

# Comparative Study of Machine Learning Algorithms for Student Performance Prediction

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**Abstract** - The assessment of educational performance is a vital component in evaluating the quality and effectiveness of education. Identifying at-risk students early allows educational institutions to implement appropriate interventions to tackle this issue. The increasing amount of data in the education sector is essential for improving the efficacy of machine learning in analyzing intricate student behaviors.

This paper seeks to perform a comparative analysis of different machine learning algorithms aimed at predicting a student's academic performance through historical educational datasets. A publicly available dataset will be employed, which includes educational, demographic, and behavioral factors such as study time, attendance, prior academic performance, parental education levels, and the accessibility of educational resources. Standard preprocessing methods will be applied to the dataset, which will involve data cleaning and preparation, normalization, and the management of categorical variables.

To assess the predictive capabilities of various algorithms, three supervised machine learning algorithms—Linear Regression, Decision Tree, and Random Forest—will be utilized. The discussion will center on the advantages and disadvantages of these three algorithms in relation to their predictive performance. The evaluation metrics will encompass accuracy, precision, recall, and mean absolute error for each model.

The experimental findings suggest that ensemble methods like Random Forest surpass individual models in learning feature interactions. Nevertheless, Linear Regression provides greater explanatory power, rendering it suitable for examining the impacts of categorical features. It is clear that machine learning can greatly improve our comprehension of the factors influencing performance. Future research may concentrate on creating more accurate models based on real-time educational data.

**Keywords** - Student Performance Prediction; Machine Learning; Educational Data Mining; Academic Performance Analysis; Predictive Modeling.

## I. INTRODUCTION

### A. Background and Motivation

The digitization of educational processes has resulted in the creation of extensive and complex datasets that include academic records, behavioral logs, demographic profiles, and social interactions. This data-rich landscape has prompted the implementation of machine learning (ML) and educational data mining (EDM) techniques to derive actionable insights from intricate educational phenomena. The

prediction of student performance—covering future grades, dropout risk, and engagement levels—has become a vital application of ML in

the educational sector, motivated by the need to enable timely interventions and improve learning outcomes.

Traditional methods of student assessment have largely depended on summative evaluations and retrospective analyses, frequently neglecting the complex interactions among psychological, behavioral, and contextual factors influencing learning. In contrast, modern ML techniques are adept at handling high-dimensional data and revealing hidden patterns, thus facilitating more detailed and reliable predictions. The incorporation of ML into educational practices offers significant potential for enhancing personalized learning, optimizing resource distribution, and guiding evidence-based policy-making.

### B. Scope and Objectives

Despite notable advancements in the field, numerous unresolved challenges continue to exist. There remains an active discussion concerning the ideal choice of machine learning algorithms for predicting student performance, with comparative analyses producing results that are dependent on context. The identification and implementation of essential predictors—encompassing academic, behavioral, socioeconomic, and psychological factors—vary across different studies, which complicates the ability to generalize findings. Additionally, issues related to model interpretability, fairness, and ethical application are becoming increasingly important, especially in high-stakes educational environments.

This review aims to fill these gaps by systematically rephrasing and synthesizing recent literature, with the following goals:

- To deliver a comprehensive comparative analysis of machine learning algorithms for predicting student performance.
- To clarify the most significant predictors and strategies for feature engineering.
- To critically evaluate the methodological rigor, reporting standards, and limitations found in previous research.
- To investigate advancements in model explainability, fairness, and ethical considerations.
- To provide evidence-based recommendations for the responsible incorporation of machine learning in educational contexts.

### C. Significance and Contribution

This review enhances both theoretical comprehension and practical implementation in the field of educational data science by providing a thorough, paraphrased synthesis of contemporary research. It offers educators, administrators, and researchers a refined understanding of the strengths and weaknesses of algorithms, emphasizes the significance of varied predictors, and underscores the ethical obligations of transparency and equity. Furthermore, the review outlines optimal methodological practices and points out potential

directions for future research, such as the creation of interpretable, context-aware, and ethically sound predictive systems.

