deploying early warning systems, and instructors seeking evidence-based strategies to support online learners [1]–[4].

BACKGROUND AND RELATED CONCEPTS

Online Learning in Higher Education

Online learning has become a central component of modern higher education, driven by advances in digital technologies, internet accessibility, and the increasing demand for flexible learning opportunities. Online learning refers to educational delivery that is mediated through digital platforms and networked technologies, allowing students to access course materials, participate in learning activities, and interact with instructors and peers remotely. This form of education can take multiple formats, including fully online learning, blended learning, hybrid learning, synchronous learning, and asynchronous learning environments. In higher education institutions, online learning platforms have become essential tools for delivering instructional content, facilitating communication, and managing assessment processes. These digital environments enable the collection of extensive data related to student interactions, engagement patterns, and academic performance. For instance, learning platforms automatically record student activities such as login frequency, time spent accessing course materials, participation in online discussions, submission behavior, and assessment outcomes. Such data provide fine-grained evidence of student engagement, learning behavior, and performance trajectories over time [2], [3].

The rapid expansion of online learning has been further accelerated by global events such as the COVID-19 pandemic, which forced many institutions to transition from traditional classroom-based teaching to digital learning environments. As a result, universities have increasingly adopted online learning technologies to support remote education, thereby generating large volumes of digital learning data. These data create opportunities for educational institutions to apply advanced data analytics and machine learning techniques to understand student behavior, predict academic performance, and provide early interventions for students who may be at risk of academic failure. Moreover, online learning environments allow researchers to examine learning behaviors in ways that are difficult to capture in traditional classroom settings. Digital traces recorded by online platforms can reveal patterns related to student motivation, learning engagement, participation in collaborative activities, and interaction with learning resources. Consequently, online learning systems have become a valuable source of information for developing predictive models aimed at improving learning outcomes and enhancing educational decision-making **[5], [6]**.

Massive Open Online Courses (MOOCs)

Massive Open Online Courses (MOOCs) represent one of the most significant innovations in online education over the past decade. MOOCs are online courses designed for large-scale participation and open access through the internet, allowing learners from diverse geographical locations to enroll and participate in educational programs offered by universities and educational institutions worldwide. Unlike traditional university courses, MOOCs typically accommodate thousands or even millions of learners simultaneously, making them a powerful platform for global knowledge dissemination. MOOCs typically include a variety of digital learning components such as recorded video lectures, quizzes, interactive assignments, discussion forums, peer assessments, and collaborative learning activities. Because these courses operate entirely in digital environments, they generate extensive amounts of learner interaction data. This includes clickstream data, video viewing behavior, quiz attempts, assignment submissions, discussion forum participation, and navigation patterns across course materials. These large-scale datasets provide valuable resources for researchers and educators interested in analyzing learner behavior and predicting academic outcomes [7]–[9].

The scale and richness of MOOC data make these environments particularly suitable for applying machine learning and learning analytics techniques. By analyzing behavioral patterns and engagement metrics, researchers can identify early indicators of learner success or failure. For example, patterns such as reduced video engagement, infrequent logins, delayed assignment submissions, or minimal participation in discussion forums may signal a higher risk of course dropout. Despite their advantages in accessibility and scalability, MOOCs often face challenges related to learner retention and completion rates. Many studies report that MOOCs typically experience high dropout rates and low completion rates, with only a small percentage of enrolled learners completing the full course. These challenges have prompted researchers to explore predictive analytics and machine learning models that can identify at-risk learners early in the course lifecycle. Such predictive models can help instructors and course designers implement timely interventions aimed at improving learner engagement, course completion rates, and overall learning outcomes **[10]**.

Learning Management Systems (LMSs)

Learning Management Systems (LMSs) are software platforms designed to support the administration, delivery, tracking, and evaluation of educational courses and training programs. In higher education, LMS platforms serve as the primary infrastructure for managing online and blended learning environments. Popular LMS platforms include Moodle, Blackboard, Canvas, and Sakai, which are widely used by universities around the world to facilitate digital learning experiences. An LMS provides a centralized platform where instructors can upload course materials, manage assignments, conduct assessments, communicate with students, and monitor learner progress. Students, in turn, can access learning resources, participate in discussions, submit assignments, and receive feedback from instructors through the platform. These interactions generate detailed log data that capture various aspects of student behavior and engagement throughout the learning process [5].

One of the most important features of LMS platforms is their ability to record and store large volumes of interaction data. LMS log files typically contain information about student login frequency, duration of platform usage, navigation patterns, resource access, participation in discussion forums, quiz attempts, and assignment submission timestamps. Such data provide valuable insights into students' learning behaviors and allow researchers to study patterns associated with academic success or failure**.** Because of the richness and availability of LMS data, these platforms have become one of the most widely used sources of information for predictive modeling and learning analytics research. By analyzing LMS log data using machine learning techniques, researchers can develop predictive models capable of identifying students who may be at risk of poor academic performance or course withdrawal. These models can support early warning systems that enable educators to provide targeted academic support and personalized learning interventions **[4]**.

