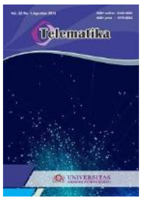

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Interpretable Machine Learning for Early Detection of Academically At-Risk Students Using Behavioral, Socio-Demographic and Learning-Related Factors

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ABSTRACT

The increasing adoption of learning analytics in higher education has encouraged the development of machine learning models for the early detection of academically at-risk students. However, many predictive models emphasize accuracy while providing limited interpretability for educators and academic advisors. This study proposes an interpretable machine learning framework for predicting academic risk using behavioral, socio-demographic, and learning-related student variables. A publicly available synthetic Kaggle dataset consisting of 500 student records was used as a controlled dataset for methodological validation. The data were preprocessed through missing-value handling, standardization, and one-hot encoding before being divided into training and testing sets. Several classifiers were evaluated, including Naive Bayes, Support Vector Machine, Random Forest, Logistic Regression, and XGBoost. Logistic Regression was employed as an interpretable baseline model, while XGBoost was used as a comparative ensemble classifier. Model performance was evaluated using accuracy, precision, recall, F1-score, AUC, and confusion matrix analysis. The results show that Logistic Regression achieved the highest accuracy and F1-score, with an accuracy of 0.8600 and an F1-score of 0.7812. XGBoost achieved the highest AUC value of 0.9278, followed closely by Logistic Regression with an AUC of 0.9246. Random Forest and XGBoost produced the lowest false negative values, indicating their ability to identify at-risk students more effectively. SHAP-based explainability revealed that weekly study hours, assignment completion, class attendance, and sleep duration were the most influential predictors. These findings suggest that interpretable machine learning can support academic early-warning systems by providing transparent prediction results. Since the dataset is synthetic, the findings should be interpreted as methodological validation rather than direct generalization to real student populations.

1. INTRODUCTION

The rapid growth of digital learning environments and learning analytics has encouraged higher education institutions to adopt data-driven approaches for monitoring student progress and identifying academically at-risk students (Gaftandzhieva et al., 2023; Susnjak et al., 2022; Yin & Ying, 2025). Early detection is essential because academic difficulties can develop into course failure, delayed graduation, or dropout when institutions do not provide timely support (Schroeder & Murphy, 2025). In recent years, machine learning techniques have been extensively utilized in educational data mining to forecast students' academic performance based on observable behavioral patterns and socio-demographic attributes, including study habits, attendance, access to learning resources, and family background. These methodologies have exhibited encouraging prediction efficacy and have facilitated the establishment of early-warning systems in scholarly settings.

Previous studies have shown that machine learning models can predict academic outcomes using behavioral and socio-demographic indicators, such as study habits, attendance, learning resource access, parental background, and employment status (Lynam et al., 2024; Mehrad et al., 2024;Bakhtiar & Hadwin, 2022; Han et al., 2022; Jiao et al., 2025). Highly motivated students typically exert greater effort and demonstrate prolonged persistence in learning endeavors, whereas individuals experiencing significant academic anxiety may find it challenging to perform at their best, even with sufficient study abilities. Students possessing robust self-regulation skills are more adept at planning, monitoring, and modifying their learning strategies, hence enhancing their academic performance(Navarro et al., 2023; Yu et al., 2022). Although their significance is acknowledged, these psychological characteristics are frequently analyzed in isolation through conventional statistical methods and seldom integrated into machine learning predictive models.

Simultaneously, several current machine learning investigations in educational settings predominantly focus on predicting accuracy, while providing minimal interpretability of model outputs(Abdrakhmanov et al., 2024; Chen & Zhai, 2023; Gligorea et al., 2022; Guevara-Reyes et al., 2025; Wang & Luo, 2024). While intricate models may attain superior performance, their "black-box" characteristics diminish their practical utility for educators and academic decision-makers, who necessitate transparent and elucidative insights to formulate suitable interventions. In the absence of a thorough comprehension of the reasons behind a student's expected risk, it becomes challenging to convert predictive outcomes into effective academic support solutions. Consequently, there is an increasing demand for interpretable machine learning methodologies that not only accurately anticipate academic risk but also furnish comprehensible explanations of the underlying variables.