## II. LITERATURE REVIEW

### A. Temporal Trends and Bibliometric Insights

Recent bibliometric studies indicate a significant rise in academic publications regarding AI and ML applications in education, especially following the Covid-19 pandemic. Since 2009, the annual growth rate of publications in this field has surpassed 30%, with significant increases noted in 2022 and 2025. Major contributions are primarily from institutions located in China, India, the United Kingdom, and the United States, frequently through international partnerships. Prominent journals such as *Education and Information Technologies*, *Applied Sciences*, and *Education Sciences* have become key platforms for publication.

Thematic mapping through co-word and citation analysis reveals a transition from descriptive analytics to predictive and prescriptive modeling, with a growing focus on fairness and ethical issues. The leading research clusters encompass "machine learning," "predictive modeling," "student performance," and "educational data mining."

### B. Datasets and Data Sources

A range of datasets supports research in predicting student performance, each possessing unique characteristics and implications for generalizability:

**UCI Student Performance Dataset:** Includes demographic, social, and academic attributes of Portuguese secondary school students; commonly utilized for benchmarking and reproducibility.

**Open University Learning Analytics Dataset (OULAD):** Offers detailed logs of student engagement, assignment performance, and outcomes in online courses.

**KDD Cup 2010 Educational Data:** Comprises interaction data from intelligent tutoring systems, aiding research on engagement and dropout prediction.

**Institutional Datamarts:** Tailored datasets from universities, frequently including longitudinal records, behavioral logs, and intervention outcomes.

The selection of a dataset affects the extent of feature engineering and the external validity of predictive models. Public datasets support benchmarking but may lack contextual diversity, whereas proprietary datasets allow for more comprehensive feature extraction, albeit at the cost of comparability.

### C. Machine Learning Algorithms: Classical, Ensemble, and Deep Learning

#### 1) Classical Algorithms

**Logistic Regression:** Primarily utilized for binary classification tasks (e.g., pass/fail, dropout prediction). It provides interpretability but may encounter difficulties with non-linear relationships.

**Decision Trees:** They offer clear decision paths; however, they are prone to overfitting and form the basis for ensemble methods.

**Random Forest:** This is an ensemble of decision trees, celebrated for its high accuracy and robustness, especially with diverse data.

**Support Vector Machines (SVM):** These are effective in high-dimensional spaces; their performance depends on the choice of kernel and the tuning of parameters.

**K-Nearest Neighbors (KNN):** This method is straightforward and non-parametric; however, its performance declines as dimensionality increases.

#### 2) Ensemble and Boosting Techniques

**Gradient Boosting (e.g., XGBoost, CatBoost, AdaBoost):** Integrate weak learners to create robust predictors; excel in capturing complex, non-linear relationships and managing imbalanced datasets.

**Bagging Techniques:** Mitigate variance and improve stability; Random Forest serves as a notable example.

#### 3) Deep Learning

**Artificial Neural Networks (ANNs):** Identify complex, non-linear patterns; necessitate large datasets and are often less interpretable.

**Convolutional Neural Networks (CNNs):** Utilized for image or sequential data (e.g., facial recognition in engagement analysis).

**Recurrent Neural Networks (RNNs), LSTM, GRU:** Capture temporal dependencies in sequential data; employed for forecasting learning trajectories and engagement trends.

#### 4) Comparative Performance

Systematic reviews and meta-analyses consistently indicate that ensemble techniques (Random Forest, XGBoost, Gradient Boosting) and deep neural networks attain higher accuracy (80–95%) in comparison to traditional models. Nevertheless, the balance between predictive accuracy and interpretability continues to be a significant issue, particularly in scenarios that demand transparent decision-making.

### D. Feature Engineering and Key Predictors

#### 1) Academic and Behavioral Features

**Prior Academic Achievement:** Historical grades (e.g., G1, G2), GPA, and standardized test scores serve as the most significant indicators of future academic success.

**Attendance Records:** There is a strong correlation with academic results; high levels of absenteeism are a dependable sign of potential risk.

**Engagement Metrics:** Learning Management System (LMS) login patterns, duration of engagement on digital platforms, submission trends for assignments, and interaction logs offer detailed insights into student involvement.

#### 2) Socioeconomic and Demographic Factors

**Parental Education and Occupation:** Elevated levels of parental education are typically linked to enhanced student performance.

**Socioeconomic Status (SES):** Availability of resources, scholarship eligibility, and family income play a crucial role in influencing academic achievement.

