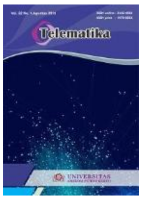

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A Systematic Analysis of the Impact of Non-Academic Factors on Student Academic Performance Prediction using Data Mining

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ABSTRACT

This study presents a Systematic Literature Review (SLR) to analyze the impact of non-academic and academic features on student academic performance prediction using machine learning techniques. Although numerous studies have explored predictive models in educational data mining, there remains no clear consensus regarding which features consistently offer the highest predictive value. This gap creates challenges for researchers and institutions seeking to design efficient and generalizable prediction models. To address this issue, a systematic search was conducted in the Scopus database using predefined keywords related to academic performance prediction, limited to publications from 2020 to 2024. The PRISMA framework was applied to guide article identification, screening, eligibility verification, and qualitative synthesis. A total of 27 articles met the inclusion criteria, focusing on machine learning applications in student performance prediction using academic, demographic, behavioral, and contextual data. The synthesis shows that behavioral features, including online learning interactions and engagement metrics, demonstrate higher predictive power compared to static demographic attributes. Random Forest consistently achieves strong and stable performance across datasets, while hybrid and deep learning models provide improved accuracy in cases involving complex or multimodal data. However, issues such as class imbalance, limited dataset diversity, and inconsistent evaluation standards remain major challenges affection model generalizability. This study contributes by identifying a minimal set of influential features, highlighting emerging multimodal approaches, and discussing the strengths and limitations of current prediction models. The findings serve as a guideline for future research to design more scalable, interpretable, and data-efficient machine learning models for educational settings. The implications of these findings extend to educational institutions seeking data driven strategies for early intervention, personalized learning pathways, and evidence based academic policy development.

1. INTRODUCTION

Predicting students' academic performance has become a compelling topic of interest in both educational research and artificial intelligence, as it plays a crucial role in enabling early intervention, personalized learning, and informed institutional decision making. With advancements in data collection technologies and the widespread use of learning management system, vast amounts of educational data (including academic records, behavioral logs, interaction traces, and textual feedback) have become available for analysis. This study aims to identify the minimal set of essential features for predicting students' future performance using machine learning models (Sengupta, 2023).

In this study, a total of 27 relevant research papers were systematically analyzed to identify the most frequently used features and approaches in student academic performance prediction. In addition to private datasets, features extracted from three widely used public educational datasets were also examined in order to identify commonalities, dependencies, and trends across research contexts.

Previous studies have consistently reported the strong performance of the Random Forest (RF) algorithm in both classification and regression tasks when compared to other traditional machine learning methods, such as Support Vector Machine (SVM) and Logistic Regression (Asiri, 2022; Bey & Champagnat, 2022). Furthermore, research has shown that the application of filter-based feature selection techniques significantly enhances predictive accuracy by eliminating irrelevant and redundant attributes (Hennebelle et al., 2024).

Beyond traditional supervised learning, clustering approaches and Artificial Neural Network (ANNs) have also demonstrated promising outcomes in academic performance prediction, with certain studies reporting accuracies approaching 100% in controlled settings (Ouatik et al., 2022). Other findings indicate that preliminary academic information, such as midterm grades, faculty affiliation, and departmental data, serves as a critical predictor of students' final academic outcomes (Hamza et. al., 2022). This result emphasize the importance of early stage academic indicators in building reliable prediction models.

Recent advancements in Natural Languange Processing (NLP) further extend the potential of educational data analysis by enabling the extraction of insights from qualitative feedback. In particular, Aspect-Based Sentiment Analysis (ABSA) has shown promise in interpreting student opinions from open-ended survey responses. Alshaikh et al. (2024) explored BERT-based models for Arabic text analysis and demonstrated that models such as FAST-LCF-ATEPC achieved strong performance in both aspect extraction and polarity classification. These findings indicate that textual data can provide valuable supplementary features for performance prediction models.

In parallel, Explainable Artificial Intelligence (XAI) techniques have been introduced to improve the transparency and interpretability of predictive models. Alwarthan et al. (2022) employed methods such as LIME, SHAP, and global surrogate models to identify at-risk students at an early stage. Their results revealed that Random Forest achieved an accuracy of 99,66% and highlighted the importance of interpretability for supporting data-driven academic interventions.

