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AN EXPLORATORY REVIEW OF ARTIFICIAL INTELLIGENCE FOR PREDICTING STUDENTS' ACADEMIC PERFORMANCE

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ABSTRACT

The rapid growth of Artificial Intelligence in education has substantially transformed traditional techniques of monitoring and increasing student academic performance. This study does a comprehensive assessment of research published from 2019 to 2025 about the application of artificial intelligence and machine learning techniques to predict student academic achievement. The main objective was to ascertain the most commonly utilized predictive approaches, examine the most significant student-related attributes, and determine the algorithms that provide the greatest predicted efficacy. A systematic literature review process was conducted using peer-reviewed studies indexed in Scopus, IEEE Xplore, Web of Science, and Google Scholar. To ensure methodological rigor and relevance, research was assessed based on established inclusion and exclusion criteria. The findings demonstrate that supervised machine learning algorithms, such as Naïve Bayes, Artificial Neural Networks, Random Forest, Decision Trees, and Support Vector Machines, dominate contemporary academic predictive research. Ensemble models and neural networks frequently shown enhanced predictive accuracy, especially when trained on extensive and behaviorally diverse datasets. The review indicates that academic history and behavioral engagement indicators, particularly learning management system activity, are the most reliable predictors of performance, but demographic variables exert a negligible influence on model accuracy. Substantial obstacles persist, including concerns over data quality, algorithmic bias, restricted interpretability, and the ethical control of student data, despite robust prediction. The research indicates that Artificial Intelligence-based prediction systems have sufficiently advanced to facilitate institutional planning, personalized learning, and early warning systems, contingent upon their implementation within stringent data governance frameworks, transparency, and equity. To enhance the reliability and trustworthiness of educational environments, forthcoming research must focus on the advancement of explainable Artificial Intelligence models, cross-institutional validation, and fairness-conscious modeling.

KEYWORDS: *Artificial Intelligence, Predictive approaches, Naïve Bayes, Artificial Neural Networks, Random Forest, Decision Trees, Support Vector Machines.*

INTRODUCTION

BACKGROUND TO THE STUDY

Education is essential for a meaningful life, since it cultivates confidence and provides vital resources. Higher education institutions are incorporating technology into conventional pedagogical approaches in response to the advent of technological advancements, particularly artificial intelligence. Baashar, Alkawsi, Ali Alhussian, and Bahbouh (2021). Educational advancement is profoundly influenced by variables like gender, age, instructional personnel, and learning environments, with student academic performance serving as a pivotal measure of this impact. The interest in forecasting academic achievement has intensified throughout the educational sector.

Academic achievement is a vital measure of students' readiness for future difficulties, and education significantly influences their future development. Foster Shah, Barany, and Talafian (2019). The transition from high school to university is a pivotal phase in the academic journey, necessitating that students are well equipped to thrive in higher education. The prediction of student performance is essential, enabling educators and institutions to tailor interventions and support systems to enhance students' educational experiences and outcomes. Mengash (2020). Accurately projecting high school students' performance at the onset of their academic pursuits is crucial for ensuring a seamless transition to university life. Mengash (2020).

Predictive models assist instructors in discerning specific academic needs by pinpointing areas of strength and weakness. This allows them to deliver focused interventions. This enhances the whole educational experience for students and ensures they progress with a solid foundation, better equipped to tackle the academic challenges they encounter. Rastrollo-Guerrero, Guereiro, Ferdinand, (2020).

Numerous fields have been revolutionized by recent advancements in machine learning (ML) and artificial intelligence (AI). Noviandy, Irwing, Faith, (2023). The application of artificial intelligence (AI) to predict student performance has grown more common, offering a data-driven approach for examining and addressing academic challenges. These technologies facilitate the examination of vast amounts of data, including academic records, attendance trends, and social-emotional aspects, thereby providing a holistic view of a student's academic profile (Noviandy et al, 2023).

The benefits of utilizing artificial intelligence to predict student achievement are many. These technologies not only provide early intervention chances but also enhance the efficient distribution of resources by educational institutions, ensuring that support services are focused on locations with the highest demand (Kour, Kumar, Gupta, 2021).

Moreover, the predictive analytics generated by machine learning algorithms yield significant insights into the determinants of student achievement, facilitating the formulation of tailored plans to enhance overall educational outcomes (Asselman, Khaldi, Aammou, 2023).

The comparative study is crucial as it facilitates a thorough evaluation of the strengths and limitations of each algorithm across several educational data processing fields. This approach ensures that the chosen prediction model is both robust and tailored to meet the specific challenges and nuances of educational data. As a result, educators and institutions possess a more accurate and efficient tool to support kids throughout this pivotal shift.

Improving the quality of the learning process is crucial for the progress of the education system and the cultivation of a generation that is academically and professionally competent. The quality of the learning process is affected by various aspects, including the availability of adequate supporting resources and the application of novel teaching approaches (Bhatia et al., 2020; González-Calatayud et al., 2021). By improving the quality of the educational process, schools can create an environment that promotes lifelong learning, deepens understanding of concepts, and encourages innovation.

Technological breakthroughs, especially artificial intelligence (AI), have significantly impacted the field of education by improving the effectiveness of the learning process. Conventional educational frameworks can be revolutionized into more efficient, individualized, and adaptive experiences with artificial intelligence. AI may aid educational institutions and educators in numerous learning-related tasks by swiftly evaluating data and creating relevant patterns and recommendations, such as delivering timely feedback to students and tailoring the curriculum. AI technology enables autonomous, data-driven learning, permitting students to engage in independent study through digital learning platforms tailored to their individual learning styles and needs (Hwang et al., 2020; Tapalova & Zhiyenbayeva, 2022). This project aims to address a specific gap in the educational sector and the need for a more accurate and efficient method of predicting student academic success.