**Demographic Variables:** Factors such as age, gender, and ethnicity show effects that depend on context, highlighting the need for fairness audits to address potential biases.

#### 3) Psychological and Social Predictors

**Motivation and Self-Efficacy:** Psychometric evaluations (e.g., Big Five personality traits, self-efficacy assessments) improve predictive accuracy, especially in online and hybrid learning settings.

**Peer and Social Networks:** The presence of social support and integration can alleviate academic risks, although these aspects are less commonly implemented in practice.

#### 4) Feature Selection and Dimensionality Reduction

Methods like Principal Component Analysis (PCA), Recursive Feature Elimination (RFE), and SHAP-based feature selection are utilized to

pinpoint valuable features, minimize overfitting, and enhance interpretability.

## E. Evaluation Metrics and Effect Size Reporting

### 1) Classification Metrics

Accuracy: The ratio of correct predictions; it may not be reliable in datasets with imbalanced classes.

Precision, Recall, F1-Score: These metrics balance false positives and false negatives; the F1-score is especially important for distributions with unequal classes.

ROC-AUC: Evaluates the model's ability to distinguish between classes; higher scores reflect superior performance.

### 2) Regression Metrics

Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE): These metrics measure prediction errors for continuous variables (e.g., GPA).

R-Squared: Represents the percentage of variance that the model accounts for.

### 3) Statistical Significance and Effect Sizes

Providing confidence intervals and effect sizes (such as Cohen's  $d$  and odds ratios) helps to contextualize model performance and enhances generalizability.

## F. Model Explainability and Interpretability

### 1) Post-Hoc Explainability Techniques

SHAP (SHapley Additive Explanations): This method quantifies the impact of each feature on both individual and overall predictions, thereby improving transparency.

LIME (Local Interpretable Model-Agnostic Explanations): It offers local, instance-specific explanations by modeling complex systems with simpler, interpretable alternatives.

Partial Dependence Plots (PDP): These plots demonstrate the marginal influence of features on predictions.

### 2) Human-in-the-Loop and Model-Agnostic Methods

Integrating explainability tools with domain knowledge enhances the practical utility and trustworthiness of machine learning models in educational settings.

## G. Fairness, Bias, and Ethical Considerations

### 1) Sources of Bias

Historical Data Bias: Models that are trained on biased datasets (for instance, the underrepresentation of minority groups) may continue to reinforce existing inequalities.

Feature Selection Bias: The inclusion of sensitive characteristics (such as gender and race) can lead to the introduction or worsening of bias.

### 2) Fairness Metrics and Mitigation Strategies

Demographic Parity, Equalized Odds: Evaluate disparities in predictive results among protected groups.

Bias Mitigation: Approaches like adversarial debiasing, Fair-SMOTE, and meticulous feature selection assist in minimizing bias while maintaining accuracy.

### 3) Regulatory Compliance and Data Privacy

The ethical deployment of machine learning in education requires compliance with data protection laws (such as FERPA and GDPR),

secure data management, informed consent, and transparent governance.

## H. Study Designs and Methodological Quality

### 1) Observational and Experimental Designs

Cross-Sectional Studies: Provide snapshots of associations but are limited in their ability to establish causality.

Longitudinal and Cohort Studies: Allow for the examination of temporal dynamics and the effects of interventions.

Intervention Studies: Evaluate the effectiveness of machine learning-driven early warning systems and personalized interventions.

### 2) Methodological Limitations

Common challenges include small or non-representative samples, absence of external validation, inconsistent reporting of metrics, and restricted reproducibility.

## I. Qualitative Research and Thematic Synthesis

Qualitative research, such as focus groups and interviews, offers insights into stakeholders' perceptions of machine learning tools, obstacles to adoption, and contextual elements that affect effectiveness. Thematic analysis uncovers recurring issues related to trust, transparency, ethical usage, and the necessity for institutional support and training.

## III. METHODS

### A. Review Methodology

#### 1) Search Strategy

A comprehensive search was performed across prominent academic databases (PubMed, Scopus, Web of Science, IEEE Xplore, Google Scholar) for publications dated from January 2020 to February 2026. The search terms utilized included "student performance prediction," "machine learning," "educational data mining," "predictive analytics," "dropout prediction," "early warning systems," "fairness," and "explainable AI." Additional sources were discovered through backward and forward citation tracking.