Innovative frameworks have also been developed to support collaborative learning environments. Deng et al. (2022) proposed the Multi-User Computer-Aided Design Collaborative Learning Framework (MUCAD-CLF), which classifies user interactions into constructive and organizational actions. Their findings showed that novice learners could significantly improve their technical skill through structured collaboration with experienced peers, demonstrating the broader educational impact of data-driven learning analytics.

In the context of opinion mining, Koufakou (2024) explored deep learning methods for topic classification and sentiment analysis of course review using transformer-based models such as BERT, RoBERTa, and XLNet. The study found that RoBERTa achieved superior sentiment classification performance, while traditional machine learning methods such as SVM remained competitive for topic classification. These results suggest that combining deep learning and classical approaches can lead to more comprehensive analyses of qualitative educational data.

The COVID-19 pandemic further accelerated the importance of dynamic, behavior-based data in educational research. Liu et al. (2023) demonstrated that online learning behaviors, such as task completion ratio, video engagement time, and assessment performance, were more predictive of academic outcomes than static demographic attributes. This shift highlights the increasing relevance of behavioral and temporal features in performance prediction systems.

Similarly, Nayak et al. (2023) emphasized the significance of incorporating behavioral attributes alongside academic and demographic features. Their study using the Kalboard 360 dataset revealed that the inclusion of behavioral data led to superior predictive performance, with Random Forest achieving 100% accuracy under certain conditions. Filter-based feature selection methods further enhanced this performance by reducing dimensionality and eliminating redundant inputs.

In online learning environments, particularly in Massive Open Online Courses (MOOCs), Nithya and Umarani (2023) proposed a hybrid Random Forest-Artificial Neural Network (RF-ANN) model to predict student dropout. Using interaction and engagement data from the KDD Cup 2015 dataset, theit model achieved an accuracy of 94,86%, reinforcing the effectiveness of hybrid architectures that combine feature importance ranking with deep learning capabilities.

Moreover, multimodal approaches are gaining increasing attention. Qu et al. (2022) introduced a Transformer-based framework that integrates both student behavioral data and textual comments into a unified vector representation. Their model showed measurable improvements over traditional methods and highlighted the significant contribution of textual features to predictive performance, as validated through SHAP-based interpretability analysis.

Addressing another major challenge in educational data mining, Tariq et al. (2023) investigated data imbalance problems in multiclass classification contexts. Their comparative evaluation of oversampling techniques such as SMOTE, BorderLineSMOTE, KMeansSMOTE, and SMOTETomek demonstrated that certain combinations, particularly SMOTETomek with KNN, yielded more balanced and accurate predictions. This emphasizes the importance of handling class imbalance in real world educational datasets.

Despite these significant advancements, a clear research gap remains. Existing studies vary greatly in terms of feature types, modeling approaches, and evaluation methods, making it difficult to identify a consistent and minimal set of influential predictors. Many studies tend to focus on isolated feature categories (academic, behavioral, or textual) without systematically evaluating their combined impact. In addition, limited attention has been given to the generalizability, interpretability, and scalability of these predictive models across different educational contexts. As a result, there is an evident need for a comprehensive synthesis that identifies the most influential features and the most reliable machine learning approaches for academic performance prediction. Based on this gap, the main research questions of this study are as follows:

1) What non-academic features are most frequently used and most influential in predicting students' academic performance?
2) Which machine learning algorithms demonstrate the highest and most consistent performance across different datasets and contexts?
3) What are the main methodological limitations and challenges (such as class imbalance lack of generalizability, and interpretability issues) found in existing studies?
4) How can future research integrate multimodal data (behavioral, textual, and contextual) more effectively to enhance prediction accuracy?
5) Accordingly, the objective of this study are to:
6) Identify and categorize the most commonly used academic and non academic features in student performance prediction studies;
7) Evaluate and compare the effectiveness of machine learning models applied in previous research;
8) Analyze common methodological limitations in current approaches; and
9) Propose future research directions through a systematic, feature based taxonomy and synthesis of best practices.

