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Student Achievement Prediction Models: A PRISMA-Based Systematic Literature Review

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Abstract. Student achievement prediction has become an important research area in educational data mining because it supports early intervention, academic monitoring, and evidence-based decision-making in educational institutions. This study aims to identify research trends, commonly used methods, predictive variables, and potential research gaps in student achievement prediction models. A Systematic Literature Review (SLR) was conducted using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. Articles published between 2020 and 2024 were collected from seven reputable databases, namely Scopus, ScienceDirect, IEEE Xplore, SpringerLink, IOP, Wiley, and MDPI. After applying the inclusion and exclusion criteria, 52 articles were selected for final analysis. The findings show that classification-based machine learning methods dominate this research area, with Random Forest being the most frequently used algorithm. Academic data, such as grades, GPA, and attendance, remain the most common predictive variables, while non-academic variables are still rarely explored. This study highlights the need for multi-source data integration, hybrid or ensemble modeling, and broader variable selection to improve prediction accuracy and applicability. The novelty of this study lies in its structured synthesis of recent studies and its proposed direction for developing more comprehensive student achievement prediction models.

Keywords: Student Achievement Prediction, Educational Data Mining, Machine Learning in Education, Systematic Literature Review, PRISMA.

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1. INTRODUCTION

Improving student achievement remains a major concern for educational institutions, particularly in higher education, where academic success is closely related to institutional quality, student retention, and graduation outcomes. In recent years, this issue has become more complex because universities have had to adapt to both conventional and digital learning environments [1]. The transition toward technology-supported learning has encouraged institutions to rely not only on traditional academic evaluation but also on data-driven approaches that can identify student performance patterns more accurately. In this context, student achievement prediction models have become increasingly important because they allow institutions to detect academic risks earlier, design targeted interventions, and support students before their performance declines significantly [2]. Data-based monitoring techniques, including performance analysis and predictive modeling, can provide timely information about students who require academic assistance [3], [4].

Machine learning has shown strong potential in supporting student achievement prediction. Several previous studies have demonstrated that predictive models can help institutions identify students who are at risk of academic failure or dropout [5]. However, the development of effective prediction systems is still challenging because many existing models depend heavily on limited academic indicators and do not fully capture the broader factors that influence student success. Ahmed [6] emphasized the importance of exploring more machine learning algorithms and data processing strategies to improve prediction accuracy. Another study suggested that prediction models should include additional attributes, such as social context and media usage, to produce more effective predictions [7]. Similarly, Pallathadka et al. [8] highlighted the importance of combining various machine learning algorithms to increase the accuracy and effectiveness of student performance prediction.

The use of more advanced algorithms and machine learning techniques has continued to grow in educational data mining research [9]. However, comprehensive model development that integrates academic, behavioral, social, and external student data is still limited [10]. Several studies have shown that external data can improve prediction accuracy because student achievement is not determined solely by grades or academic

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history [11]. The integration of relevant features has also been shown to strengthen model performance by providing a more complete representation of student characteristics [12]. In addition, research on learning behavior has revealed that behavioral patterns can provide meaningful insights into academic outcomes and may contribute to the improvement of prediction models [13]. These findings show that student achievement prediction is not only a technical problem related to algorithm selection, but also a conceptual problem related to how student performance is represented through data.

Although research on student achievement prediction models has developed rapidly, several limitations remain. First, many studies still focus on comparing algorithms without deeply analyzing the quality and diversity of predictive variables. Second, most prediction models rely on academic data, such as GPA, grades, and attendance, while non-academic variables, including socioeconomic background, psychological factors, student motivation, and learning behavior, are less frequently used. Third, although hybrid and ensemble models have the potential to improve prediction performance, many studies still use single-algorithm approaches. These limitations indicate a need for a systematic review that maps recent methodological trends, identifies commonly used datasets and variables, and highlights research opportunities for improving student achievement prediction models.

Several previous studies have examined student performance prediction using machine learning algorithms. Nirmala et al. [3] found that Random Forest and XGBoost classification models provided effective performance in predicting undergraduate student study completion status. However, their study did not fully consider external factors that may affect students' academic completion. This limitation suggests that prediction results may not completely reflect the actual conditions faced by students, since student success can be influenced by many academic and non-academic variables. Matzavela and Alepis [15] applied a Decision Tree algorithm to predict academic performance in intelligent mobile learning environments, but their study focused more on the algorithmic aspect and did not explore the influence of external variables in detail. This indicates the need to integrate non-academic factors into prediction models to obtain more realistic and useful results.

From the dataset perspective, Yauri et al. [16] showed that academic records, intelligence scores, and attendance levels can influence academic performance prediction. Their findings support the view that prediction systems should optimize academic data usage while also considering additional attributes that may strengthen prediction accuracy. Yekun and Haile [17] developed a model using historical data from previous semesters to predict student performance in the following semester. This longitudinal approach demonstrates that past academic information can provide valuable signals for predicting future outcomes. However, based on the review of existing studies, most research still focuses primarily on student academic variables. More effective approaches, such as hybrid algorithms and the utilization of non-academic variables, remain underexplored.