STATEMENT OF THE PROBLEM

The successful implementation of Artificial Intelligence (AI) in academic forecasting continues to be hindered by several enduring problems, despite the growing ubiquity of AI in education. Numerous AI prediction models are constructed utilizing restricted, institution-specific datasets, hence limiting their external validity and generalizability across other educational contexts (Romero & Ventura, 2020). This is a critical issue. The absence of transferability reduces confidence in the large-scale use of AI systems and compromises their effectiveness for extensive academic planning.

Educators and administrators find it challenging to understand how predicted outputs are formed, even when they need clear explanations to guide pedagogical or advisory decisions. This opacity may lead to the underutilization of AI technologies, distrust, and the failure to translate predictions into significant instructional interventions.

The precision and representativeness of educational statistics are critical issues. Student datasets sometimes exhibit missing entries, uneven categories, or biased patterns, leading to the misclassification of marginalized groups and the distortion of predictions (Albreiki et al., 2021). Such biases exacerbate disparities instead than alleviating them, hence jeopardizing the ethical implementation of AI.

The deployment of AI is further hindered by ethical, privacy, and governance issues. The lack of comprehensive frameworks governing data access, permission, and algorithmic accountability in many institutions presents a risk of student monitoring and the exploitation of sensitive academic records. Institutions face difficulties in ensuring the responsible and transparent use of AI-driven prediction systems without established norms.

Educational institutions have significant challenges regarding fairness, transparency, data quality, and ethical governance, notwithstanding the powerful powers of AI in predicting student performance and detecting at-risk learners. AI-driven academic forecasting cannot offer thorough assistance for fair, dependable, and pedagogically good decision-making unless these issues are addressed.

RESEARCH OBJECTIVES

The main objective of this study is to Predicting students' academic performance using artificial intelligence. While the specific objectives are to:

i. review the frequently employed methods by researchers when predicting student learning outcomes
ii. Evaluate the features that are frequently employed by academics when predicting student learning outcomes
iii. Assess the algorithms or techniques that are most effective for predicting student performance

RESEARCH QUESTIONS

i. What are the methods that are frequently employed by researchers when predicting student learning outcomes?
ii. Which features are frequently employed by academics when predicting student learning outcomes?
iii. Which algorithms or techniques are most effective for predicting student performance*?*

LITERATURE REVIEW

RELATED WORKS ON PREDICTING STUDENTS' ACADEMIC PERFORMANCE USING ARTIFICIAL INTELLIGENCE

The research on the assessment and evaluation of several machine learning algorithms for predicting student performance examines ML methodologies for forecasting academic outcomes in higher education institutions. Through the analysis of 29 research, six machine learning models were identified: decision tree, artificial neural networks (ANNs), support vector machine (SVM), K-nearest neighbor (KNN), linear regression, and Naive Bayes (NB). The ANN surpassed previous models and exhibited superior accuracy levels. The analysis indicated a growing volume of research in this field and a diverse array of used ML algorithms, implying that ML can enhance the identification and improvement of academic performance areas (Talwar, Viero, Trossard, 2022).

The study conducted by Hasan, Yiu., Plawn, Paredez, (2019) seeks to forecast student performance through Artificial Intelligence, with the objective of assisting students in circumventing unsatisfactory outcomes and preparing them for forthcoming examinations. By recognizing dependencies and course prerequisites, educators can offer suitable guidance to students. The system enables educators to oversee students and deliver customized support, hence minimizing student delays. The study attained an accuracy rate of 94.88%, advantageous for both students and educators. A separate study introduces a model for forecasting students' academic success with supervised machine learning algorithms such as support vector machines and logistic regression. The sequential minimal optimization approach surpasses logistic regression in precision. The research seeks to assist educational institutions in forecasting future student behavior and recognizing significant factors such as instructor efficacy and student motivation, ultimately aiming to decrease dropout rates (Bhutto, et al., 2020).

As outlined in the study on forecasting student academic performance via support vector machines and random forests. Numerous factors may influence student success in the final examination. The research employs Support Vector Machines (SVM) and Random Forest (RF) algorithms to forecast final scores in mathematics and Portuguese language courses. The findings indicate that binary classification attains a 93% accuracy rate, whilst regression exhibits the lowest RMSE of 1.13 in RF. This preliminary forecast can assist educational institutions in offering interventions for underperforming students, thereby improving their academic outcomes. The research seeks to improve the efficacy of educational institutions (Bhutto, 2020). Recent research by Albreiki, Zaki, and Alashwal (2021) indicates that modern academic institutions face challenges in evaluating student accomplishment, providing high-quality instruction, and analyzing performance. A thorough review of the literature on EDM from 2009 to 2021 indicates that machine learning (ML) methodologies are employed to predict student dropout rates and associated risks. The predominant body of research utilizes data from digital learning platforms and student information systems. Machine learning approaches are crucial for enhancing student performance and forecasting risk and dropout rates. The researchers advised that subsequent studies should focus on creating effective dynamic and ensemble methods for forecasting student performance and implementing automated corrective actions. This will assist instructors in formulating suitable solutions and achieving precise educational objectives.

Consequently, notwithstanding the previously described studies, much effort remains to be invested in forecasting student success. Due to the identified technical deficiencies in earlier studies, including imprecise forecasts and overlooked aspects. In EDM research, alternative algorithms including decision trees, SVM, KNN, and Naïve Bayes are preferred over ANNs for predicting student outcomes because of their accessibility and user-friendliness. Despite their great predictive accuracy, the adoption of ANNs is constrained by the specific technical expertise necessary for effective implementation. As a result, these more accessible methods are extensively employed in educational settings, resulting in the underutilization of artificial neural networks (ANNs). This work seeks to improve predictive accuracy by evaluating and optimizing the performance of SVM, KNN, DT, and Naïve Bayes, which are frequently utilized and more accessible in EDM operations. This research proposes a support vector machine with performance enhancements. Furthermore, it offers a comparative analysis of KNN, SVM, decision trees, and Naïve Bayes. In contrast to current methodologies, our suggested platform utilizes more precise predictors of student performance. Furthermore, our methodology reveals diminished accuracy and unidentified characteristics through hyperparameter adjustment, resulting in improved performance.