Therefore, this study conducts a systematic literature review guided by the PRISMA framework to synthesize existing findings and provide a structured understanding of how machine learning can effectively predict students' academic performance. The main contribution of this research lies in presenting a comprehensive feature based analysis, evaluating algorithmic performance trends, and highlighting emerging multimodal approaches that integrate behavioral, textual, and contextual data to support the development of more accurate, interpretable, and robust prediction models (Hussain & Khan, 2023; Shou & Lu, 2025).

2. RESEARCH METHODS

2.1. Research Design

This study adopts a Systematic Literature Review (SLR) approach to identify and analyze previous studies related to predicting students' academic performance (see figure 1). The SLR approach ensures a systematic and structured collection of information to guarantee valid and reliable results (Sengupta, 2023). The main steps in SLR include:

1) Defining specific research questions.
2) Conducting literature searches using relevant keywords in database Scopus.
3) Filtering articles based on inclusion and exclusion criteria.
4) Extracting data from selected articles to analyze the features used in machine learning models.

2.2. Search Strategy

The literature search was conducted exclusively in the Scopus database due to its broad coverage of reputable peer-reviewed journals. The search string was developed using combinations of keywords such as:

1) “student performance prediction”
2) “machine learning”
3) “academic features”
4) “non academic factors”
5) “educational data mining”

The keyword selection was based on terminology frequently used in prior studies to maximize sensitivity and relevance.

2.3. Publication Range

The search was limited to articles published from 2020 to 2024 to ensure the inclusion of recent machine learning advancements and modern educational datasets.

2.4. Inclusion Criteria

Articles were included if they:

1) Used machine learning or deep learning models,
2) Evaluated academic performance prediction,
3) Reported feature types and model performance metrics,
4) Were published in peer-reviewed journals or conferences,
5) Were written in English.

2.5. Exclusion Criteria

Articles were excluded if:

1) Full text was unavailable,
2) They focused solely on qualitative analysis,
3) They did not specify feature types or datasets,
4) They were published before 2020.

2.6. Quality Assessment

Each article was scored from 0 to 2 across all criteria, and only studies scoring at least 7 out of 10 were included in the final synthesis. Each selected article was evaluated based on:

1) Clarity of feature descriptions,
2) Transparency of methodology,
3) Reporting of evaluation metrics,
4) Dataset completeness,
5) Reproducibility of experimental procedures.

2.7. Data Extraction and Synthesis

A thematics synthesis was then conducted to generate feature groups and compare algorithmic trends across studies. For each article, data were extracted on:

1) Dataset characteristics,
2) Feature categories,
3) Machine learning algorithms,
4) Performance metrics,

5) Limitations and challenges.