Systematic Literature Review (SLR) has become a useful method for identifying and evaluating academic work in a structured way [19]. Through an SLR, researchers can formulate stronger arguments, identify knowledge gaps, and provide a more reliable basis for future research. García-Peñalvo [19] emphasized that systematic reviews help researchers develop robust state-of-the-art reports. Su et al. [20] also suggested that future studies could explore more advanced deep learning algorithms for analyzing student learning features and performance prediction. The PRISMA framework is widely used to guide systematic review processes because it supports transparent documentation from identification to final selection. Sekeroglu et al. [21] conducted a systematic literature review on student performance prediction and recommended the use of evaluation metrics such as AUC, F1-score, and ROC, especially in classification studies involving imbalanced data.

Based on these considerations, this study conducts a Systematic Literature Review using the PRISMA framework to analyze recent studies on student achievement prediction models published between 2020 and 2024. This study focuses on three main research questions:

1) RQ1: What methodologies are most frequently used in developing student achievement prediction models?
2) RQ2: What factors are most frequently used as predictive variables?
3) RQ3: How are student achievement prediction models used in various studies between 2020 and 2024?

By answering these questions, this study aims to provide a structured understanding of current research trends, identify methodological and variable-related gaps, and propose future research directions for developing more accurate, comprehensive, and applicable student achievement prediction models.

2. METHODS

This study employed a Systematic Literature Review approach using the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. PRISMA was selected because it provides a clear and systematic structure for identifying, screening, evaluating, and selecting relevant studies. In the context of this research, PRISMA helps ensure that the literature selection process is transparent, reproducible, and aligned with the research objectives. Since the study focuses on reviewing student achievement prediction models, PRISMA is suitable for mapping recent research developments, identifying commonly used algorithms and variables, and synthesizing research trends in educational data mining.

The data used in this study consisted of scientific articles obtained from seven reputable international databases: Scopus, ScienceDirect, IEEE Xplore, SpringerLink, IOP, Wiley, and MDPI. These databases were selected because they contain a wide range of publications related to education, data mining, machine learning, artificial intelligence, and information systems. The article search was limited to publications between 2020 and 2024 to ensure that the analyzed studies reflected recent developments in student achievement prediction. The selected publication types included international journal articles and conference proceedings written in English. This limitation was applied to maintain consistency in analysis and ensure that the reviewed studies met international academic publication standards.

The search strategy was developed using keywords related to student performance prediction and machine learning. The keywords used in the search process were "student performance," "academic achievement," "student prediction," "machine learning," and "educational data mining." To improve search precision, Boolean operators were applied. The main search string used in this study was:

("student performance" OR "academic achievement" OR "student prediction") AND ("machine learning" OR "educational data mining").

This search string was designed to capture studies that specifically focused on predicting student achievement or performance using data mining or machine learning approaches.

The inclusion criteria consisted of articles published between 2020 and 2024, written in English, and published in international journals or conference proceedings. In addition, the selected studies had to focus on student performance or student achievement prediction using machine learning, data mining, or related computational approaches. Studies that only discussed general educational issues without predictive modeling were not included. The exclusion criteria consisted of review papers, short papers, editorials, workshop summaries, non-English publications, and studies that were not directly related to prediction models. Articles that did not provide sufficient methodological information or did not clearly describe the dataset, algorithm, or evaluation process were also excluded from the final analysis.

The study selection process followed several PRISMA stages. In the identification stage, 77 articles were initially collected from the selected databases. In the screening stage, titles, abstracts, and conclusions were reviewed to assess their relevance to the research topic. At this stage, 7 articles were removed because they were not relevant to student achievement prediction. In the eligibility stage, articles were further filtered based on publication year and topic suitability. A total of 14 articles were excluded because they did not match the required publication period or did not meet the inclusion criteria. After full-text assessment and dataset relevance checking, 52 articles were selected for final analysis.

To reduce bias during the selection process, this study used a structured review procedure. The first step involved screening titles and abstracts to identify articles that matched the research scope. The second step involved full-text evaluation to ensure that each article met the inclusion criteria. The review process followed predefined guidelines, including relevance to student achievement prediction, clarity of methodology, dataset appropriateness, algorithm description, and evaluation metric availability. This procedure

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helped ensure that the selected articles were suitable for systematic comparison and synthesis.