Prior research has extensively investigated the utilization of machine learning methodologies to forecast students' academic outcomes and identify individuals at risk of underachievement(Mao et al., 2025; H. Singh et al., 2024). Diverse classification and regression models have been utilized, incorporating behavioral and socio-demographic attributes, such as study habits, attendance patterns, parental background, and access to educational resources; however, these studies have not consistently clarified how learning-related factors are operationalized as measurable dataset attributes within an interpretable early-warning framework (Kassaw & Demareva, 2025; Malik et al., 2025; Matz et al., 2023; Pelima et al., 2024; H. P. Singh & Alhulail, 2022). These research repeatedly illustrate that machine learning models can offer significant predictive insights for early warning systems in educational contexts. Frequently utilized algorithms encompass Logistic Regression, Support Vector Machine (SVM), Naïve Bayes, Random Forest, and gradient boosting techniques, which have demonstrated commendable efficacy in many educational settings(Cheng et al., 2024; Li & Zhou, 2025; Musa, 2024; Nachouki et al., 2023; Syed Mustapha, 2023).

Numerous comparative studies have indicated that interpretable models, including Logistic Regression and decision tree-based methods, can attain competitive performance while providing transparent explanations of prediction results(Ahmed et al., 2024; Muraina et al., 2023; Sevvanthi et al., 2023). The interpretability of these models is especially significant in educational settings, as stakeholders necessitate comprehensible justifications for model decisions to formulate suitable academic interventions. Conversely, while more intricate models like deep neural networks and ensemble learners may achieve superior predictive accuracy, their restricted explainability hinders their practical use in real-world academic assistance systems(Tang et al., 2024; Tao et al., 2022; Wen & Juan, 2023).

Simultaneously, educational psychology literature discusses psychological constructs as theoretical factors associated with students' academic achievement, although these constructs are not directly measured in the dataset used in this study. Learning motivation has been demonstrated to affect students' persistence, engagement, and readiness to exert effort in educational activities. Academic anxiety, especially over examinations and performance assessment, has been linked to diminished academic success and compromised cognitive functioning(Almarzouki, 2024; Cai et al., 2024). Moreover, self-regulated learning is acknowledged as a crucial factor in academic performance, as it demonstrates students' capacity to plan, monitor, and adjust their learning practices efficiently. These psychological constructs are typically investigated using survey methodologies and analyzed through conventional statistical approaches, including regression or structural equation modeling(Cao, 2023; Deng & Yuan, 2023; Rosseel & Loh, 2022).

Although psychological and learning-related factors are theoretically important in explaining academic performance, the dataset used in this study does not directly measure validated psychological constructs. Therefore, this study focuses on measurable behavioral, socio-demographic, and learning-related indicators available in the synthetic dataset. The discussion of psychological factors is used as theoretical background to explain why observable learning behaviors may be meaningful for academic risk prediction. Consequently, current prediction models may neglect significant latent factors that influence students' learning processes and academic risk profiles. Furthermore, research that includes psychological variables frequently considers them as separate explanatory elements instead of integrating them into cohesive prediction models that facilitate early detection and intervention.

Recent studies have underscored the significance of interpretability in educational machine learning, asserting that mere predictions are inadequate without practical explanations(Nnadi et al., 2024). Techniques of explainable artificial intelligence (XAI), including feature importance analysis and post-hoc explanation approaches, have been introduced to augment the transparency of prediction models and expand their applicability for educators. Nonetheless, empirical research integrating interpretable machine learning with behavioral, socio-demographic, and learning-related indicators for the early detection of academically at-risk students remains limited. This gap highlights the necessity for cohesive frameworks that not only ensure dependable forecasting performance but also yield significant insights into the psychological and behavioral determinants of academic risk.