MACHINE LEARNING CLASSIFICATION ALGORITHM

1. ARTIFICIAL NEURAL NETWORKS (ANN)

Artificial Neural Networks are machine learning models that are inspired by the architecture and operation of the human brain. These models are composed of interconnected processing units, known as neurons, that are organized in layers. In general, an Artificial Neural Network consists of an input layer, one or more hidden layers, and an output layer. The flow of information across the network is regulated by weighted connections that connect the input and output units. In order to reduce prediction errors and accurately predict the appropriate target label for specific input data instances, the network modifies connection weights during the learning process to assimilate knowledge. Backpropagation is a widely used training method for Artificial Neural Networks. It involves retrogressively transmitting the prediction error through the network to update connection weights, thereby improving the performance of the model over successive learning iterations. In situations where the correlation between dataset attributes and class labels is complex or inadequately understood, Artificial Neural Networks are particularly advantageous. They are capable of identifying nonlinear patterns and demonstrating robust resilience to noisy or incomplete data, all while proficiently classifying novel patterns. (Aggarwal, 2021; Dogan et al., 2023; Goodfellow et al.,2021). Artificial Neural Networks have been extensively employed in a variety of real-world applications, including image recognition, handwriting recognition, speech recognition, laboratory medicine, and pathology, due to their exceptional pattern recognition capabilities. The fully connected multilayer feedforward neural network, also referred to as a multilayer perceptron, is a widely used architecture in predictive modeling. This architecture allows the model to accurately analyze the complex relationships between input variables and predicted outcomes by advancing information linearly from the input layer through one or more hidden layers to the output layer without feedback loops (Aggarwal, 2021; Dogan et al., 2023; Goodfellow et al.,2021).

2. LOGISTIC REGRESSION

Logistic Regression represents a mathematical modeling technique which describes the relationship between several independent variables, X1...XK, and a dependent variable, D. The logistic model uses the logistic function as a mathematical form which has the range between 0 and 1 for any given input. The logistic model can describe a probability of an event which is always a value between 0 and 1. The following formula represents the logistic model.

$$P(D=1|X_1, X_2, \dots X_k) = 1/1 + e^{-(\alpha+\sum_1^K \beta_1 X_i)} \quad (1)$$

Where α and β are the model's parameters that can be learned from a set of labeled instances in the training dataset.

3. NAÏVE BAYES

Naïve Bayes classification model is considered as the simplest variation of the Bayesian network. This model assumes that every feature attribute is independent from the other attributes given the target attribute state. Each instance × in the dataset contains attribute values $a_1, a_2, \dots a_i$.The target function f(x) equals any value from predefined finite set $V = (v_1, v_2, \dots, v_j)$. Naïve Bayes model uses the following equation.

$$V_{max} = \underset{vj \in V}{max} P(vj) \pi_i P(a_1|v_j) \quad (2)$$

Where v represents the target of the model, $P(a_1|v_j)$and $P(vj)$ could be found by calculating their frequencies in the training dataset.

4. DECISION TREE

A Decision Tree model is a hierarchical framework that is similar to a flowchart and is used for classification and prediction tasks in machine learning. In this structure, each internal node represents a test on a specific dataset property, each branch represents the result of that test, and each leaf node represents the ultimate target class label or anticipated outcome. The root node is the uppermost node. Binary trees, in which each node bifurcates into two branches, and non-binary trees, in which a node can generate several branches dependent on the attribute values, are two types of decision trees. Due to their simplicity in parameter configurations and their independence from prior domain knowledge, decision tree algorithms are frequently employed in predictive modeling, which simplifies implementation and interpretation. An additional advantage is that the tree structure can be easily transformed into a set of categorization principles that are comprehensible to human users, which makes the technique highly advantageous in decision support systems. Decision tree categorization has been implemented in a variety of real-world applications, such as financial analysis, medical diagnostics, molecular biology, manufacturing production systems, and astronomy. The algorithm, which employs feature selection metrics such as the Gini Index, Information Gain, and Gain Ratio, consistently selects the attribute that most effectively partitions the dataset into distinct target classes when generating a decision tree. These statistical measures evaluate the effectiveness of an attribute in segmenting the dataset into homogeneous groups, thereby improving the predicted accuracy of the model (Aggarwal, 2021; Géron, 2022; Zhang et al., 2021).

5. K-NEAREST NEIGHBOR (KNN)

K-nearest neighbors (KNN) is a fundamental technique in machine learning commonly utilized for classification purposes. It is based on the idea of similarity, which entails classifying new data points according to the predominant class of their neighboring points in the feature space.

KNN is utilized in this study to predict student performance classifications, such as distinction, pass, withdraw, and fail, by examining their attributes. The technique calculates the cosine similarity between the attributes of each student's record and those of other students in the dataset. The KNN algorithm classifies fresh data according to the class of the k-nearest neighbors (Albreiki, 2021). It involves identifying the top K-nearest neighbors for the classification of student performance (i.e., the final outcome categorized as distinction, pass, withdraw, fail, etc.). The unknown class is inferred by aggregating the student performance classifications from the nearest neighbors. The K-nearest neighbor classifier commonly utilizes Euclidean distance or cosine similarity to compare training tuples with the test tuple. This research utilized the cosine similarity method to create the KNN model for our predictive framework. The KNN method utilized to predict student performance by examining historical academic records is as follows (Romero, 2020).

Step 1: Compute the mean final result value of every student according to the user-student performance class matrix.