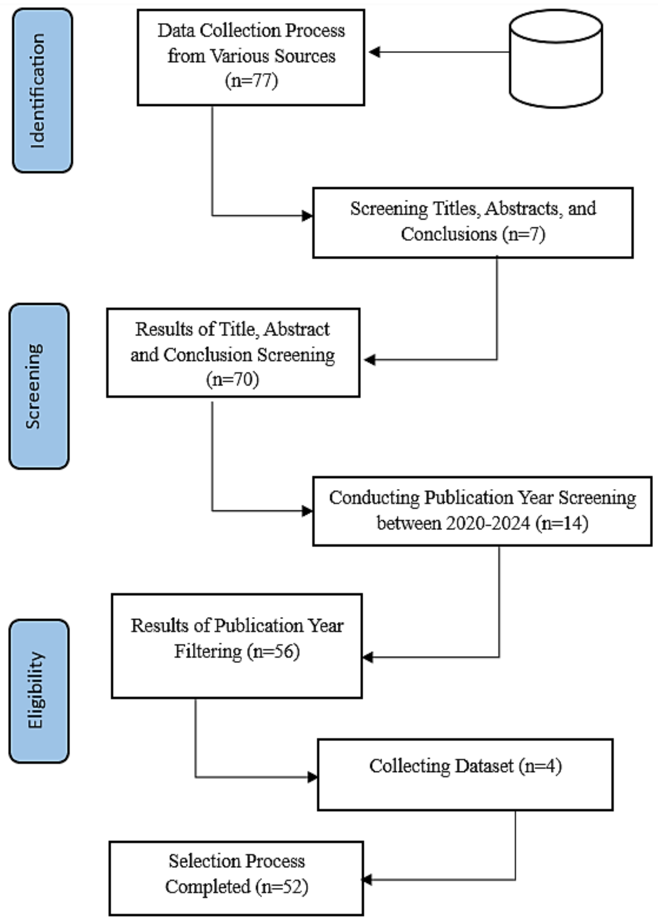

Figure 1. Prisma flow diagram of the study

Quality assessment was conducted to evaluate the methodological clarity of each selected study. The assessment criteria included the clarity of research objectives, the appropriateness of datasets and variables, the explanation of machine learning or data mining algorithms, and the use of evaluation metrics such as accuracy, F1-score, ROC, or AUC. Studies that lacked basic methodological information were excluded because they could reduce the reliability of the synthesis. This quality assessment was important because student achievement prediction studies vary widely in terms of dataset size, educational context, algorithm choice, and evaluation strategy.

Data extraction was conducted using a structured data extraction form. The extracted information included article title, author, publication year, educational context, predictive variables, and machine learning algorithms. Educational contexts were grouped into higher education, secondary school, elementary school, and other learning environments. Predictive variables were categorized into academic data, attendance data, demographic data, non-academic data, and combined variables. Algorithms were grouped into Random Forest, Decision Tree, Support Vector Machine, Naïve Bayes, K-Nearest Neighbor, Artificial Neural Network, XGBoost, and other methods.

Table 1. Research identification

No	Identification	Research Information
1	Title	Title of article in journal
2	Author	Author of articles in journals
3	Year	Year publication of journal in article
4	Variants Institutions	Higher institutions, elementary, secondary schools.
5	Variables	Demographics, academics, attendance, others.
6	Algorithm Data Mining	Random forest, naive bayes, support vector machine, neural network, decision tree, others

The extracted data were analyzed using qualitative synthesis. The analysis focused on identifying patterns in the selected studies, including the most frequently used algorithms, the dominant types of predictive variables, the educational contexts in which prediction models were applied, and the main research gaps. The results were then grouped and visualized to support interpretation. This synthesis approach allowed the study to provide a broad overview of research trends while also identifying specific limitations in existing student achievement prediction models.

3. RESULTS AND DISCUSSION

This section presents the findings obtained from 52 selected articles published between 2020 and 2024. The articles were analyzed based on the research questions formulated in this study. The analysis focuses on three main aspects: the methodologies used in student achievement prediction models, the predictive variables applied in previous studies, and the educational contexts in which student achievement prediction models have been implemented. The results are presented according to each research question to provide a clear connection between the review findings and the objectives of this study.

3.1. Overview of Selected Studies

The selected studies show that student achievement prediction has become an increasingly important topic in educational data mining. Most of the reviewed articles focused on predicting student academic performance, identifying at-risk students, estimating dropout probability, or supporting academic advising. The models developed in these studies generally used structured educational data, such as GPA, grades, attendance records, demographic information, and other student-related attributes. However, the level of data diversity varied across studies. Some studies used only academic records, while others incorporated additional variables such as demographic profiles, learning behavior, attendance, or student engagement indicators.

The distribution of selected studies also indicates that student achievement prediction research has been conducted across various educational levels. The analyzed articles covered higher education institutions, secondary schools, elementary schools, and other learning contexts such as online courses and training platforms. However, higher education appeared as the most dominant research context. This shows that universities and higher education institutions have a strong interest in using prediction models to support student retention, graduation monitoring, academic intervention, and institutional decision-making.

3.2. RQ1: What methodologies are most frequently used in developing student achievement prediction models?

The first research question focuses on identifying the methodologies most frequently used in the development of student achievement prediction models. The results show that classification-based machine learning methods are the dominant approach in the selected studies. Most studies formulated student achievement prediction as a classification problem, where students are grouped into specific performance categories such as pass and fail, high and low achievement, at-risk and not at-risk, or successful and unsuccessful academic outcomes.