Educational Data Mining and Learning Analytics

Educational Data Mining (EDM) and Learning Analytics (LA) are two closely related research fields that focus on analyzing educational data to improve learning outcomes and educational decision-making. Although these fields share similar goals and methodologies, they differ slightly in their focus and research perspectives. Educational Data Mining primarily concentrates on the development and application of computational methods for discovering patterns, relationships, and structures within educational datasets. EDM researchers typically apply data mining techniques such as classification, clustering, association rule mining, and pattern recognition to identify meaningful insights from large-scale educational data. The primary objective of EDM is to uncover hidden patterns that can help explain learning behaviors, predict academic outcomes, and support the development of intelligent educational systems [6].

Learning Analytics, on the other hand, emphasizes the measurement, collection, analysis, and reporting of data about learners and their learning environments. The primary goal of learning analytics is to use data-driven insights to optimize learning processes and enhance educational experiences. Learning analytics focuses not only on predictive modeling but also on providing actionable insights that educators, administrators, and students can use to improve learning outcomes. In practice, the boundaries between EDM and LA are often blurred, especially in online education research. Both fields rely on similar datasets, such as LMS logs, MOOC interaction data, and student information system records. Moreover, both disciplines employ similar analytical techniques, including machine learning algorithms, statistical analysis, and data visualization tools. As a result, many studies in online learning environments integrate concepts and methodologies from both educational data mining and learning analytics **[11]**.

Machine Learning for Student Performance Prediction

Machine learning has become an essential tool for analyzing educational data and predicting student performance in online learning environments. Machine learning refers to a set of computational methods that enable computer systems to learn patterns from data and make predictions or decisions without being explicitly programmed for each task. In the context of education, machine learning algorithms are used to analyze complex datasets generated by digital learning platforms and to identify patterns associated with student success, engagement, and academic achievement. Machine learning approaches used in student performance prediction can be broadly categorized into several types, including supervised learning, unsupervised learning, ensemble learning, and deep learning methods. Supervised learning algorithms are the most commonly used techniques in this research domain. These algorithms learn relationships between input features and target variables using labeled datasets. In student performance prediction, supervised learning models are typically trained using historical data that include student demographic information, academic records, and behavioral indicators derived from LMS or MOOC platforms. Common supervised learning algorithms include Decision Tree, Random Forest, Support Vector Machine, Logistic Regression, Naïve Bayes, and K-Nearest Neighbors. These models are widely used because they provide relatively high predictive accuracy and are well suited for classification and regression tasks [12], [13].

Unsupervised learning algorithms are used to discover hidden patterns or groupings within datasets without predefined target labels. Techniques such as clustering are often applied to group students based on similar learning behaviors or engagement patterns. For example, clustering methods can identify groups of highly engaged learners, moderately engaged learners, and disengaged learners based on their interaction with online learning platforms. Ensemble learning techniques combine multiple machine learning models to improve predictive performance and robustness. Algorithms such as Random Forest and Gradient Boosting fall into this category and are frequently used in educational data mining studies because they can handle complex datasets and reduce overfitting. Deep learning approaches represent another emerging area in student performance prediction research. Deep learning models, such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN), are capable of learning complex nonlinear relationships within large datasets. These models are particularly useful when dealing with high-dimensional data such as sequential interaction logs, textual data from discussion forums, and multimodal learning analytics. Across the literature, classification models are the most commonly used approaches for predicting student performance, followed by regression models and clustering methods. Classification tasks typically involve predicting categorical outcomes such as pass/fail status, course completion, or dropout risk, while regression models estimate continuous outcomes such as final grades or cumulative grade point averages. By leveraging machine learning techniques, educational institutions can develop predictive systems that identify at-risk students early in the learning process, enabling timely interventions that support student success and improve overall educational outcomes **[3], [6], [14], [15]**.

METHODOLOGY

Review Design

This study adopts a systematic literature review (SLR) methodology to comprehensively examine the application of machine learning techniques for predicting student performance in online learning environments. A systematic literature review is a rigorous and structured approach used to identify, evaluate, and synthesize existing research evidence in a transparent and reproducible manner. Unlike traditional narrative reviews, systematic reviews follow a predefined protocol that ensures methodological consistency and minimizes bias during the selection and analysis of relevant studies. To ensure methodological rigor, this study follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines. The PRISMA framework provides a standardized approach for conducting and reporting systematic reviews by outlining clear procedures for identifying, screening, evaluating, and selecting relevant research articles. By using the PRISMA protocol, researchers can ensure transparency in the literature selection process while improving the reliability and reproducibility of the review [3].