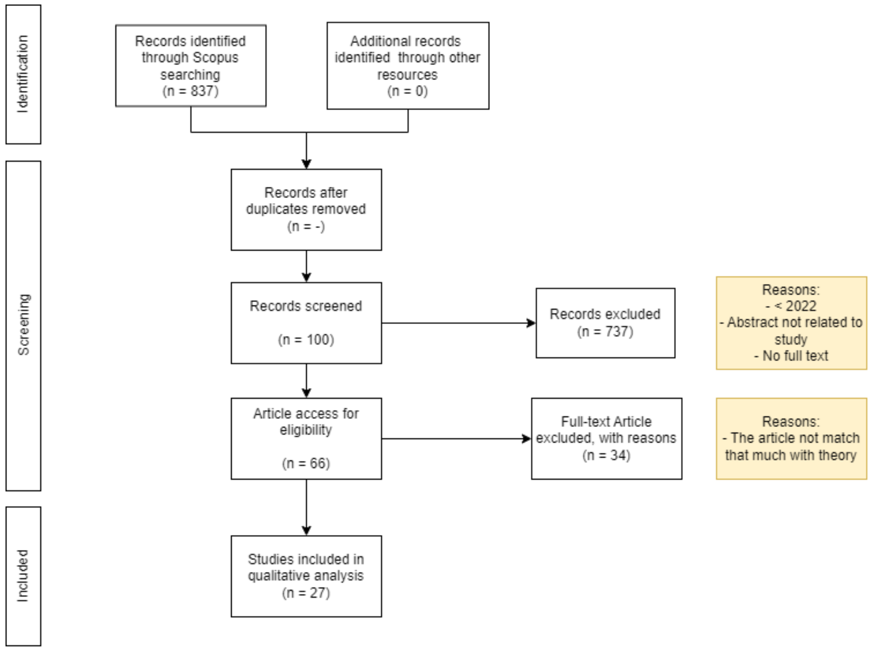

Figure 1. PRISMA Diagram

3. RESULTS AND DISCUSSION

The result of the research can be presented in the form of tables, graphs or figures. They can be compiled with written text to build a discussion of the findings, that is about the new, the modification or the established theory.

3.1. Key Findings

From the analysis of 27 relevant research articles, the following key findings were identified regarding the prediction of students' academic performance using machine learning models.

3.1.1. Key Features for Prediction

Features such as midterm grades, faculty, department, and demographic data are critical factors influencing students' academic performance. Preliminary data, such as pre-admission scores, can also be used to identify at-risk students early (Bey & Champagnat, 2022; Chen & Zhai, 2023; Sengupta, 2023).

Features derived from dynamic learning behaviors and campus attributes yielded good classification results, outperforming the baseline (Nawang et.al., 2022). Nayak et al. (2023) highlighted the importance of incorporating behavioral attributes, such as raised hands, resource visits, and participation in discussions, which significantly improved the accuracy of predictive models, with Random Forest achieving 100% accuracy when these features were included.

Nithya and Umarani (2023) highlighted the effectiveness of a hybrid Random Forest-Artificial Neural Network (RF-ANN) model in predicting MOOC dropouts. Their approach combined the feature selection capabilities of Random Forest with the classification strengths of ANN, focusing on behavioral features such as assignment completion rates, video accesses, and interaction logs. This hybrid model achieved a high accuracy of 94.86% on the KDD Cup 2015 dataset, outperforming traditional models like Logistic Regression and SVM. The study emphasized the importance of incorporating these behavioral features to enhance prediction accuracy and support retention strategies in online education contexts.

Parhizkar et al. (2023) explored the generalizability of machine learning models trained on Iranian data for predicting student performance and tested them on international datasets. Using a questionnaire-based dataset of 536 responses, the study applied models like Random Forest and CNN to evaluate performance on GPA prediction across undergraduate and graduate levels. The findings revealed that Random Forest achieved a generalizability accuracy of 77%, showcasing minimal performance differences (less than 5%) when tested on geographically diverse datasets. This research highlights the potential for using localized data to develop predictive models applicable across regions, emphasizing the importance of feature prioritization and class balance to enhance model robustness and accuracy. highlighted the effectiveness of a hybrid Random Forest-Artificial Neural Network (RF-ANN) model in predicting MOOC dropouts. Their approach combined the feature selection capabilities of Random Forest with the classification strengths of ANN, focusing on behavioral features such as assignment completion rates, video accesses, and interaction logs. This hybrid model achieved a high accuracy of 94.86% on the KDD Cup 2015 dataset, outperforming traditional models like Logistic Regression and SVM. The study emphasized the importance of incorporating these behavioral features to enhance prediction accuracy and support retention strategies in online education contexts.

Qu et al. (2022) demonstrated the efficacy of combining textual data with behavioral data to create more robust predictive models. Their Transformer-based framework integrates course comments and behavioral metrics, achieving superior performance in classification tasks and offering enhanced insights into student learning outcomes. Tariq et al. (2023) further validated the effectiveness of combining oversampling techniques like SMOTETomek with classifiers like KNN, achieving high accuracy in multi-class educational datasets. Their study highlighted that addressing class imbalance through advanced oversampling significantly boosts model reliability and accuracy.

3.1.2. Effective Machine Learning Models

The Random Forest (RF) algorithm demonstrated superior performance compared to other methods, such as Support Vector Machine (SVM) and Logistic Regression, across various datasets (Asiri, 2022; Chen & Zhai, 2023; Yağcı, 2022). The combination of K-Nearest Neighbors (KNN) with SMOTETomek achieved an accuracy of 83.72%, while RF models achieved over 85% accuracy on three different datasets (Ali, 2022; Chen & Zhai, 2023). Clustering-based models were more effective in predicting students' academic performance compared to other data mining techniques (Poudyal et al., 2022).