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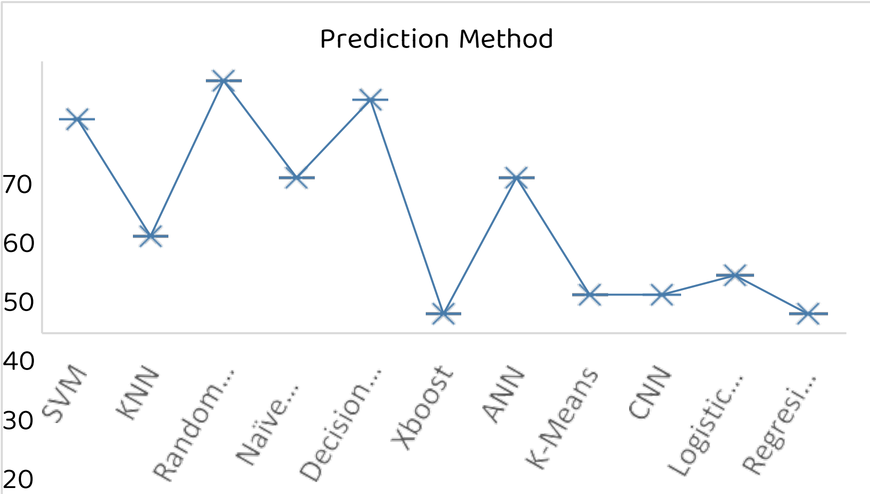

Figure 2. Algorithm that has been used

The algorithms most frequently found in the reviewed studies include Random Forest, Decision Tree, Support Vector Machine, Naïve Bayes, K-Nearest Neighbor, Artificial Neural Network, Logistic Regression, and XGBoost. Among these methods, Random Forest emerged as the most dominant algorithm. This finding indicates that Random Forest is widely considered suitable for educational datasets because it can handle complex variable relationships, reduce overfitting, and provide relatively stable prediction performance. This result is consistent with previous research showing that Random Forest can produce effective prediction results in student academic performance and study completion prediction [3], [29].

Decision Tree was also frequently used because of its interpretability and simple structure. In educational settings, interpretability is important because teachers, academic advisors, and administrators need to understand why a student is predicted to be at risk. Matzavela and Alepis [15] demonstrated the use of Decision Tree learning in predicting student academic performance in intelligent mobile learning environments. Although Decision Tree is easier to interpret, it may be less robust than ensemble-based models when dealing with complex datasets. This explains why Random Forest, as an ensemble extension of Decision Tree, is more frequently preferred in recent studies.

Support Vector Machine, Naïve Bayes, KNN, and Artificial Neural Network were also used in several studies. These algorithms were applied to predict student performance based on different combinations of academic, demographic, and attendance data. Yağcı [23]

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showed that several machine learning algorithms can be used to predict student academic performance with varying accuracy levels. Sharma et al. [24] analyzed student academic performance using machine learning techniques and found that algorithm performance depends strongly on dataset characteristics and selected features. Adnan et al. [5] also applied machine learning models to identify at-risk students at different percentages of course length, showing the potential of predictive models for early intervention.

The review also indicates that most studies still focus on comparing several individual algorithms rather than developing integrated or hybrid models. Although ensemble learning has been used through algorithms such as Random Forest and XGBoost, the use of more advanced hybrid frameworks remains limited. Some studies suggest that combining algorithms can improve prediction performance, especially when educational data contain multiple types of variables and complex relationships [8]. However, based on the selected studies, hybrid modeling has not yet become the dominant approach. Therefore, the answer to RQ1 is that classification-based machine learning methods are the most frequently used methodologies, with Random Forest as the most dominant algorithm, while hybrid and more advanced ensemble approaches remain underexplored.

3.3. RQ2: What factors are most frequently used as predictive variables?

The second research question focuses on identifying the factors most frequently used as predictive variables in student achievement prediction models. The results show that academic variables are the most dominant type of data used in the reviewed studies. Academic variables include Grade Point Average (GPA), course grades, examination scores, previous semester performance, cumulative academic records, and prior academic achievement. These variables are widely used because they are directly related to student learning outcomes and are usually available in institutional academic information systems.

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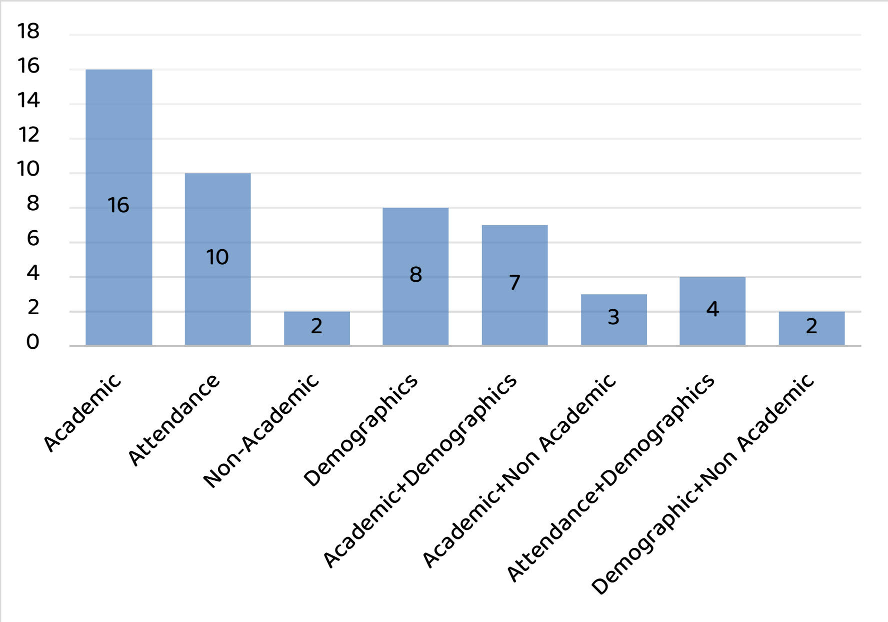