The PRISMA framework structures the systematic review process into four key stages: identification, screening, eligibility assessment, and inclusion. During the identification stage, relevant articles are collected from selected academic databases using predefined search queries. In the screening stage, titles and abstracts of the retrieved articles are evaluated to determine their relevance to the research objectives. The eligibility stage involves reviewing the full text of potentially relevant articles to ensure that they meet the predefined inclusion criteria. Finally, the inclusion stage identifies the studies that are ultimately selected for qualitative synthesis and analysis. By applying this systematic and transparent approach, the review aims to provide a comprehensive synthesis of existing studies related to machine learning-based student performance prediction in online learning environments. The adoption of the PRISMA methodology ensures that the selection process is traceable and that the findings are based on a carefully curated body of scholarly literature **[16]**.

Data Sources

The literature search for this review is conducted across several major academic databases to ensure broad coverage of relevant research in the fields of education, computer science, artificial intelligence, and learning analytics. Selecting multiple databases is essential for capturing interdisciplinary studies, as research on machine learning applications in education is often published across different academic domains. The primary databases used in this review include Scopus and Web of Science, which are widely recognized as leading indexing platforms for high-quality peer-reviewed research. These databases provide comprehensive coverage of journals and conference proceedings across multiple disciplines and are commonly used in systematic reviews due to their extensive citation indexing and advanced search capabilities. In addition to Scopus and Web of Science, the review also includes IEEE Xplore and ACM Digital Library, which specialize in computer science, artificial intelligence, and data mining research. These platforms are particularly relevant for identifying studies that focus on machine learning algorithms, predictive modeling techniques, and data analytics methods applied in educational contexts. Other databases included in the search process are ScienceDirect and SpringerLink, which host a large collection of journals in educational technology, learning analytics, and computational sciences. These databases provide access to numerous studies that explore the intersection of digital learning environments and machine learning applications [17].

Furthermore, ERIC (Education Resources Information Center) is included as a specialized database for educational research. ERIC contains extensive records related to pedagogy, instructional design, and educational policy, which are relevant to understanding how predictive analytics can support student success in higher education. Finally, Google Scholar is used as a supplementary search engine to capture additional relevant studies that may not be indexed in the previously mentioned databases. Google Scholar enables the identification of recent conference papers, preprints, and interdisciplinary studies that contribute to the research topic. By utilizing multiple databases across education and technology disciplines, this review ensures comprehensive coverage of the literature related to machine learning-based prediction of student performance in online learning environments [11].

Search Strategy

A structured search strategy is developed to identify relevant studies related to machine learning applications for student performance prediction in online learning environments. The search strategy is designed to capture studies that combine three key conceptual areas: online learning environments, predictive analytics or machine learning techniques, and student performance outcomes. To achieve this objective, representative search strings are formulated by combining relevant keywords and Boolean operators. These search queries are designed to retrieve articles that explicitly address the intersection of online learning platforms, predictive modeling, and student academic outcomes. Examples of representative search queries include combinations such as “online learning” AND “student performance prediction” AND “machine learning,” which target studies that focus on predicting academic performance in digital learning environments using machine learning techniques. Another commonly used search string is “MOOC” AND “academic performance” AND “predictive analytics,” which identifies research specifically related to predictive models developed for massive open online courses [10], [13], [18].

Additional search combinations include “learning management system” AND “student success” AND “machine learning,” which focuses on studies analyzing LMS data to predict student outcomes. Similarly, the search string “LMS log data” AND “at-risk students” is used to identify research that examines behavioral interaction data recorded by learning platforms to detect students who may be at risk of academic failure or course withdrawal. Another search phrase, “learning analytics” AND “online learners” AND “prediction,” captures studies that apply learning analytics techniques to forecast academic performance or learning engagement in online education. To ensure that the search process retrieves the most relevant studies, the search queries are adapted to match the syntax and search functionalities of each database. For example, some databases allow the use of field-specific searches that limit results to titles, abstracts, and keywords. When possible, the search queries are restricted to these fields to improve the precision of the search results and reduce the retrieval of unrelated articles. The search strategy also incorporates time filters to limit the results to studies published within the selected review period. By applying consistent search terms and adapting them appropriately across multiple databases, the review ensures a systematic and replicable process for identifying relevant literature [17], [19].