3.1.3. Feature Selection Approaches

Removing irrelevant attributes using filter-based feature selection methods improved the accuracy of machine learning-based classification models (Hennebelle et. al., 2024; Li, 2023). Interpretability analysis using the SHAP method revealed that text features had a significant influence on the classification model (Tian et al., 2023).

3.1.4. Natural Language Processing Applications

BERT-based models, particularly FAST-LCF-ATEPC, have been effectively utilized for extracting nuanced aspects and sentiments from textual survey data in educational contexts. This approach enables educational institutions to analyze open-ended survey responses for better decision-making. FAST-LCF-ATEPC achieved an F1 score of 0.58 in aspect extraction and 84% accuracy in polarity classification, demonstrating its utility in understanding student feedback (Alshaikh et al., 2024).

3.1.5. Explainable AI for Identifying At-Risk Students

Alwarthan et al. (2022) developed explainable models to predict at-risk students at an early stage, achieving high performance with Random Forest models using datasets from preparatory year students. The study identified key courses influencing at-risk classification and applied XAI techniques like SHAP and LIME for interpretability. The findings enable institutions to proactively address students' challenges, offering timely interventions to improve outcomes.

3.1.6. Collaborative Learning in MUCAD

The Multi-User Computer-Aided Design Collaborative Learning Framework (MUCAD-CLF) introduced by Deng et al. (2022) emphasizes the role of collaborative CAD systems in fostering skill acquisition and teamwork. This approach leverages analytics from design activities to assess participants' learning behaviors and effectiveness in team settings.

3.1.7. Integration of Multimodal Data

Qu et al. (2022) introduced a method to integrate tabular and textual data using a Transformer-based framework. **Their** approach, which utilized both behavioral data and course comments, demonstrated improved performance in predictive modeling with notable enhancements in F1-score and AUC metrics. This method highlights the value of combining multimodal data to better understand and predict academic performance.

Table 1. Comparative Summary of Algorithms and Features

Study	Dataset Type	Feature Categories	Best Algorithm	Accuracy (%)
Nayak et al. (2023)	Behavioral and Academic	Behavioral (hands, visits, discussions)	Random Forest	100

Chen and Zhai (2023)	Academic	Academic scores, attendance	Random Forest	94,5
Nithya and Umarani (2023)	Behavioral (MOOC)	Activities, logs	RF-ANN Hybrid	94,86
Tariq et al. (2023)	Multiclass	Mixed attributes	KNN + SMOTETomek	83,72
Qu et al. (2022)	Multimodal	Textual and Behavioral	Transformer	Increase 4,37 AUC
Asiri (2022)	Academic	Grade relared	SVM	92
Yağcı (2022)	Academic	Course performance	Random Forest	88

3.2. Experimental Results

The RF model achieved 100% accuracy in some cases when considering students' classroom behavior (Hennebelle et al., 2024). SMO and SVM-based models showed the best performance in terms of execution time and classification results(Chauhan, 2022). Deep Neural Networks (DNNs) demonstrated the ability to extract high-level feature values from large volumes of raw data (Altaf et al., 2023).

3.3. Discussion

3.3.3. Analysis of Findings

The findings in this study highlight that machine learning algorithms such as Random Forest (RF), Naive Bayes (NB), and Artificial Neural Network (ANN) have proven effective in predicting students' academic performance. RF consistently delivers superior results across various scenarios and datasets, demonstrating its flexibility in handling classification tasks for both balanced and imbalanced datasets. These findings are supported by consistent results across multiple articles, including Articles by Asiri (2022), Yağcı (2022), and Chen and Zhai (2023).

The use of dynamic features such as students' learning behaviors and campus attributes has shown high relevance in predicting students' academic outcomes. Article 18 specifically emphasizes the importance of dynamic learning behavior data in enhancing classification accuracy. Additionally, text-based feature analysis (Article by Tian et al. (2023)) demonstrates that non-numerical data also significantly impacts predictive models, opening opportunities for further integration with natural language processing (NLP) techniques.