Figure 3. Prediction Variable

Based on the variable grouping, academic variables appeared as the most frequently used category, with 16 studies relying primarily on academic data. Attendance variables were used in 10 studies, while demographic variables were used in 8 studies. Several studies used combined variables, including academic and demographic variables in 7 studies, attendance and demographic variables in 4 studies, academic and non-academic variables in 3 studies, non-academic variables in 2 studies, and demographic and non-academic variables in 2 studies. This distribution shows that most student achievement prediction models still depend heavily on structured academic data.

Attendance data appeared as the second most commonly used variable category. Attendance is often considered a meaningful indicator because it reflects student participation, discipline, and engagement in learning activities. Students with low attendance may have a higher probability of academic difficulty, especially when attendance is closely related to coursework participation, classroom interaction, and assessment completion. Several prediction models used attendance together with academic records to improve prediction accuracy. This indicates that attendance can function as both a behavioral indicator and an academic support variable.

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Demographic variables were also used in several studies, although less frequently than academic and attendance data. These variables may include gender, age, educational background, socioeconomic background, or other personal attributes. Demographic data can help explain variations in student achievement, especially when combined with academic variables. However, the use of demographic data requires careful consideration because such variables may raise ethical concerns if they are used without proper interpretation or fairness assessment. In predictive modeling, demographic variables should not be used merely to label students, but to support more inclusive and contextual academic intervention.

The results also show that non-academic variables are still rarely included in prediction models. This is an important finding because student achievement is influenced not only by academic history but also by factors such as motivation, learning behavior, social environment, psychological condition, family support, and digital learning activity. Hussain and Khan [7] suggested that additional attributes, such as social context and media usage, can make student performance prediction more effective. Mai et al. [13] also showed that learning behavior data can provide useful insights for predicting academic outcomes. However, despite their potential value, non-academic variables remain underutilized in the reviewed literature.

Based on RQ2, it can be concluded that academic variables are the most frequently used predictive factors in student achievement prediction models. Attendance and demographic variables are also used, but with lower frequency. Meanwhile, non-academic variables and combined multi-source variables are still limited. This result indicates a research gap in the development of more comprehensive prediction models that integrate academic and non-academic data to better represent the multidimensional nature of student achievement.

3.4. RQ3: How are student achievement prediction models used in various studies between 2020 and 2024?

The third research question focuses on how student achievement prediction models have been used in studies published between 2020 and 2024. The results show that these models are mainly applied in higher education contexts. From the 52 selected articles, 27 studies focused on higher education institutions, 12 studies focused on secondary

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schools, 8 studies focused on elementary schools, and 5 studies focused on other learning contexts, such as courses, online learning, or training programs.

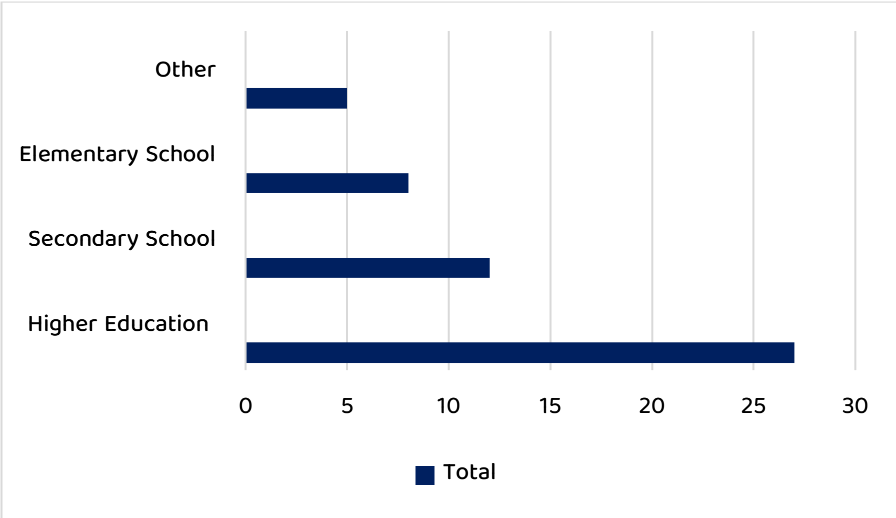

Figure 4. Education Institutions

The dominance of higher education indicates that universities have become the primary context for implementing student achievement prediction models. This may be due to the availability of structured academic data, such as GPA, course grades, attendance records, credit completion, semester performance, and graduation status. Higher education institutions also have a strong need for prediction systems because they must monitor student retention, reduce dropout rates, improve graduation quality, and support academic advising. Mengash [30] showed that data mining techniques can be used to predict student performance and support decision-making in university admission systems. This supports the finding that student prediction models can be used not only for academic monitoring but also for broader institutional decision-making.