Inclusion and Exclusion Criteria

To ensure that the systematic review focuses on studies that are relevant to the research objectives, a set of inclusion and exclusion criteria is established prior to the screening process. These criteria help determine which studies should be considered eligible for analysis and which should be excluded from the review. The inclusion criteria specify that studies must be published between 2015 and 2025. This timeframe is selected to capture recent developments in machine learning and learning analytics while ensuring that the review reflects current research trends in online education. Eligible studies must also be peer-reviewed journal articles or conference papers, as these types of publications typically undergo rigorous academic review processes and provide reliable research findings. Another important inclusion requirement is that the studies must be conducted within a higher education context. This criterion ensures that the review focuses on university-level learning environments rather than primary or secondary education settings. Additionally, the studies must specifically examine online learning environments such as MOOCs, learning management systems, or other virtual learning platforms where digital interaction data can be collected and analyzed. Furthermore, the studies must apply machine learning techniques or related predictive analytics methods to analyze educational data. Eligible studies should focus on predicting student outcomes such as academic performance, course completion, dropout risk, retention, or other indicators of learning success or failure [2], [20], [21].

In contrast, several types of studies are excluded from the review. Studies that focus exclusively on K–12 education are excluded because the learning environments, instructional approaches, and data characteristics differ substantially from those found in higher education. Purely conceptual or theoretical papers without empirical data analysis are also excluded, as the review aims to examine practical applications of machine learning in real educational datasets. Non-English publications are excluded due to practical limitations in language translation and interpretation. Studies that do not involve machine learning-based prediction are also removed from consideration, as they fall outside the scope of the research objective. Additionally, studies that do not analyze data from online learning platforms are excluded to maintain a clear focus on digital learning environments. Finally, editorial articles, theses, books, duplicated records, and other non-peer-reviewed materials are excluded to ensure the quality and reliability of the selected literature [22]–[25].

Data Extraction and Quality Appraisal

Once the eligible studies have been identified, a systematic data extraction process is conducted to collect key information from each selected article. The purpose of data extraction is to ensure that relevant details from each study are consistently recorded and organized for analysis and synthesis. For each included study, several important variables are documented. These variables include the authors and publication year, which provide

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basic bibliographic information about the study. The country or research context is also recorded in order to understand the geographical distribution of studies and the educational environments in which the predictive models were developed Information about the learning platform used in the study is also extracted, including whether the research was conducted using data from MOOCs, learning management systems, or other online learning platforms. Details regarding the data sources and sample size are documented to provide insights into the scale and scope of the datasets used in the predictive models [3].

The predictive features used in the study are also carefully recorded. These features may include variables such as student demographic information, prior academic performance, LMS interaction logs, participation in discussion forums, or behavioral indicators derived from clickstream data. In addition, the target variable being predicted in each study is documented. This may include outcomes such as final grades, course completion, dropout risk, or other indicators of student success. The machine learning algorithms used in the predictive models are also extracted, along with details about the model validation strategies. These validation strategies may include methods such as cross-validation, hold-out validation, or other techniques used to assess the reliability of the predictive models. Performance evaluation metrics reported in each study, such as accuracy, precision, recall, F1-score, or area under the ROC curve, are also recorded [4], [17].

In addition to data extraction, a quality appraisal process is conducted to evaluate the methodological rigor of the included studies. The quality assessment examines several factors, including the clarity of research objectives, the transparency of the dataset description, the preprocessing procedures applied to the data, and the adequacy of feature reporting. The evaluation also considers whether the authors provide clear justification for their choice of machine learning models and whether appropriate validation methods are used to assess model performance. Finally, the practical relevance of each study is assessed by examining whether the research provides actionable insights for improving educational practices, such as identifying at-risk students or supporting early intervention strategies. By systematically extracting and evaluating these variables, the review ensures that the synthesis of findings is based on reliable and well-documented research evidence [26].

RESULTS

Prisma Flow

The PRISMA flow diagram serves as a visual summary of the study selection process used in this systematic literature review. Its purpose is to clearly document how records were identified, screened, assessed for eligibility, and finally included in the review. In a high-quality systematic review, the PRISMA flow is essential because it improves transparency and allows readers, reviewers, and editors to understand exactly how the final body of literature was derived from the broader pool of search results [2], [19].