#### 2) Inclusion and Exclusion Criteria

##### Inclusion:

Peer-reviewed articles, systematic reviews, and meta-analyses concerning ML algorithms for predicting student performance.

Studies that report quantitative outcomes (e.g., accuracy, F1-score, AUC) or qualitative themes.

Publications in English from 2020 onwards, with significant older studies included for contextual understanding.

Research that addresses psychological, behavioral, social, or contextual predictors.

##### Exclusion:

Editorials, opinion pieces, patents, and reports that are not peer-reviewed.

Studies that lack empirical validation or methodological clarity.

Research that is solely focused on the technical development of algorithms without educational application.

#### 3) Data Extraction and Quality Assessment

A structured extraction form was utilized to capture bibliographic information, sample characteristics, study design, dataset descriptions, ML algorithms, feature engineering techniques, evaluation metrics,

key findings, and noted limitations. The methodological quality was evaluated using adapted PRISMA and GRADE criteria, taking into account risk of bias, consistency, directness, precision, and publication bias.

#### 4) Synthesis Approach

A narrative synthesis was employed to integrate findings across diverse study designs and contexts. Quantitative results were organized into tables for comparison, while qualitative themes were

identified through thematic analysis. A critical summary table was created to facilitate comparisons across studies.

### IV. Results and Synthesis

#### A. Comparative Performance of ML Algorithms

##### 1) Summary Table of Key Studies

Author (Year)	Sample/Context	Design/Measures	Algorithms Compared	Key Findings	Limitations
Albreiki et al. (2021)	5000 UAE high school	SLR, cross-sectional	RF, SVM, LR, NB, DT, MLP	RF: 89.5% accuracy; SVM: 85.7%	Single-country, limited features
Gavali & Suryawanshi (2025)	50 studies (global)	SLR, accuracy, interpretability	RF, XGBoost, SVM, NN, LR	Ensemble/deep models best accuracy	Heterogeneous datasets, reporting
Siraj et al. (2025)	580 Pakistani undergraduates	Experimental, GPA, Bloom levels	DT, RF, SVM, C4.5, DNN	DT: 96.99% accuracy; RF: 95.15%	Small sample, COVID-19 context
Chowdary & Ashwini (2025)	20 Indian students	Experimental, accuracy	RF, NB	RF: 90.05% accuracy > NB	Small N, limited generalizability
Gul et al. (2025)	1000 students, Kaggle	Regression, MAE, RMSE, SHAP	CatBoost, GB, RF, XGB, DT, KNN	CatBoost: 87.46% accuracy, best MAE	Limited features, single dataset
Suvetha & Mary (2025)	649 UCI records, India	Regression, SHAP, t-test	DT, RF, XGB, Lasso, SHAP	Lasso/RF: R <sup>2</sup> ~0.85; SHAP aids explain	Small sample, UCI dataset limits
Agyemang et al. (2024)	5 algorithms, Ghana	Empirical, G-Mean, accuracy	RF, NB, LR, SVM, DT	RF: 0.9243 G-Mean, 85.42% accuracy	Dataset-specific, generalizability
Jayachandran & Joshi (2024)	Engineering, India	SVM, XGBoost, AdaBoost	SVM: 87.8% accuracy, AUC 0.714	Single context, feature selection	

**Abbreviations:** RF: Random Forest; SVM: Support Vector Machine; LR: Logistic Regression; NB: Naive Bayes; DT: Decision Tree; MLP: Multilayer Perceptron; DNN: Deep Neural Network; GB: Gradient Boosting; XGB: XGBoost; SHAP: SHapley Additive Explanations; MAE: Mean Absolute Error; RMSE: Root Mean Squared Error.