In higher education, student achievement prediction models are commonly used for early detection of students at risk of academic failure, delayed graduation, or dropout. Predictive models can help institutions identify students who require academic support before their performance declines further. For example, Adnan et al. [5] developed machine learning models to predict at-risk students at different percentages of course length, allowing early intervention to be carried out before the course ends. Similarly, Okoye et al. [2] developed a machine learning model and ensemble algorithm for

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predicting student retention and graduation, showing that prediction models can support long-term academic planning.

In secondary school contexts, prediction models are generally used to classify student academic performance and identify factors that influence learning achievement. Hussain and Khan [7] developed a model to predict students' academic performance at secondary and intermediate levels using machine learning. These studies show that prediction models can support teachers and school administrators in understanding student learning conditions and identifying students who may require additional support. However, the number of studies in secondary education remains lower than in higher education, indicating that this area still has room for further development.

In elementary school contexts, student achievement prediction models are less frequently applied. This may be related to limitations in data availability, ethical considerations, or the complexity of collecting structured data from younger students. However, early prediction at the elementary level can be valuable because it allows schools to identify learning difficulties from an early stage. If properly designed, prediction models at this level can support personalized learning strategies and early academic assistance. Nevertheless, the reviewed studies show that elementary school prediction remains less explored compared to university-level prediction.

The selected studies also show that prediction models are used in other contexts, including online learning platforms, courses, and training systems. Alsubaie [18], for example, investigated student performance prediction to improve the quality assurance of online training through the Maharat platform. In online learning environments, prediction models can use digital traces such as login frequency, course progress, assignment submission, quiz scores, and interaction patterns. These data provide new opportunities for developing prediction models that are more dynamic and behavior-oriented. However, compared with formal higher education studies, prediction research in online training and non-formal learning contexts is still limited.

Based on RQ3, it can be concluded that student achievement prediction models are mainly used in higher education, especially for early warning systems, dropout prediction, academic advising, retention monitoring, and decision support. Although the models have also been applied in secondary schools, elementary schools, and online learning contexts, their implementation remains concentrated in higher education. This finding shows that future research should expand the application of student achievement prediction models to more diverse educational levels and learning environments.

3.5. Proposed Framework for Student Learning Achievement Prediction

Based on the synthesis of the reviewed studies, this research proposes a framework for developing student learning achievement prediction models. The framework is designed to address the main limitations identified in previous studies, particularly the overreliance on academic variables, limited use of hybrid models, and lack of integrated data processing pipelines. The proposed framework emphasizes the integration of academic and non-academic data, structured preprocessing, hybrid modeling, and model evaluation.

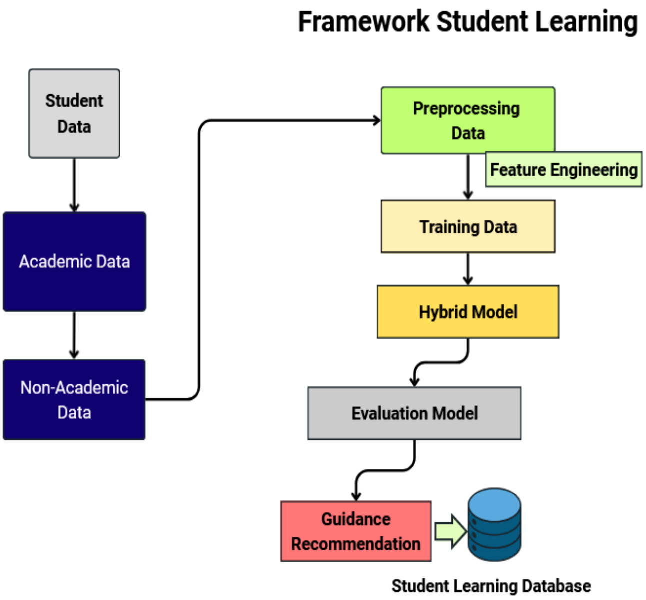

Figure 5. Model Framework Student learning

The proposed framework begins with the collection of student data. The data may include academic variables such as GPA, grades, previous semester performance, and examination results, as well as non-academic variables such as attendance, demographics, learning behavior, social factors, motivation, and interaction patterns. The inclusion of multiple data sources is important because student achievement is influenced by various academic and contextual factors. By integrating these variables, prediction models can produce more comprehensive and realistic outputs.

After data collection, the next stage is data preprocessing. This stage includes data cleaning, duplicate removal, missing value handling, data transformation, and format standardization. Preprocessing is essential because educational datasets often contain incomplete, inconsistent, or noisy data. Poor data quality can reduce prediction accuracy and affect model reliability. Therefore, the preprocessing stage must be carefully conducted before training the prediction model.