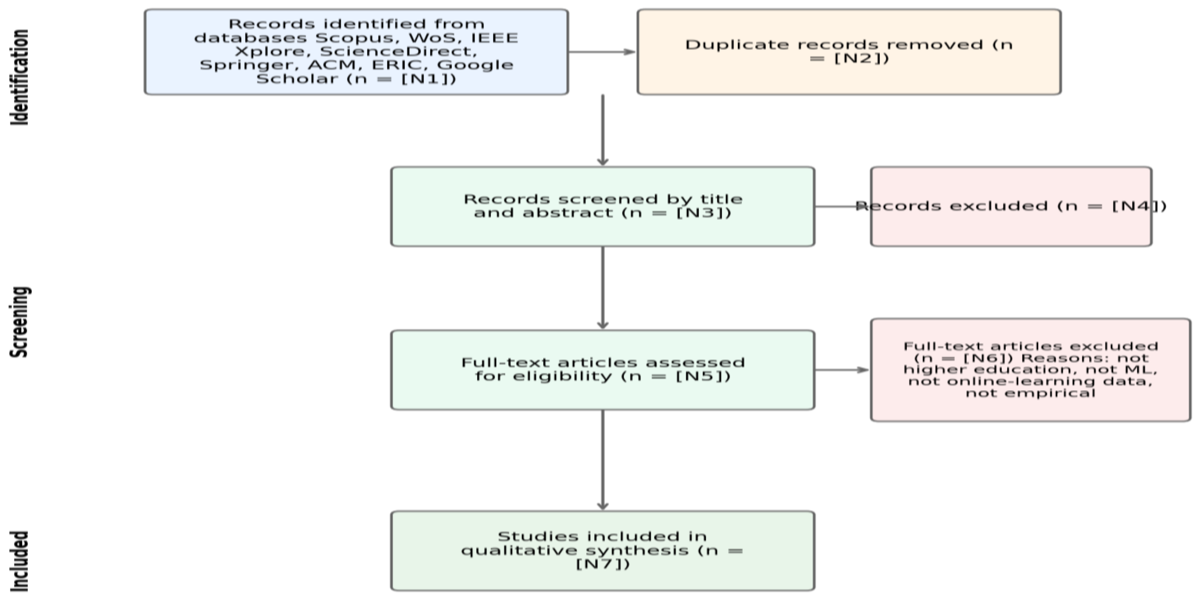

Fig 1. PRISMA 2020 flow diagram template for final database search counts.

In this study, the PRISMA flow diagram should be completed using the final search log obtained from the selected scholarly databases. These databases include major sources relevant to education, computer science, and interdisciplinary technology research, and the final diagram should reflect the exact number of records retrieved from each source. The first stage of the PRISMA flow, identification, should report the total number of records found across all databases before duplicate removal. The second stage, screening, should indicate how many duplicate records were removed and how many remaining titles and abstracts were screened for relevance. The third stage, eligibility, should report the number of full-text articles assessed and explain how many were excluded after full-text review, together with the reasons for exclusion. The final stage, inclusion, should present the exact number of studies that were ultimately selected for qualitative synthesis. At this stage, the PRISMA figure is best treated as a submission-ready template that allows the final counts to be inserted once the database search and screening process have been fully completed and verified. This approach ensures that the manuscript remains methodologically sound because the reported numbers will match the actual screening records used by the author. It also supports journal submission requirements, especially for Scopus-indexed and higher-tier journals, where reviewers often examine whether the PRISMA counts are internally consistent across the manuscript, tables, appendices, and diagram. A properly completed PRISMA flow diagram therefore strengthens the credibility of the review by demonstrating that the literature selection process was systematic, traceable, and reproducible [1].

Publication Trend and General Characteristics

The reviewed literature indicates a clear and sustained growth in research on machine learning-based student performance prediction in online learning environments. This increase has been particularly noticeable in recent years, largely due to the rapid expansion of digital education, the wider adoption of Learning Management Systems, the growth of Massive Open Online Courses, and the increasing availability of educational data generated through online learning platforms. As higher education institutions continue to digitize teaching, learning, and assessment processes, researchers have gained access to richer and larger datasets, which in turn has encouraged more extensive use of predictive analytics and machine learning methods. A substantial proportion of the literature has emerged in response to the broader transformation of higher education toward flexible, technology-mediated learning. This trend intensified further with the expansion of distance education and the widespread institutional shift toward online and blended learning models. As a result, scholarly attention has increasingly focused on understanding how data from digital learning environments can be used to identify patterns of engagement, detect academic risk, and improve student success outcomes. The overall publication trend suggests that this field is no longer emerging in a preliminary sense but is developing into an established research area at the intersection of educational data mining, learning analytics, and artificial intelligence in education [5], [11].

In terms of study characteristics, most of the published work is empirical rather than conceptual. The literature is dominated by quantitative research designs that rely on real-world datasets collected from online learning systems. These studies typically develop and test predictive models using historical academic records, digital trace data, or combinations of multiple data sources. Compared with qualitative or mixed-methods research, quantitative modeling studies are far more common because the central objective of this field is usually to measure predictive performance and compare machine learning algorithms. The dominant study population in the literature is university students, which is consistent with the higher education focus of this review. Most studies examine learners enrolled in undergraduate or postgraduate courses delivered fully online, through blended formats, or via open online platforms. Learning Management Systems and MOOCs are the most frequently analyzed digital environments, largely because they automatically record detailed learner interactions such as logins, clicks, assessment behavior, resource access, and communication patterns. These systems provide the structured and timestamped data needed for machine learning analysis, making them highly suitable for predictive modeling. Overall, the general characteristics of the literature show a maturing research field grounded in empirical, data-driven investigations of student performance in digitally mediated higher education contexts [11], [27].