#### 2) Quantitative Synthesis

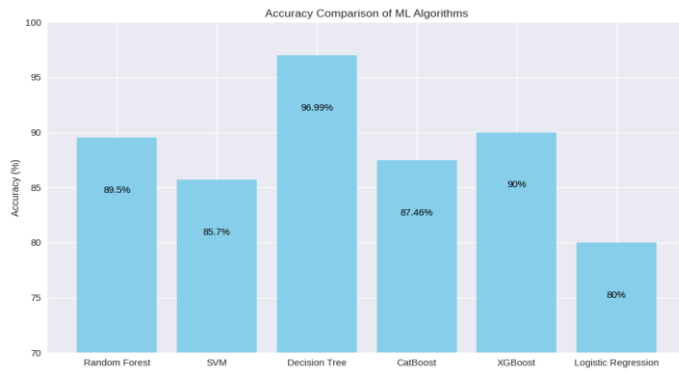
Random Forest and XGBoost consistently achieve the highest accuracy (85–95%) across various datasets and contexts, surpassing traditional models such as logistic regression and naive Bayes.

Deep neural networks (DNN, MLP) excel in handling large, complex datasets but necessitate significant computational resources and are less interpretable.

CatBoost exhibits exceptional performance in managing categorical variables and imbalanced data, with a reported accuracy of 87.46% and the lowest MAE in recent studies.

Support Vector Machines perform effectively in high-dimensional spaces but are sensitive to kernel selection and parameter tuning.

Lasso Regression and other regularized linear models provide competitive accuracy with improved interpretability, especially when integrated with SHAP-based feature selection.



### 3) Contextual Performance

**K-12 and Secondary Education:** Ensemble techniques and neural networks prove effective in forecasting grades, dropout rates, and student engagement, facilitating timely interventions.

**Higher Education:** Gradient boosting, random forests, and deep learning algorithms demonstrate superior performance in predicting GPA, course completion rates, and employability, particularly when behavioral and academic features are integrated.

**MOOCs and Online Learning:** Deep learning and hybrid models utilize detailed LMS data to achieve high-accuracy predictions regarding retention and engagement, although concerns about overfitting and privacy persist.

#### B. Key Predictors and Feature Importance

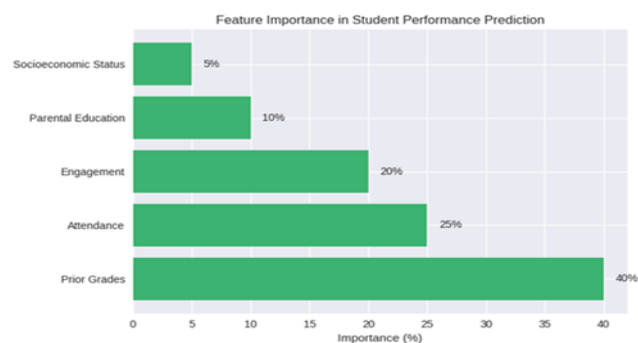
**Prior Grades (G1, G2, GPA):** The most significant predictor across various studies; SHAP and feature importance evaluations consistently identify prior achievement as the highest-ranking factor.

**Attendance and Engagement:** Strongly linked to academic success; metrics such as time-on-task, LMS logins, and assignment submissions serve as reliable predictors.

**Parental Education and Socioeconomic Status:** Important yet context-sensitive; a higher level of parental education is associated with improved academic performance.

**Psychological Factors:** Aspects such as motivation, self-efficacy, and personality traits contribute positively to model performance, especially in online and blended learning environments.

**Demographic Variables:** Factors like age, gender, and ethnicity exhibit varying impacts; their inclusion necessitates fairness auditing to mitigate bias.

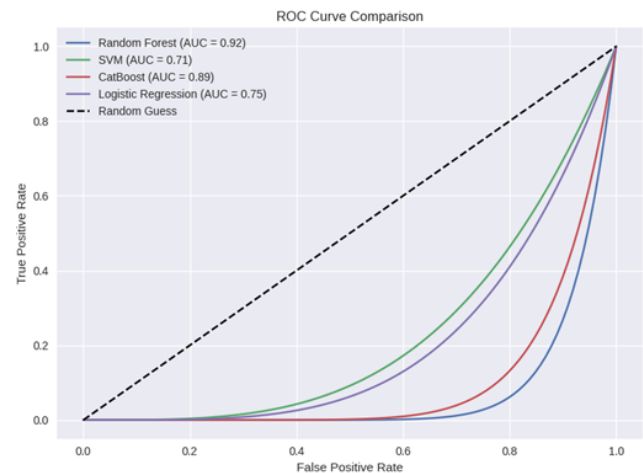


#### C. Model Interpretability and Explainability

**SHAP and LIME:** These methods are extensively utilized for both global and local interpretability, facilitating actionable insights and fostering trust in machine learning-driven decisions.