This study combines behavioral, socio-demographic, and learning-related indicators in an interpretable machine learning framework to facilitate the early detection of academically at-risk students using a synthetic educational dataset. This research integrates educational psychology with explainable machine learning, advancing beyond accuracy-focused prediction models to foster the creation of more human-centered, practical early-warning systems in higher education.

2. RESEARCH METHODS

This study employed a quantitative experimental design using a publicly available synthetic dataset obtained from Kaggle. The dataset was used as a controlled dataset to evaluate the feasibility of interpretable machine learning for academic risk prediction. The study focuses on how machine learning models classify academic risk status and how interpretability methods explain the contribution of each predictor. Figure 1 illustrates the research process.

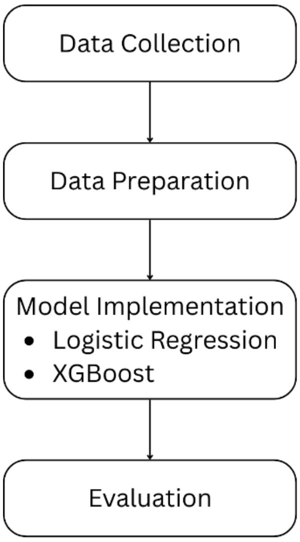

Figure 1. Research Methodology

The study framework has four primary stages such as data collection, data preparation, model implementation, and evaluation. This workflow facilitates the systematic use of behavioral, socio-demographic, and academic indicators in the predictive modeling process, ensuring that both predictive performance and interpretability are considered.

2.1. Data Collection

This study used a publicly available synthetic dataset obtained from Kaggle entitled "Student Study Habits." The dataset consists of 500 student records and captures key academic behaviors, including weekly study hours, daily sleep duration, attendance rate, assignment completion, and final grade. It also includes socio-academic factors such as parental education, internet access, and part-time job status. The dataset was synthetically generated for research and academic use; therefore, it does not represent primary survey data collected directly from a specific student population. In this study, the dataset was used as a controlled dataset for methodological validation of interpretable machine learning models in academic risk prediction.

The target variable is academic risk status, which is represented as a binary classification outcome: at-risk and not-at-risk. In this study, the target variable is used to evaluate the ability of machine learning models to distinguish students who may require academic support from those who are classified as not at risk. In this study, students with final grades below 60 were labeled as at-risk (1), while students with final grades equal to or above 60 were labeled as not-at-risk (0). Table 1 summarizes the variables used in the study.

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Table 1. Description of Behavioral, Socio-Demographic and Academic Variables

Variable Category	Variable	Description	Data Type
Behavioral Factors	study_hours_per_week	Weekly study hours	Numerical
Behavioral Factors	sleep_hours_per_day	Daily sleep duration	Numerical
Behavioral Factors	attendance_percentage	Attendance rate	Numerical
Behavioral Factors	assignments_completed	Number or proportion of completed assignments	Numerical
Socio-Demographic Factors	parental_education	Parental education level	Categorical
Socio-Demographic Factors	internet_access	Internet access availability	Categorical/Binary
Socio-Demographic Factors	part_time_job	Part-time employment status	Categorical/Binary
Academic Outcome	final_grade	Final academic grade used to construct risk status	Numerical
Target Variable	academic_risk_status	0 = not-at-risk, 1 = at-risk	Binary

Although the dataset comprises 500 student records, it is synthetically generated and should be interpreted as a controlled representation for methodological validation rather than direct population inference.

2.2. Data Preparation

Before model construction, several preprocessing steps were conducted. First, incomplete records were checked to ensure data consistency. Second, numerical features were standardized using z-score normalization to maintain comparable feature scales. Third, categorical variables were transformed using one-hot encoding to enable machine learning processing. The dataset was then divided into training and testing sets using an 80:20 ratio. The target distribution consisted of 340 not-at-risk students and 160 at-risk students, indicating a moderately imbalanced classification problem.