Machine Learning Algorithms Used

The literature consistently shows that classification-based machine learning approaches dominate student performance prediction in online learning environments. This dominance is largely due to the nature of the outcomes commonly studied in the field, such as pass or fail status, dropout risk, course completion, and identification of at-risk students. These outcomes are often represented as categorical variables, making classification algorithms especially well suited for the task. As a result, most studies focus on determining whether a learner belongs to a particular academic risk category rather than estimating a purely continuous outcome. Among the machine learning algorithms used in the literature, Random Forest appears most frequently and is widely regarded as one of the strongest performers in online learning prediction studies. Its popularity stems from its ability to handle large numbers of features, reduce overfitting through ensemble averaging, and model complex nonlinear relationships in educational data. Decision Tree is also commonly used because it is relatively easy to interpret and provides clear rule-based structures that can help explain prediction outcomes to educators and administrators. Support Vector Machine appears repeatedly in the literature as a strong classifier, especially in studies with smaller or ŭɦϩ-sized datasets where clear class separation can be achieved. Naïve Bayes remains common due to its simplicity, speed, and usefulness as a benchmark model, even though its assumptions may not always align with the complexity of learner behavior data. Artificial Neural Networks are also widely reported, particularly in studies that aim to capture more complex patterns across academic, behavioral, and demographic variables [5], [26], [27].

In addition to these established models, ensemble methods are increasingly favored for their predictive strength. The literature suggests that ensemble approaches often outperform single classifiers because they combine the strengths of multiple models and improve robustness across different educational datasets. This is especially evident in research on at-risk student detection, dropout prediction, and retention analysis, where the relationships among variables are often highly complex and influenced by both behavioral and academic factors. Ensemble learning methods such as Random Forest, Gradient Boosting, and related hybrid models are therefore gaining prominence as researchers seek to improve prediction accuracy and stability. Another important observation is that although traditional supervised algorithms remain dominant, the field is gradually expanding to include more advanced neural and hybrid approaches. However, the strongest concentration of evidence still supports the central role of classification methods based on traditional machine learning, with Random Forest, Decision Tree, Support Vector Machine, Naïve Bayes, and Artificial Neural Network remaining the most frequently cited and most widely applied algorithms. Taken together, the literature suggests that the field has reached a level of methodological consistency in which a relatively stable group of algorithms forms the core of student performance prediction research in online learning settings.

Types of Online Learning Data and Predictive Features

The reviewed literature shows that the most common data sources used for student performance prediction in online learning environments are Learning Management System logs, MOOC interaction traces, student assessment records, historical academic performance data, and demographic variables. These data sources are especially valuable because they capture both what students achieve and how they behave during the learning process. In online and distance education settings, learner interactions with digital platforms generate detailed traces that can be analyzed using machine learning techniques to uncover patterns associated with academic success or failure. LMS log data represent one of the most frequently used sources because they provide structured and timestamped evidence of student engagement within institutional learning platforms. These logs typically record how often students access the platform, when they log in, how long they remain active, what resources they view, and how they navigate across course content. Similar forms of data are found in MOOC environments, where learner interactions often include video viewing patterns, quiz attempts, discussion participation, completion of course modules, and other clickstream-based activity traces. Because both LMS and MOOC platforms are designed to support digital learning at scale, they generate large volumes of behavioral data that can be directly linked to student outcomes [27]–[30].

In addition to digital trace data, student assessment records are also widely used. These records may include quiz scores, assignment results, midterm marks, final examination grades, and submission timing. Historical academic performance, such as prior grade point average or previous course achievements, is another frequent input because prior success is often strongly associated with later academic performance. Demographic variables, including gender, age, prior educational background, and socioeconomic indicators, are also commonly incorporated into predictive models, especially when researchers aim to improve model completeness or study educational risk across learner groups. The most frequently used behavioral variables include login frequency, time spent on the platform, number of clicks, page views, access to learning materials, discussion posts, quiz attempts, and assignment submission behavior. These variables are useful because they provide indirect but meaningful indicators of learner engagement, consistency, self-regulation, and participation in the online learning process. For example, frequent access to course materials, regular quiz participation, and timely submission of assignments are often associated with stronger academic outcomes, while irregular activity, reduced engagement, and late submissions may signal elevated academic risk. Across the literature, academic and engagement-related variables emerge most consistently as useful predictors. This suggests that student performance prediction in online learning is most effective when models combine evidence of what students do in the platform with evidence of how well they perform academically. In other words, behavioral indicators alone may reveal patterns of participation, but when combined with grades, assessments, and historical academic records, they provide a more comprehensive picture of learner success. The literature therefore supports the view that predictive accuracy is often strengthened by integrating multiple data sources rather than relying on a single type of feature [3], [4].