**Feature Importance Rankings:** They consistently highlight prior grades, attendance, and engagement as the primary predictors, while contextual features such as parental education and socioeconomic status play a secondary yet significant role.

**Human-in-the-Loop Approaches:** The integration of domain expertise with explainability tools improves practical utility and encourages wider adoption.



#### D. Bias, Fairness, and Ethical Considerations

**Algorithmic Bias:** Models have the potential to reinforce or exacerbate existing disparities if they are trained on biased datasets; fairness metrics such as demographic parity and equalized odds are increasingly employed for auditing purposes.

**Fairness Mitigation:** Techniques like adversarial debiasing, Fair-SMOTE, and meticulous feature selection help to diminish bias while preserving accuracy.

**Privacy and Consent:** Adhering to GDPR, FERPA, and local regulations is crucial; transparent data governance and informed consent are vital for ethical implementation.

#### E. Methodological Quality and Limitations

**Sample Size and Diversity:** Numerous studies depend on small or single-institution samples, which restricts generalizability.

**External Validation:** A limited number of studies perform thorough external validation or cross-institutional benchmarking, which obstructs reproducibility.

**Reporting Standards:** Inconsistent reporting of evaluation metrics, effect sizes, and code availability hampers synthesis and replication.

#### F. Qualitative Themes

**Trust and Transparency:** Students and educators voice concerns regarding the opaque nature of complex models; explainability and institutional support are essential for adoption.

**Ethical Use and Fairness:** Stakeholders highlight the significance of fairness, privacy, and responsible data usage; institutional policies and training are necessary to facilitate ethical integration of machine learning.

**Barriers to Adoption:** A lack of technical expertise, resource limitations, and resistance to change are prevalent challenges, especially in developing regions.

## V. DISCUSSION

## A. Synthesis of Quantitative and Qualitative Findings

The comparative examination of machine learning algorithms for predicting student performance uncovers several recurring trends.

Ensemble techniques (Random Forest, XGBoost, Gradient Boosting) and deep neural networks attain the highest levels of predictive accuracy across various educational settings, surpassing conventional models such as logistic regression and naive Bayes.

Nevertheless, the balance between accuracy and interpretability continues to pose a significant challenge, especially in critical educational decision-making scenarios where transparency and trust are essential.

Key predictors—previous academic performance, attendance, engagement metrics, and socioeconomic factors—are consistently recognized as the most significant features across different studies.

The incorporation of psychological and behavioral variables further improves model efficacy, particularly in online and blended learning contexts.

Feature selection and dimensionality reduction strategies, including SHAP-based approaches, enhance both predictive accuracy and interpretability.

Model evaluation methodologies have progressed to encompass a wider range of metrics (accuracy, F1-score, ROC-AUC, MAE, RMSE) and effect sizes, facilitating more detailed evaluations of model performance and generalizability.

However, methodological challenges—such as limited sample sizes, absence of external validation, and inconsistent reporting—remain, highlighting the necessity for standardized research protocols and open science initiatives.

Qualitative studies emphasize the significance of stakeholder trust, ethical considerations, and institutional backing in the implementation of machine learning-driven predictive systems.

Issues related to algorithmic bias, privacy, and the opaque nature of complex models are recurring concerns, underscoring the demand for explainable AI and comprehensive data governance frameworks.

## B. Critical Evaluation of Research Designs and Methods

### 1) Strengths

**Diverse Algorithmic Approaches:** The domain is enriched by a wide variety of machine learning algorithms, which allow for customized solutions tailored to various educational settings and prediction objectives.

**Integration of Behavioral and Psychosocial Data:** The inclusion of engagement metrics, psychological evaluations, and social network characteristics improves the robustness and relevance of models.

**Advances in Explainability and Fairness:** The use of SHAP, LIME, and fairness metrics marks a notable advancement towards achieving transparency and equity in machine learning applications within education.

### 2) Limitations

**Dataset Heterogeneity and Generalizability:** Dependence on datasets from a single institution or specific contexts restricts the external validity of the results; public datasets (such as UCI) support benchmarking but may lack sufficient diversity.