Based on this distribution, model evaluation did not rely only on accuracy, but also included precision, recall, F1-score, AUC, and confusion matrix analysis. Recall and false negative values were considered especially important because early-warning systems should minimize the possibility of failing to detect students who are actually at risk.

2.3. Machine Learning Algorithms

This study compared several machine learning classifiers to provide a more comprehensive baseline evaluation. Logistic Regression was used as an interpretable baseline model because its coefficients can be examined to understand the direction and strength of predictor effects. Additional baseline classifiers, including Naive Bayes, Support Vector Machine, and Random Forest, were used to compare predictive performance across different modeling approaches. XGBoost was included as an ensemble-based classifier to evaluate whether a more complex model could improve predictive performance. This comparison was intended to determine whether the proposed interpretable framework offers competitive performance while maintaining explainability. Hyperparameters of the model were tuned by cross-validation to mitigate overfitting and enhance generalization performance.

The efficacy of the machine learning models was assessed by various metrics, including accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC). These indicators offer a thorough evaluation of predictive efficacy, especially in recognizing students at academic risk. A confusion matrix was employed to analyze prevalent forms of misclassification errors.

An interpretability analysis was conducted to improve the transparency and practical applicability of the predictive models. Feature importance and coefficient analysis were employed to ascertain the most significant determinants of academic risk. Furthermore, post-hoc explainability methods were utilized to deliver both localized and global elucidations of model predictions. This interpretability feature allows educators to comprehend the rationale behind predictions of student risk and facilitates the development of focused intervention measures.

3. RESULTS AND DISCUSSION

3.1. Comparison of Model Performance

The predictive performance of several classifiers was evaluated using accuracy, precision, recall, F1-score, and AUC. The comparison included Naive Bayes, Support Vector Machine, Random Forest, Logistic Regression, and XGBoost. This baseline comparison was conducted to provide a broader evaluation of model performance and to identify whether the ensemble-based model provided meaningful improvement over simpler classifiers. The comparison findings are displayed in Table 2.

Table 2. Comparative Performance of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-score	AUC
Naive Bayes	0.7100	0.5405	0.6250	0.5797	0.7716
SVM (RBF)	0.7700	0.6216	0.7188	0.6667	0.8796
Random Forest	0.8400	0.7222	0.8125	0.7647	0.9019
Proposed Framework (LR + SHAP)	0.8600	0.7812	0.7812	0.7812	0.9246
XGBoost	0.8400	0.7222	0.8125	0.7647	0.9278

This table presents the performance metrics of the proposed interpretable framework and comparative models, including Naive Bayes, SVM, Random Forest, and XGBoost.

Table 2 shows that the proposed interpretable framework achieved the highest accuracy and F1-score, with values of 0.8600 and 0.7812, respectively. This indicates that the proposed approach outperformed the baseline models in overall classification accuracy and balanced predictive performance. XGBoost achieved the highest AUC value of 0.9278, indicating strong discriminative ability in distinguishing at-risk and not-at-risk students. Random Forest and XGBoost produced the same recall value of 0.8125, suggesting that both ensemble-based models were effective in detecting at-risk students. Therefore, the proposed framework provides competitive performance while offering greater interpretability for academic decision-making. The confusion matrix summary is shown in Table 3 for a more in-depth analysis of categorization behavior.

Table 3. Summary of Classification Results via Confusion Matrix

Model	TN	FP	FN	TP
Naive Bayes	51	17	12	20
SVM (RBF)	54	14	9	23
Random Forest	58	10	6	26
Proposed Framework (LR + SHAP)	61	7	7	25
XGBoost	58	10	6	26

Note:This table delineates true negatives (TN), false positives (FP), false negatives (FN), and true positives (TP) for each model.