Prediction Targets

The reviewed studies examine a range of prediction targets, but the most common outcomes are final grades, pass or fail status, course completion, risk of failure, dropout, retention, and graduation-related measures. These targets reflect the main practical concerns of higher education institutions in online learning settings, namely academic performance, persistence, and progression. Because universities seek both to improve learner achievement and to reduce student attrition, the literature tends to focus on outcomes that can support early intervention and decision-making. Final grades are among the most frequently studied targets because they provide a direct measure of academic achievement and are often available in structured institutional records. Predicting final grades can help instructors identify students who may be underperforming before the course ends, which allows for earlier academic support. Pass or fail status is another common target because it transforms academic performance into a categorical outcome that is well suited to classification models. Similarly, risk of failure is widely studied as a way of identifying learners who may need intervention before poor performance becomes irreversible. Course completion is especially important in online learning research because completion rates often serve as a key indicator of student success in digital environments. In MOOCs and distance education, dropout and retention are particularly prominent targets due to persistent challenges with learner persistence and sustained engagement. Many online courses attract large numbers of enrollees, but a substantial proportion of learners disengage before completing the course. This makes dropout prediction highly relevant, particularly in contexts where institutions aim to provide timely warnings, personalized support, or retention strategies [2], [31].

Retention is closely related to dropout but focuses more broadly on whether students remain engaged in their studies over time. Graduation-related outcomes extend this perspective further by examining whether students progress successfully through programs and ultimately complete their degrees. These longer-term outcomes are especially useful for institutional planning, policy development, and program evaluation. Although academic performance outcomes remain slightly more common overall, the prominence of dropout and retention in online and distance learning settings highlights a defining feature of this research area. Online environments often provide rich behavioral data but also face well-documented completion challenges, making persistence-related prediction especially important. As a result, the literature reflects a dual emphasis: on the one hand, predicting achievement in the form of grades and course success, and on the other hand, predicting disengagement, withdrawal, and non-completion. This combination of academic and persistence-focused targets shows that the field is closely aligned with the practical needs of higher education institutions seeking to improve both student learning and student survival within digital education systems [1], [32], [33].

Evaluation Metrics and Validation

The literature shows that accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve are the most commonly used metrics for evaluating model performance in student performance prediction studies. These metrics are widely adopted because the field is dominated by classification tasks, where the goal is often to identify whether a student belongs to a specific category such as at risk, likely to fail, or likely to complete a course successfully. Each metric captures a different dimension of predictive quality, which allows researchers to assess model performance from multiple perspectives rather than relying on a single indicator. Accuracy is the most frequently reported metric because it provides a simple measure of the proportion of correct predictions made by the model. However, accuracy alone can be misleading in educational datasets where class imbalance is common, such as when the number of students who fail or drop out is much smaller than the number who succeed. For this reason, many studies also report precision and recall. Precision measures the proportion of predicted positive cases that are actually correct, while recall indicates the proportion of actual positive cases that the model successfully identifies. These metrics are particularly important in at-risk and dropout prediction, where missing vulnerable students can have serious consequences for institutional intervention efforts. The F1-score is also widely used because it balances precision and recall into a single measure, making it useful in cases where both false positives and false negatives matter. The area under the ROC curve is another common metric because it reflects the model's ability to distinguish between classes across different threshold settings. Together, these classification metrics provide a more comprehensive assessment of predictive effectiveness than accuracy alone. In studies framed as regression tasks, researchers may also report mean absolute error or root mean square error. These metrics are used when the outcome variable is continuous, such as a final numerical grade. Nevertheless, regression-based studies remain less common than classification-based studies, so classification metrics clearly dominate the field [3], [4], [6].

The literature also indicates that reported performance varies substantially by context, dataset, and outcome definition. Some studies report very strong results within specific courses, institutions, or platforms, often achieving high levels of predictive accuracy. However, these strong local results do not necessarily imply that the models are broadly generalizable. Many studies rely on single-institution datasets, limited course contexts, or platform-specific interaction patterns, which means that the resulting models may perform well in one setting but not in another. This leads to a key methodological concern in the literature, namely the limited use of cross-institutional validation. While many studies use internal validation methods such as hold-out sets or cross-validation within the same dataset, relatively few test their models across institutions, programs, or platforms. As a result, external validity remains weak in much of the field. Without broader validation, it is difficult to determine whether a model is genuinely robust or simply well fitted to a local dataset. This limitation weakens the generalizability of existing findings and highlights the need for future research that compares models across different institutional and online learning contexts [3], [21].