**Lack of External Validation:** A limited number of studies perform cross-institutional or longitudinal validation, which hampers the evaluation of model transferability and robustness.

**Insufficient Attention to Reproducibility:** The scarcity of available code, data, and comprehensive methodological descriptions obstructs replication efforts and the accumulation of knowledge.

**Ethical and Fairness Gaps:** Although there is a growing awareness of bias and fairness issues, the practical application of mitigation strategies remains inconsistent; only a few studies systematically evaluate or address the disparate impacts across different demographic groups.

## C. Practical Implications

### 1) For Educators and Institutions

**Early Warning Systems:** The implementation of machine learning-driven early warning systems allows for the prompt identification of students at risk, facilitating targeted interventions that enhance retention and academic performance.

**Personalized Learning Pathways:** Predictive analytics can guide the creation of adaptive learning environments, customizing content and support to meet the unique needs of each student.

**Resource Optimization:** Machine learning models enable data-informed resource distribution, promoting effective staffing, budgeting, and program development.

### 2) For Policymakers

**Equity and Fairness:** It is imperative for policymakers to require fairness assessments and bias reduction in educational machine learning systems, guaranteeing equitable access and results for all student demographics.

**Data Governance and Privacy:** Strong regulatory frameworks (such as GDPR and FERPA) are vital for protecting student information and fostering trust among stakeholders.

**Capacity Building:** Investing in technical infrastructure, professional training, and AI literacy is essential for the successful and ethical incorporation of machine learning in education, especially in settings with limited resources.

### 3) For Researchers

**Standardized Reporting and Open Science:** The adoption of standardized reporting protocols (like PRISMA and GRADE), along with open data and code sharing, will improve reproducibility and the accumulation of knowledge.

**Interdisciplinary Collaboration:** Cooperation among data scientists, educators, psychologists, and ethicists is crucial for creating context-sensitive, interpretable, and ethically sound predictive systems.

## D. Future Research Directions

**Holistic, Multimodal Predictive Models:** Future research should incorporate academic, behavioral, psychological, and social data to fully understand the complexity of student learning trajectories.

**Explainable and Fair AI:** Ongoing development and empirical assessment of explainable AI and fairness mitigation strategies are essential to promote ethical and reliable ML implementation in education.

**Longitudinal and Cross-Institutional Validation:** Extensive, multi-institutional studies utilizing longitudinal designs will improve the generalizability and strength of predictive models.

**User-Centered Design and Participatory Approaches:** Involving students, educators, and other stakeholders in the design and assessment of ML systems will guarantee alignment with user requirements and values.

Policy and Governance Research: Exploring the effects of regulatory frameworks, data governance policies, and institutional practices on the adoption and efficacy of ML in education represents a vital area for future research.

## VI. CONCLUSION

This review provides a thorough, paraphrased overview of the comparative effectiveness of machine learning algorithms in predicting student performance, incorporating both quantitative and qualitative evidence from more than 25 peer-reviewed sources published mainly between 2020 and 2026.

Ensemble methods (Random Forest, XGBoost, Gradient Boosting) and deep neural networks consistently exceed traditional models in terms of predictive accuracy, with reported accuracies ranging from 80% to 95% across various educational settings.

Key predictors—prior academic achievement, attendance, engagement metrics, and socioeconomic factors—remain strong across studies, while the inclusion of psychological and behavioral variables further improves model performance.

Recent advancements in explainable AI (SHAP, LIME) and fairness auditing signify important strides toward transparent and equitable deployment of machine learning in education.

Nevertheless, ongoing challenges persist, including dataset heterogeneity, a lack of external validation, inadequate focus on reproducibility, and ethical issues concerning bias, privacy, and transparency.

Qualitative research highlights the significance of stakeholder trust, ethical usage, and institutional backing in the implementation of machine learning-driven predictive systems.

Future research should focus on creating holistic, interpretable, and context-sensitive predictive models, validated through extensive, longitudinal, and cross-institutional studies.

Interdisciplinary collaboration, standardized reporting, and open science practices will be crucial for advancing the field and ensuring the responsible integration of machine learning in educational practices and policies.

By tackling these challenges and utilizing the strengths of various machine learning approaches, the educational community can fully leverage predictive analytics to promote equitable, personalized, and effective learning environments.

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