The next stage is model development using hybrid or ensemble approaches. The framework encourages the use of multiple algorithms or combined modeling strategies to improve prediction accuracy and robustness. Hybrid models can combine the strengths of different algorithms, while ensemble methods can reduce prediction error by aggregating multiple learners. Previous studies have shown that ensemble approaches can improve student retention and graduation prediction [2], while combining machine learning methods can enhance prediction effectiveness [8].

The final stage is model evaluation. Evaluation should not rely only on accuracy, because accuracy can be misleading when the dataset is imbalanced. Metrics such as precision, recall, F1-score, ROC-AUC, and confusion matrix should be used to provide a more complete evaluation of model performance. Sekeroglu et al. [21] emphasized the importance of using AUC, F1-score, and ROC in classification studies, especially when dealing with imbalanced educational datasets. A reliable evaluation process ensures that the model is not only accurate but also applicable and trustworthy in real educational contexts.

3.6. Discussion

The results of this systematic literature review show that student achievement prediction research has developed significantly during the 2020–2024 period. The reviewed studies demonstrate that machine learning and data mining methods have been widely used to support academic prediction, early warning systems, dropout identification, and institutional decision-making. However, the findings also reveal several important limitations that need to be addressed in future research. These limitations are mainly related to methodological concentration, limited data diversity, insufficient use of non-academic variables, and the lack of practical implementation frameworks.

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The dominance of classification-based methods indicates that most studies view student achievement prediction as a categorization task. This approach is practical because educational institutions often need clear categories to guide decision-making. For example, a model may classify students into at-risk and not-at-risk groups, allowing academic advisors to prioritize students who require support. Classification outputs are easier to interpret and can be directly connected to intervention strategies. However, student achievement is not always a simple binary or categorical condition. Academic performance develops over time and may be influenced by many interacting factors. Therefore, while classification methods are useful, future research should also consider time-series models, longitudinal prediction, regression-based estimation, and explainable learning analytics to capture the dynamic nature of student achievement.

Random Forest was found to be the most frequently used algorithm. This finding is reasonable because Random Forest has several advantages in educational prediction. It can handle high-dimensional data, reduce overfitting, and process non-linear relationships among variables. Compared with a single Decision Tree, Random Forest generally provides more stable results because it combines multiple trees. This explains why many studies prefer Random Forest when working with student datasets. However, frequent use of one algorithm also indicates a potential methodological limitation. If studies continue to focus mostly on Random Forest and similar conventional algorithms, the field may miss opportunities to explore more advanced methods such as deep learning, graph neural networks, stacking ensembles, and explainable AI.

The limited exploration of hybrid models is one of the key gaps identified in this review. Although some studies have used ensemble algorithms, many still compare individual models without developing a fully integrated framework. In practice, student achievement prediction may benefit from hybrid approaches because educational data are complex and heterogeneous. Academic records, attendance, demographics, learning behavior, and psychological factors may interact in ways that cannot be fully captured by a single algorithm. A hybrid framework can combine multiple methods to improve robustness and reduce prediction bias. For example, one model may be strong in handling structured academic data, while another may be better at identifying behavioral patterns. Combining these strengths can lead to more accurate and meaningful predictions.

Another important finding is the dominance of academic variables. This result is understandable because academic data are easier to access, structured, and directly related to student outcomes. GPA, grades, and previous academic performance are strong indicators because they represent students' learning history. Priyambada and Usagawa [27] showed that previous academic performance and learning behavior can be used to predict student performance. However, relying too much on academic variables may produce models that are incomplete. Students do not succeed or fail only because of previous grades. Their performance may also be influenced by motivation, mental health, family conditions, economic background, learning environment, digital engagement, and social support.

The limited use of non-academic variables suggests that current prediction models may not fully capture the multidimensional nature of student achievement. Non-academic variables can provide important contextual information. For example, learning behavior data can reveal how actively students engage with learning materials, while social and psychological variables can explain why students may experience academic decline despite having good previous grades. Mai et al. [13] showed that learning behavior data in programming education can support community analysis and outcome prediction. Hussain and Khan [7] also emphasized the importance of additional attributes in predicting academic performance. These findings support the argument that future prediction models should integrate both academic and non-academic data.

However, the inclusion of non-academic variables also brings methodological and ethical challenges. Non-academic data are often more difficult to collect, less structured, and more sensitive than academic records. For example, psychological condition, socioeconomic background, or social behavior data must be handled carefully to protect student privacy. Researchers and institutions must ensure that prediction models do not create unfair labeling or discriminatory decisions. The purpose of prediction should be to support students, not to punish or stigmatize them. Therefore, ethical data governance, informed consent, fairness evaluation, and transparency must become important considerations in future student achievement prediction research.