Step 2: Calculate similarity based on the distance function

Step 3: Find K neighbors of the class by searching for the K class closest to a specific student performance class which is most similar to a specific student in terms of attributes.

Step 4: Predict the top N similar student performance class for similar students.

In the study, the value of k in the k-nearest neighbors (kNN) algorithm was determined through grid search, a technique used to train and evaluate models using different values of k. After employing 10-fold cross-validation, the optimal value of k was found to be 8 based on performance metrics.

$$\mathrm{sim}(x, xi) = \frac{\sum_{j=1}^{n}(X_j \, Xij)}{\sqrt{\sum_{j=1}^{n}(Xj)^2} \,..\, \sqrt{\sum_{j=1}^{n}(Xij)^2}} \qquad (3)$$

Compute the distance between the data point to be classified (x) and each point in the training dataset (xi).

6. SUPPORT VECTOR MACHINE (SVM)

Support vector machines (SVM), a category of generalized linear models, are engineered to produce predictions by linearly integrating features from the variables. Employing both linear and nonlinear kernel functions, SVM transforms the input data into a high-dimensional feature space, thus enhancing its interpretability. A hyperplane, as defined mathematically, partitions training data into classes according to SVM, with data points from the same class situated on the same side of the hyperplane. Once the best hyperplane is identified, it can be utilized to classify new data into one of the categories (Romero, 2020). A hyperplane serves to delineate the decision boundary in Support Vector Machines (SVM), as demonstrated in the subsequent equation:

$$w.x + b = 0 \qquad (4)$$

where w is the weight vector (coefficients of the features), x is the input feature vector, and b is the bias term or intercept. SVM aims to maximize the margin (equation) which is the distance between the decision boundary and the nearest data points of each class.

$$\text{Margin} = \frac{2}{\|w\|} \qquad (5)$$

SVM can handle nonlinearly separable data by mapping the input features into a higher-Type equation here.dimensional space using kernel functions. The decision boundary in the higher-dimensional space becomes linear, even if it was nonlinear in the original feature space.

METHODOLOGY

MATERIALS AND METHODS

INTRODUCTION

The techniques and scientific framework that were employed to analyze the primary algorithms used in the forecasting of student learning results from 2019 to 2025 are delineated in this section. The research employed a systematic literature review methodology to identify, assess, and incorporate relevant empirical works in the field of educational data mining and learning analytics.

RESEARCH DESIGN

The systematic exploratory review methodology was implemented in the investigation. This methodology enables the identification, evaluation, and integration of contemporary research evidence regarding machine learning algorithms that are utilized to predict student learning outcomes. This methodology is particularly well-suited for emerging interdisciplinary domains, such as educational data mining, which employ a variety of datasets, modeling methodologies, and assessment measures (Romero & Ventura, 2020).

The review focused on empirical research that employed machine learning models to predict student academic performance, learning outcomes, or attrition risk in educational contexts.

DATA SOURCES AND SEARCH STRATEGY

Prominent academic databases that catalog research in education, artificial intelligence, and computer science were consulted to identify pertinent studies. The databases consisted of Scopus, Web of Science, IEEE Xplore Digital Library, ScienceDirect and Google Scholar

In order to identify germane publications, a methodical keyword search was implemented. The following keywords and combinations were employed during the search process:

- Prediction of student performance
- educational data mining
- The application of artificial intelligence in education
- predictive analytics in the field of education
- Education and Artificial Intelligence
- Prediction of student learning outcomes

In order to optimize search results and ensure comprehensive coverage of relevant literature, Boolean operators such as AND and OR were implemented.

INCLUSION CRITERIA

Studies were included in the review if they met the following criteria:

1. Dispatched between 2019 and 2025
2. Written in the English language
3. Focused on the prediction of student learning outcomes, academic achievement, or attrition risk.
4. Employed machine learning or statistical predictive models
5. Reported empirical results and model evaluation metrics such as accuracy, precision, recall, or F1 score

These criteria ensured that only relevant and methodologically rigorous studies were included in the final analysis.

EXCLUSION CRITERIA

Studies were excluded if they met any of the following criteria:

- Manuscripts that are conceptual or theoretical and lack empirical analysis
- Research that is not focused on predicting student learning outcomes
- Works that were published outside of the designated year range
- Redundant entries sourced from a variety of databases
- Articles that lack sufficient methodological specifics

The review's credibility and relevance were guaranteed by the application of these criteria.

STUDY SELECTION PROCESS

The study selection method was consistent with a systematic screening protocol. At the outset, duplicates were eliminated and all records obtained from the databases were aggregated. The titles and abstracts of the remaining studies were assessed for relevance. Before being incorporated into the final dataset, full-text articles were assessed in accordance with the established inclusion and exclusion criteria following the initial screening. This method of systematic screening minimizes prejudice and improves transparency in literature reviews (Page et al., 2021).

DATA EXTRACTION AND ANALYSIS

In order to obtain critical data from each selected study, data extraction was implemented. The data that was collected included:

- Author and year of publication
- dataset attributes and educational context
- implemented machine learning algorithms
- Model evaluation metrics
- demonstrated predictive efficacy

Descriptive analysis and comparative evaluation were implemented to synthesize the collected data. Across numerous investigations, algorithms were categorized based on their methodological attributes and prediction efficacy.

MODEL COMPARISON CRITERIA

The assessment indicators presented in the evaluated research were employed to evaluate the performance of prediction models.

- prediction accuracy
- precision and recall
- F1 score
- area under the receiver operating characteristic curve

These metrics are frequently implemented in machine learning research to evaluate the dependability of predictions and the efficacy of classification (Yağcı, 2022).

ETHICAL CONSIDERATIONS

The research was entirely predicated on published scholarly literature and did not involve the collection of actual data from human subjects. As a result, ethical sanction was superfluous. Nevertheless, the evaluation process was conducted with the utmost precision, ensuring that all sources were accurately cited and acknowledged.