3.3.4. Interpretation of Results

Approaches like filter-based feature selection (Hennebelle et al., 2024) and interpretability analysis using SHAP (Tian et al., 2023) help improve model accuracy while maintaining classification transparency. This indicates that selecting relevant attributes is a critical step in building effective models. However, limitations in model generalizability, as mentioned in Article by Asiri (2022), highlight the need for additional experiments on datasets with more diverse characteristics. Furthermore, while models like KNN with SMOTETomek show potential, deep learning-based approaches as proposed in Article by Ali (2022) still require further exploration to enhance performance.

A deeper synthesis of the reviewed studies reveals several important insights that extend beyond simple summarization. First, the dominance of behavioral and dynamic learning features (such as online interaction patterns, assessment engagement, and resource usage) indicates a shift from static demographic variables toward more context sensitive predictors. This suggests that future predictive models should prioritize real time behavioral data to improve accuracy and early detection of at-risk students.

Second, the consistent effectiveness of Random Forest across diverse datasets highlights the importance of algorithms capable of handling heterogeneous features and noisy data. However, the superior performance of hybrid models such as RF-ANN and Transformer based framework in several studies implies that combining feature selection with deep representation learning could yield more robust and generalizable predictions.

Third, challenges in dataset imbalance and lack of diversity remain prevalent across the literature. Models trained on localized datasets exhibit limited generalizability when applied to broader student populations. This indicates an urgent need for multi-institutional datasets and standardized evaluation protocols to validate model reliability.

Finally, the increasing involvement of NLP-based features, especially those derived from course feedback or open-ended surveys, demonstrates that integrating textual and tabular data enriches the predictive space. This multimodal approach offers a promising direction for future research seeking to capture latent factors influencing student performance.

These thematic findings directly address the objectives of this review, particularly in identifying the minimal set of influential features and comparing the effectiveness of different machine learning models. The synthesis reveals that behavioral and contextual features frequently outperform demographic variables, providing clearer guidance on feature prioritization for future predictive modeling. Furthermore, the emergence of hybrid and multimodal approaches demonstrates a shift toward more comprehensive frameworks that align with the study's goal of improving generalizability and model robustness across diverse educational settings.

3.3.5. Practical Implications

These findings have significant practical implications for educational institutions. By applying predictive models like RF or ANN, institutions can identify at-risk students early and take appropriate intervention measures. Articles by Sengupta (2023) and by Chen and Zhai (2023) emphasize the importance of features such as pre-admission scores and demographic data for early detection of at-risk students. Clustering-based approaches (Poudyal et al., 2022) also offer opportunities to segment students based on their learning patterns and backgrounds. This can assist in developing more personalized and effective teaching strategies.

4. CONCLUSIONS AND RECOMMENDATIONS

This study systematically analyzed 27 empirical studies to identify the essential nonacademic features and machine learning strategies that contribute to accurate student academic performance prediction. Based on the synthesis, several key conclusions are drawn: Ensemble models (such as Random Forest and Gradient Boosting), hybrid deep learning architectures, and feature engineered neural networks consistently outperform conventional classifiers. These models demonstrate stronger robustness across diverse datasets and are more capable of capturing complex behavioral and contextual patterns compared to traditional statistical models.

The review highlights that behavioral, interaction-based, and learning-engagement attributes provide greater predictive value than demographic variables alone. Studies that applied filter, wrapper, or hybrid-based feature selection techniques reported higher accuracy and reduced model overfitting, indicating that careful feature curation is essential for generalizable performance prediction. Models built using multimodal inputs (such as log data, text based indicators, learning analytics, and affective signals) achieve better performance than those relying solely on academic records. The integration of dynamix behavioral tracer enables early detection of learning risks and supports more adaptive and personalized interventions.

Generalizability remains a major challenge in current predictive models, largely due to imbalanced and limited datasets. The findings of this study emphasize that integrating relevant behaviora and contextual features with appropriate machine learning techniques can improve institutions' ability to predict academic performance and support early interventions. To enhance model robustness in future research, more diverse datasets and advanced deep learning approaches should be explored, particularly for handling complex classification tasks and reducing performance instability across different learning environments.

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