The dominance of higher education contexts also deserves attention. Universities are more likely to have structured academic databases, student information systems, and institutional needs related to retention and graduation. This makes higher education a suitable setting for predictive analytics. However, the smaller number of studies in elementary and secondary education indicates that prediction models are not yet equally developed across educational levels. Early prediction at school level could be highly valuable because learning difficulties can be identified before they become more serious. Future research should therefore explore how prediction models can be adapted for younger learners, with appropriate ethical safeguards and pedagogical interpretations.

The application of prediction models in online learning and training platforms also presents important opportunities. Online learning environments generate large amounts of digital trace data, such as login frequency, video viewing behavior, quiz attempts, discussion activity, assignment submission time, and learning resource access. These data can provide more detailed insights into student engagement and learning behavior. Alsubaie [18] showed that machine learning can be used to predict student performance in online training to improve quality assurance. As digital learning continues to grow, prediction models should move beyond static academic records and incorporate dynamic behavioral data from learning management systems.

The findings also show that many studies focus primarily on prediction accuracy. While accuracy is important, it should not be the only measure of model quality. In educational settings, a model must also be interpretable, fair, actionable, and useful for decision-making. A highly accurate model may have limited value if educators cannot understand its results or if the institution does not know how to respond to the prediction. For example, identifying a student as at risk is only useful if the institution can provide appropriate intervention, such as counseling, tutoring, mentoring, or academic advising. Therefore, future studies should evaluate not only technical performance but also practical usefulness and educational impact.

Model evaluation also needs improvement. Some studies still rely heavily on accuracy, even though accuracy can be misleading when datasets are imbalanced. If most students in a dataset pass a course, a model can achieve high accuracy simply by predicting that most students will pass. This situation can hide poor performance in identifying at-risk students. Therefore, evaluation metrics such as precision, recall, F1-score, ROC-AUC, and confusion matrix should be used more consistently. Sekeroglu et al. [21] recommended the use of AUC, F1-score, and ROC in classification studies, particularly for imbalanced datasets. Consistent evaluation metrics would make it easier to compare results across studies.

The proposed framework in this study contributes to addressing the gaps identified in the review. The framework emphasizes multi-source data integration, which can reduce dependence on academic variables alone. It also encourages the use of hybrid modeling approaches to improve prediction performance and model robustness. In addition, the framework includes structured preprocessing and evaluation stages to ensure data quality and model reliability. Unlike studies that only compare algorithms, the proposed framework connects data collection, preprocessing, model development, and evaluation into a complete prediction pipeline. This makes the framework more suitable for future research and possible institutional implementation.

From a practical perspective, student achievement prediction models can support educational institutions in several ways. First, they can help identify students who need academic support before failure occurs. Second, they can assist academic advisors in prioritizing intervention. Third, they can support institutional planning by identifying patterns related to dropout, delayed graduation, or low achievement. Fourth, they can help evaluate the effectiveness of learning programs. However, these benefits can only be achieved if prediction models are implemented responsibly. Institutions must ensure that predictive analytics are used to empower students and improve learning outcomes, not to create rigid labels or reduce educational decisions to algorithmic outputs.

This review also has several limitations. The analysis was limited to articles published between 2020 and 2024, written in English, and indexed in selected databases. Therefore, relevant studies outside this period, written in other languages, or published in other sources may not have been included. In addition, some selected studies did not provide complete information about datasets, preprocessing methods, or evaluation procedures. This limitation may affect the depth of analysis, especially in comparing model performance across studies. Nevertheless, the selected articles provide a strong basis for identifying current trends, dominant methods, commonly used variables, and future research directions in student achievement prediction.

Based on the results and discussion, future research should focus on several directions. First, researchers should develop prediction models that integrate academic, demographic, behavioral, psychological, and social variables. Second, hybrid and ensemble models should be explored more deeply to improve prediction accuracy and robustness. Third, future studies should use standardized evaluation metrics to allow better comparison across models. Fourth, prediction models should be tested in real educational settings to evaluate their usefulness for teachers, advisors, and institutional decision-makers. Finally, ethical considerations, including data privacy, fairness, transparency, and responsible intervention, should become central components of future student achievement prediction research.

4. CONCLUSION

This study systematically reviewed 52 articles published between 2020 and 2024 using the PRISMA framework to identify trends, methods, predictive variables, and research gaps in student achievement prediction models. The findings show that classification-based machine learning methods dominate this research area, with Random Forest being the most frequently used algorithm, followed by Decision Tree, Support Vector Machine, Naïve Bayes, K-Nearest Neighbor, Artificial Neural Network, and XGBoost. Academic variables, including GPA, grades, previous achievement, and attendance, remain the most commonly used predictors, while non-academic variables such as behavioral, social, psychological, and socioeconomic factors are still rarely explored. The review also reveals that most studies rely on single-model approaches and have limited use of hybrid or integrated prediction frameworks. These findings indicate that future research should focus on multi-source data integration, the adoption of hybrid and ensemble models, and the development of prediction systems that are more explainable, generalizable, and applicable in real educational environments. The impact of this study lies in providing a structured synthesis of recent research and offering evidence-based directions for developing more accurate and comprehensive student achievement prediction models to support educational decision-making and early academic intervention.

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