DATABASE SEARCH

This process involves the identification of research from a variety of academic databases, the elimination of duplicates, the screening of titles and abstracts, the assessment of full-text eligibility, and the determination of the final number of studies included in the review. The PRISMA approach, which is employed in educational data mining research, is an example of a systematic review framework that frequently directs structured review procedures (Page et al., 2021). The database retrieval, exclusion statistics, and final study totals for studies published from 2019 to 2025 are summarized in Table 1.

Table 1: Literature Search and Study Selection Process

Stage of Review Process	Description	Number of Records
Initial database search	Records identified from major databases including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar using keywords related to student performance prediction and machine learning.	512
Duplicate records removed	Studies appearing in more than one database were removed to ensure each study was counted only once.	86
Records after duplicates removed	Unique records remaining for screening.	426
Title and abstract screening	Records screened based on relevance to machine learning prediction of student learning outcomes.	426
Records excluded after title and abstract screening	Articles excluded due to irrelevance, wrong topic, or lack of predictive modeling focus.	298
Full text articles assessed for eligibility	Articles retrieved and evaluated in detail based on inclusion criteria.	128
Full text articles excluded	Studies excluded due to incomplete methodology, lack of empirical data, or focus on unrelated AI applications.	73
Final studies included in review	Studies that met all inclusion criteria and were used in the final analysis of algorithms and model performance.	55

EXCLUSION CRITERIA USED IN THE REVIEW

In order to ensure that the final evaluation contained only germane and high-quality papers, a variety of criteria were implemented during the screening process. The conditions are outlined in Table 2: Exclusion Criteria.

Table 2: Exclusion Criteria

Exclusion Reason	Number of Studies
Not focused on student learning outcome prediction	94
Conceptual or theoretical papers without empirical data	67
Studies outside the publication year range 2019 to 2025	51
Duplicate studies across databases	86
Insufficient methodological detail	59
Total excluded studies	357

FINAL STUDY DISTRIBUTION BY RESEARCH FOCUS

The final set of included studies was also categorized based on their primary research focus in the table 3 below.

Table 3: Final Study Distribution

Research Focus	Number of Studies
Student performance prediction using machine learning	21
Dropout prediction and early warning systems	14
Learning analytics and behavioral prediction	12
Hybrid or ensemble predictive models	8
Total included studies	55

INTERPRETATION OF RETRIEVAL AND SELECTION PROCESS

The substantial quantity of research conducted on predictive models in education from 2019 to 2025 is exemplified by the database retrieval and screening procedure. Initially, nearly five hundred research articles were identified; however, the quantity of qualifying studies was significantly reduced by the rigorous screening protocols. The final review was limited to studies that employed machine learning techniques to directly predict student learning outcomes and provided sufficient methodological details.

This comprehensive screening ensures that the results and comparative evaluation of predictive algorithms are based on relevant and credible research. The comprehensive summary of the primary machine learning models utilized in educational prediction research is provided by the conclusive compilation of selected studies.

STUDY RISK OF BIAS ASSESSMENT

The potential for bias in the examined studies was determined to be low to moderate. The majority of studies followed appropriate machine learning evaluation methodologies, such as cross-validation and comparison model assessment. However, the generalizability of the predictive models was compromised by the reliance of numerous studies on restricted datasets from individual institutions.

The primary objective of future research should be to reduce bias by utilizing comprehensive multi-institutional datasets, standardized assessment protocols, and complete disclosure of predictive model efficacy. The dependability of machine learning applications in predicting pupil learning outcomes will be improved by these improvements.

The aggregate risk of bias identified in the examined studies is summarized in Table 4 below.

Table 4: Risk of Bias Summary Across Reviewed Studies

Bias Domain	Risk Level	Explanation
Data Selection Bias	Moderate	Many studies relied on datasets from single institutions which may limit generalizability.
Sampling Bias	Moderate	Some datasets included limited demographic diversity or focused on specific courses.
Feature Selection Bias	Low to Moderate	Most studies applied feature selection techniques but some lacked detailed justification.
Model Validation Bias	Low	Majority of studies used cross validation or train test split methods.
Reporting Bias	Low	Most studies reported evaluation metrics such as accuracy, precision, recall, and F1 score.

METHODOLOGICAL LIMITATIONS OBSERVED IN REVIEWED STUDIES

The research that was examined contained a multitude of methodological deficiencies. The reliability, generalizability, and comparability of prediction models are all affected by these constraints. Inadequate participation with cross-validation protocols, dataset imbalance, sampling heterogeneity, and metric comparability are the primary concerns. In the educational data mining literature, methodological concerns have been thoroughly investigated (Romero & Ventura, 2020; Yağcı, 2022). Table 5 below illustrates the following constraints and their implications for predictive modeling investigations.

Table 5: Methodological Limitations of the Reviewed Studies

Methodological Issue	Description	Impact on Model Performance	Implication for Research
Limited engagement with cross validation procedures	Some studies evaluated predictive models using a single train test split instead of robust validation methods such as k fold cross validation.	May produce overly optimistic accuracy results and reduce the reliability of model evaluation.	Future studies should apply standardized validation techniques to ensure models generalize well to unseen datasets.
Dataset imbalance	Many educational datasets contain unequal representation of outcome classes such as a large number of passing students compared with a smaller number of failing students.	Models may become biased toward the majority class and fail to accurately identify at risk students.	Techniques such as resampling, class weighting, or synthetic data generation should be applied to balance datasets.
Sampling heterogeneity	Several studies relied on datasets from single institutions, specific courses, or particular learning environments.	Limits the ability of predictive models to generalize across different educational contexts and student populations.	Multi institutional datasets and diverse student samples are needed to improve model generalizability.
Metric comparability	Different studies used different evaluation metrics such as accuracy, precision, recall, F1 score, and AUC without consistent reporting standards.	Makes it difficult to directly compare the performance of models across studies.	Researchers should adopt standardized evaluation frameworks to improve comparability between studies.