DISCUSSION, CONCLUSION AND RECOMMENDATIONS

Main Findings

This review shows that machine learning for online student performance prediction is a mature and rapidly growing field, but one that remains uneven in methodological depth and practical implementation. Traditional supervised learning models continue to dominate, while Random Forest appears especially favored in LMS and dropout-related studies. Online learning data are behaviorally rich, but models are often most useful when behavioral traces are combined with assessment and academic history variables. Compared with broader student-performance SLRs, this review highlights a more specific cluster of data types and use cases. The online-learning literature depends heavily on behavioral trace data recorded by digital platforms and is especially concerned with dropout and early intervention. For universities, the review supports investment in LMS-based early warning systems that combine assessment, engagement, and activity features. For educators, behavior patterns such as delayed assignment submission, reduced session participation, low click activity, and limited engagement with materials can provide useful signals for earlier support. For system designers, dashboards should not only predict risk but also explain the main contributing factors in teacher-friendly terms [4], [19].

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Conclusion

Machine learning-based student performance prediction in online learning environments is now a significant and expanding research area. The evidence suggests that Random Forest, Support Vector Machine, Decision Tree, Naïve Bayes, and Artificial Neural Network remain central to the literature, while LMS logs, MOOC clickstreams, assessment data, historical grades, and demographics are the dominant predictive inputs. The next step for the field is not only better prediction, but also stronger explainability, broader validation, fairness-aware design, and measured educational impact through timely interventions. The proposed framework links five layers: Input, Processing, Modeling, Output, and Action. It emphasizes that prediction is not the final goal. Instead, online-learning analytics should feed into early warnings, personalized support, instructor intervention, academic advising, and evidence-based course redesign [11], [27].

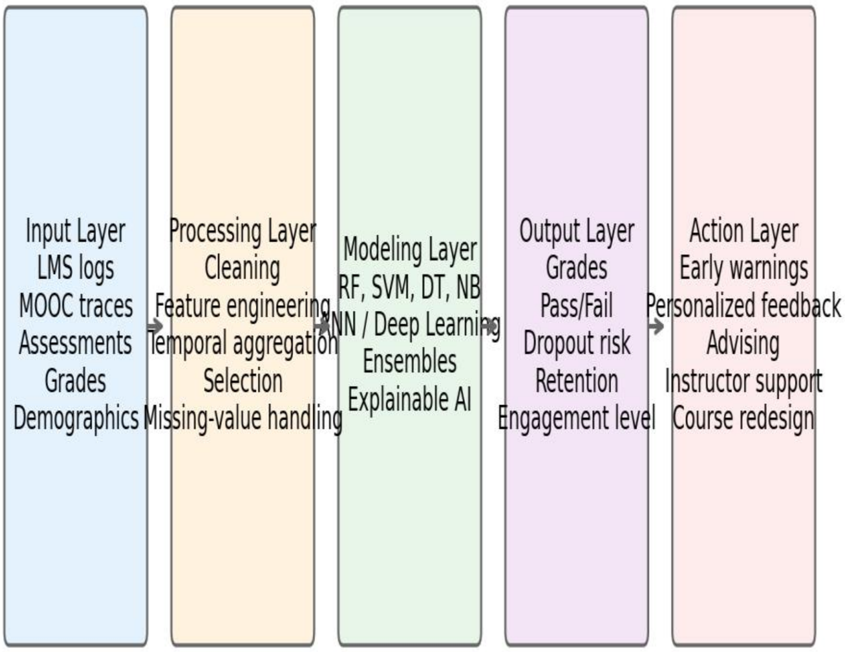

Fig 2. Conceptual framework for machine learning-based student performance prediction in online learning.

This review is limited by its planned database coverage, language restrictions, and the methodological heterogeneity of included studies. Publication bias is also possible because studies with stronger results may be more likely to be published. Moreover, many reviewed studies rely on local datasets, which limits the generalizability of the field as a whole [5], [26].

Research Gaps and Future Directions

Many studies report predictive performance without adequately explaining why a learner is classified as at risk. Explainable AI, interpretable feature reporting, and instructor-facing decision support remain underdeveloped. A large proportion of models are trained and tested within a single institution, course, or platform. Cross-institutional and cross-platform validation is still limited, making it difficult to assess whether strong results transfer to new settings. The field is better at predicting than at proving educational impact. Future research should test whether acting on predictions through advising, feedback, tutoring, or course redesign improves student outcomes. Online learning data are sensitive, and predictive models raise issues of consent, fairness, surveillance, and responsible use. Future research should build privacy-preserving and fairness-aware analytics into model design rather than treating them as afterthoughts. Temporal models, multimodal learning analytics, ontology-enhanced approaches, and richer cross-platform benchmarks remain comparatively underused. These approaches offer promising directions for next-generation Scopus-indexed work [17], [19], [26], [27] .

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