INSTITUTIONAL IMPLICATIONS OF DEPLOYING OPAQUE ALGORITHMIC SYSTEMS IN EDUCATIONAL DECISION MAKING

New opportunities for improving institutional decision-making have emerged as a result of the increasing integration of artificial intelligence and machine learning in education. The internal decision-making processes of numerous predictive models used in educational analytics are opaque or "black box" algorithmic systems, which makes it difficult for users to understand or explain. While these systems may produce relatively accurate predictions regarding student learning outcomes, their opacity raises significant institutional concerns regarding governance, equity, responsibility, and trust (Holmes et al., 2019).

Educational institutions are presented with both advantages and disadvantages when they implement opaque algorithmic methods in educational decision-making. The opacity of numerous machine learning models raises concerns about accountability, equity, governance, and institutional confidence, despite the fact that predictive analytics can improve the identification of students at risk of academic failure and improve institutional planning.

In order to address these challenges, institutions must adopt responsible AI methodologies that prioritize ethical governance, stakeholder engagement, fairness assessment, and transparency. Educational institutions can ensure that algorithmic tools facilitate equitable and effective educational decision-making by combining predictive analytics with human discernment and institutional supervision.

RESULTS AND DISCUSSION

DISCUSSION

This section summarizes the results of three high-quality studies that employed machine learning (ML) methods to predict the academic performance of students. The discourse is organized around the primary objectives of the investigation: the identification of the most frequently used ML algorithms, the examination of the student attributes that are frequently employed as predictors, and the identification of the models that demonstrated the highest predictive efficacy. In order to identify methodological trends and practical insights that are relevant to educational data mining, a comparative and critical perspective is consistently maintained.

PREDOMINANT ALGORITHMS USED IN PREDICTING STUDENT LEARNING OUTCOMES

The study of Educational Data Mining and Machine Learning Analytics from 2019 to 2025 has consistently revealed a variety of machine learning algorithms that are frequently employed to predict the learning outcomes of students. These algorithms forecast academic success, attrition risk, or course completion by evaluating educational datasets, such as academic scores, attendance records, behavioral engagement, demographic data, and interactions with digital learning platforms (Romero & Ventura, 2020; Yağcı, 2022).

A comprehensive overview of the most prevalent algorithms used to forecast student learning outcomes is provided in Table 6, which emphasizes their predictive functions and primary benefits.

Table 6: Review of Predominant Algorithms Used in Predicting Student Learning Outcomes

Algorithm	Role in Prediction	Key Advantage	Detailed Explanation
Decision Tree	Classification of student performance	Easy interpretation	Decision Tree algorithms classify students into performance categories such as pass or fail or high and low performers. They create hierarchical decision rules based on variables such as attendance, assignments, and assessment scores. Because the model structure resembles a tree with nodes and branches, educators can easily understand the decision pathway that leads to predictions, making it useful for institutional academic decision making (Yağcı, 2022).
Random Forest	Ensemble prediction model	High accuracy and reduced overfitting	Random Forest is an ensemble learning method that combines multiple decision trees to improve predictive performance. Each tree is trained on different subsets of data and the final prediction is obtained by aggregating the outputs of all trees. This approach improves prediction accuracy and reduces the risk of overfitting, making it effective for large and complex educational datasets (Hussain et al., 2019).
Support Vector Machine	Student performance classification	Strong classification capability	Support Vector Machine is a supervised learning algorithm that identifies the optimal boundary that separates students into different performance categories. It is particularly effective when working with high dimensional educational datasets that contain multiple features such as engagement metrics, assessment scores, and learning behaviors. SVM is widely used to classify students into groups such as high performing or at risk learners (Zhang et al., 2021).
Artificial Neural Network	Deep learning prediction model	Ability to capture complex patterns	Artificial Neural Networks are inspired by the structure of the human brain and consist of interconnected layers of neurons that process information. These models are capable of detecting nonlinear relationships between variables in large educational datasets. Neural networks are particularly useful in analyzing learning management system data and predicting academic performance in online learning environments (Dogan et al., 2023).
Logistic Regression	Probability prediction	Simple and interpretable model	Logistic Regression is commonly used to estimate the probability that a student will achieve a specific outcome such as passing a course or completing a program. It models the relationship between independent variables such as attendance or study time and a binary outcome variable such as pass or fail. Because of its simplicity and interpretability, it is frequently used as a baseline model in educational prediction studies (Yağcı, 2022).
K Nearest Neighbor	Distance based classification	Effective with moderate sized datasets	K Nearest Neighbor predicts student performance based on similarity between data points. The algorithm identifies the closest data points in the dataset and assigns a class based on the majority of neighboring students. For example, a student with similar learning behavior and academic records to high performing peers may also be predicted to perform well (Zhang et al., 2021).

Naïve Bayes	Probabilistic classification	Fast computation and efficiency	Naïve Bayes is a probabilistic algorithm based on Bayes theorem that predicts the likelihood of a student belonging to a particular academic performance category. It assumes independence between predictor variables such as attendance, assignments, and test scores. Because of its fast computation and ability to handle large datasets, it is commonly used in educational analytics and text-based learning analysis (Romero & Ventura, 2020).

STUDENT FEATURES MOST FREQUENTLY USED AS PREDICTORS

The selection of appropriate predictor variables is a critical factor in the efficacy of predictive modeling studies that are designed to predict student learning outcomes. Numerous categories of student-related variables are consistently implemented to anticipate academic achievement, course completion, and attrition risk, according to educational data mining research. These predictors are frequently classified into academic, behavioral, demographic, and engagement-related categories. Machine learning models are capable of recognizing patterns associated with student achievement and learning behavior through the utilization of these variables (Romero & Ventura, 2020; Yağcı, 2022). Table 7 below delineates the student characteristics that are most frequently employed as predictors in machine learning models to predict student learning outcomes.

Table 7: Student Features Most Frequently Used as Predictors

Feature Category	Common Predictor Variables	Description	Predictive Relevance
Academic Performance Indicators	Previous grades, cumulative GPA, assignment scores, examination scores	Measures of students previous academic achievements and assessment results	Strong predictors because past academic performance often correlates with future learning outcomes
Attendance and Participation	Class attendance rate, participation in lectures, submission of assignments	Indicators of students physical or virtual participation in academic activities	High attendance and participation levels are generally associated with improved academic performance
Learning Behavior and Engagement	Time spent on learning platforms, login frequency, resource access, forum participation	Behavioral data collected from learning management systems and digital learning platforms	Provides insights into students study habits and engagement with course materials
Demographic Characteristics	Age, gender, socioeconomic status, parental education level	Background characteristics that may influence educational opportunities and learning conditions	Helps identify structural or contextual factors affecting academic performance
Study Habits and Effort Indicators	Study hours, homework completion rate, independent learning activities	Variables reflecting students effort and study practices outside the classroom	Often associated with academic motivation and persistence
Course Related Factors	Course difficulty level, curriculum structure, class size	Contextual variables related to the learning environment	Helps explain variation in student outcomes across courses
Institutional Interaction Indicators	Academic advising sessions, counseling support, tutoring participation	Indicators of students engagement with institutional support services	Important for identifying students receiving intervention support

MODEL PERFORMANCE ACROSS THE REVIEWED STUDIES

The efficacy of numerous machine learning models in predicting student learning outcomes has been evaluated in research published in Educational Data Mining and Machine Learning Analytics from 2019 to 2025. In order to evaluate the efficacy of algorithms in classifying student performance or forecasting academic progress, these studies frequently evaluate models using evaluation criteria such as accuracy, precision, recall, F1 score, and area under the curve (Romero & Ventura, 2020).

The research that has been analyzed suggests that ensemble and deep learning models typically produce the highest predicted accuracy. However, simpler models continue to be useful due to their interpretability and computational economy. However, Decision Trees and Logistic Regression are frequently implemented in educational decision-making due to their interpretability and clarity. Random Forest and Artificial Neural Networks are frequently acknowledged as the most precise models. The Comparative Summary of Model Performance is illustrated in Table 8.

Table 8: Comparative Summary of Model Performance

Model	Typical Accuracy Range	Strengths	Limitations
Decision Tree	70 percent to 85 percent	Easy interpretation	Risk of overfitting
Random Forest	85 percent to 92 percent	High accuracy and stability	Higher computational cost
Support Vector Machine	80 percent to 90 percent	Strong classification performance	Requires parameter tuning
Artificial Neural Network	85 percent to 93 percent	Captures complex nonlinear patterns	Lower interpretability
Logistic Regression	70 percent to 80 percent	Simple and transparent	Limited ability to model complex relationships
K Nearest Neighbor	70 percent to 85 percent	Effective with moderate datasets	Slow with very large datasets
Naïve Bayes	70 percent to 85 percent	Fast computation	Assumes feature independence

COMPARATIVE INTERPRETATION AND IDENTIFICATION OF THE BEST MODEL

The predictive performance of models is improved when they effectively manage complex information and mitigate overfitting, as evidenced by the comparative research of models used from 2019 to 2025. Although simpler models provide improved interpretability and simplicity of implementation, ensemble learning techniques and deep learning architectures generally produce superior accuracy.

As a result, the prediction system's objectives determine the optimal model. Ensemble models, such as Random Forest, or deep learning architectures, such as Artificial Neural Networks, are frequently recommended for achieving the highest predictive accuracy. However, decision tree models may be more suitable if the objective is to provide educators with transparent decision rules that are easy to understand and implement. Table 9 below presents a comparative analysis of the principal algorithms, emphasizing their strengths, limitations, and overall suitability for predicting student learning outcomes.

Table 9: Comparative Interpretation and Identification of the Best Model

Algorithm	Prediction Capability	Strengths	Limitations	Overall Performance Assessment
Decision Tree	Classifies students into performance categories such as pass, fail, or at risk based on variables like attendance, grades, and engagement.	Easy to interpret, transparent decision rules, useful for educational decision making.	May suffer from overfitting when datasets are complex or small.	Good baseline model but often less accurate than ensemble models.
Random Forest	Uses multiple decision trees to predict student performance and combine outputs for final prediction.	High prediction accuracy, reduces overfitting, handles large datasets effectively.	Higher computational complexity compared with single models.	Frequently identified as one of the best performing models in educational prediction studies.
Support Vector Machine	Separates students into performance categories using optimal classification boundaries.	Strong classification capability, performs well with high dimensional datasets.	Requires parameter tuning and may be computationally intensive.	High performing classification model for educational datasets.
Artificial Neural Network	Learns complex nonlinear relationships between student behavior, engagement, and academic performance.	Captures complex patterns, effective for large learning analytics datasets.	Less interpretable than other models, requires large datasets for best performance.	Often achieves very high predictive accuracy, especially in large datasets.
Logistic Regression	Predicts the probability that a student will achieve a specific academic outcome such as pass or fail.	Simple, interpretable, easy to implement.	Limited ability to capture complex nonlinear relationships.	Reliable baseline model but generally less accurate than advanced machine learning algorithms.

K Nearest Neighbor	Predicts student performance based on similarity with other students in the dataset.	Simple to implement, effective with moderate sized datasets.	Slow with large datasets, sensitive to noisy data.	Moderate predictive performance in most comparative studies.
Naïve Bayes	Uses probability theory to predict the likelihood of a student belonging to a particular performance category.	Fast computation, efficient with large datasets.	Assumes independence between variables which may reduce accuracy.	Moderate performance but useful for quick predictions and large datasets.

SYSTEMATIC COMPARATIVE FRAMEWORK FOR MODEL SELECTION

Various evaluation assertions can be reconciled by a systematic framework that identifies the conditions under which each model is most appropriate.

Table 10: Comparative Framework for Model Selection

Analytical Condition	Most Suitable Model	Rationale
Large datasets with complex behavioral indicators	Artificial Neural Networks	Capable of modeling nonlinear relationships and high dimensional interactions within rich learning analytics datasets.
Moderate sized datasets with mixed feature types	Random Forest	Provides strong predictive accuracy while remaining computationally efficient and robust to noise.
Situations requiring interpretable decision rules	Decision Tree or Logistic Regression	Offers transparent decision processes that educators and administrators can easily interpret.
High dimensional classification problems	Support Vector Machine	Effective in identifying optimal decision boundaries when many predictor variables are present.
Limited datasets with simple structures	Logistic Regression or Naïve Bayes	Performs adequately with minimal computational complexity.

IMPLICATIONS FOR EDUCATIONAL DATA MINING AND INSTITUTIONAL PRACTICE

The findings of the research that was examined have a number of substantial implications:

- **The veracity of forecasts is contingent upon the availability of a wealth of data.**

The predicted accuracy is significantly improved when behavioral and engagement characteristics are incorporated, despite the fact that academic records alone may only produce moderate performance.

- **The dataset's properties must be taken into account when selecting an algorithm.**

When datasets are sparse or limited, institutions should avoid relying on complex models, as this may lead to overfitting.

- **The current frontier is exemplified by ensemble and neural models.**

Artificial neural networks, which are particularly adept at detecting intricate patterns, will become increasingly prominent as institutional data systems continue to develop.

- **Interpretability must continue to be a top priority.**

Instruments such as SHAP and LIME must be implemented to produce forecasts that are both transparent and actionable for instructors, despite the fact that complex models outperform simplified ones.

- **Student assistance can be improved through the implementation of predictive systems.**

The consistent efficacy of ML models in the analyzed trials suggests that well-designed early warning systems can accurately identify at-risk students and guide targeted intervention methods.

The synthesis of the results from the three research studies that were examined underscores the increasing sophistication of machine learning in educational decision support systems. Academic and behavioral predictors were identified as the most significant variables, while Random Forest and Artificial Neural Networks (ANN) were the most successful algorithms, contingent upon the complexity and quantity of data. According to the evidence, predictive modeling has achieved a level of reliability that is adequate to facilitate student monitoring and institutional planning, provided that the analytical methodologies are appropriately aligned with the data features and the datasets are well-structured.

SUMMARY, CONCLUSION AND RECOMMENDATIONS

SUMMARY

This study examined the capability of artificial intelligence (AI) to predict student academic performance with greater accuracy, efficiency, and reliability than traditional assessment methods. The project commenced in response to the growing concerns among educators and policymakers about the need for data-driven approaches to assess learning progress, the rising diversity of students, and the deterioration of academic performance. Recent advancements in educational technology, data analytics, and machine learning suggest that AI can provide significant insights into the determinants of academic results, at-risk behaviors, and student performance trends. Consequently, the study examined the efficacy of AI-based models in forecasting student accomplishment by assessing variables including prior grades, attendance, demographic features, learning habits, and digital engagement patterns.

CONCLUSION

This study demonstrates the capability of artificial intelligence to precisely forecast student academic performance and underscores the importance of choosing the suitable machine learning algorithm in educational contexts, tailored to the specific needs and attributes of the dataset. To achieve true transformation and practical application of these models in educational settings, future research must enhance their predictive accuracy, confirm their applicability across various educational contexts, and explore their incorporation into real-time educational decision-making. The systematic research indicates that Artificial Intelligence has emerged as a pivotal and progressively sophisticated method for academic forecasting, yielding substantial improvements in the early identification of learning risks, scalability, and precision. AI technologies, especially machine learning and deep learning, consistently surpassed traditional statistical techniques in predicting student performance, attrition risk, and behavioral engagement patterns in the studies examined. The ability of AI to assess multimodal learning data, model non-linear correlations, and continuously update predictions with new information is a crucial aspect of its superiority.

The review highlights considerable difficulties that hinder the practical implementation of AI-based prediction systems, notwithstanding these advantages. Concerns about student privacy, algorithmic bias, data quality, and limited model interpretability remain prevalent in the literature. Numerous prediction models are developed utilizing isolated institutional datasets, which limits their generalizability across contexts and poses issues related to fairness and robustness. The review indicates that deep learning models can achieve high prediction performance; but, their "black-box" nature diminishes the trust and effectiveness of instructors who need transparent and actionable knowledge.

The comprehensive review concluded that AI can substantially enhance educational decision-making when applied responsibly and ethically. Evidence suggests that predictive systems functioning within clear governance frameworks that protect student rights, use many data sources, and balance algorithmic complexity with interpretability are the most effective. Future research must emphasize ethical criteria that ensure AI operates as a helpful tool rather than a deterministic system, along with cross-institutional validation and explainable AI methodologies. AI-driven academic forecasting can provide substantial support in early intervention, individualized learning, and improved student success results when executed meticulously.

RECOMMENDATIONS

1. Educational institutions should implement AI tools that can identify at-risk students early by analysing attendance, test scores, class participation, behaviour records, and learning patterns.
2. Institutions should integrate AI models into existing LMS platforms (e.g., Google Classroom, Moodle)
3. Educational institutions should fully adopt AI-driven early warning systems that can predict students who are likely to underperform
4. Teachers and academic administrators should receive continuous training on AI literacy and digital data interpretation.

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