Table 3 shows that Random Forest and XGBoost produced the lowest number of false negatives, with FN = 6. This indicates that both models were effective in identifying students who were actually at risk. The proposed interpretable framework produced FN = 7 and the lowest number of false positives, with FP = 7, indicating a balanced performance between detecting at-risk students and avoiding incorrect risk classification. Figure 2 shows the ROC curve comparison of all classifiers. Logistic Regression and XGBoost achieved the highest AUC values of approximately 0.93, indicating strong discriminative ability in classifying at-risk and not-at-risk students. Random Forest and SVM also showed good performance, while Naive Bayes produced the lowest AUC. The results indicate that Logistic Regression provides competitive predictive performance despite being more interpretable than complex ensemble models.

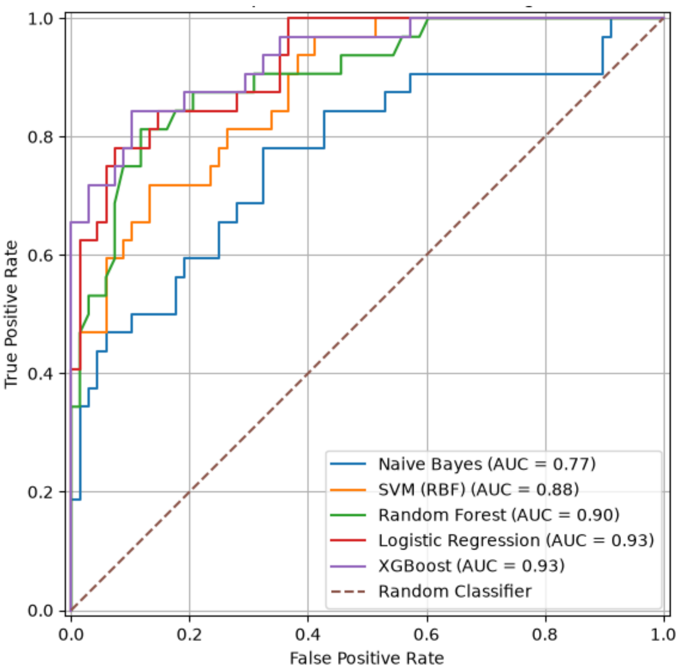

Figure 2. ROC Curve Comparison of Machine Learning Classifiers

3.2. Ablation Analysis Based on Feature Groups

To further examine the contribution of different feature groups, an ablation analysis was conducted by comparing model performance using different subsets of variables. The first feature set used only behavioral indicators, including weekly study hours, sleep duration, attendance percentage, and assignment

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completion. The second feature set used only socio-demographic indicators, including parental education, internet access, and part-time job status. The third feature set combined all available predictor variables, including behavioral and socio-demographic indicators after preprocessing. The final grade was not used as an input predictor because it was used to construct the binary academic risk status. Table 4 presents the ablation analysis based on different feature groups.

Table 4. Ablation Analysis Based on Feature Groups

Feature Set	Accuracy	Precision	Recall	F1-score	AUC	TN	FP	FN	TP	Number of Features
Behavioral indicators only	0.8100	0.6970	0.7188	0.7077	0.8667	58	10	9	23	7
Socio-demographic indicators only	0.5800	0.3913	0.5625	0.4615	0.5811	40	28	14	18	5
Combined feature set	0.8600	0.7812	0.7812	0.7812	0.9246	61	7	7	25	12

The results show that behavioral indicators achieved better predictive performance than socio-demographic indicators, with an accuracy of 0.8100, F1-score of 0.7077, and AUC of 0.8667. In contrast, socio-demographic indicators alone produced lower performance, with an accuracy of 0.5800, F1-score of 0.4615, and AUC of 0.5811. The combined feature set achieved the best overall performance, with an accuracy of 0.8600, F1-score of 0.7812, and AUC of 0.9246. These findings indicate that behavioral indicators provide the strongest predictive contribution in the synthetic dataset, while socio-demographic variables offer complementary information when combined with behavioral features.

3.3. Significance of Features and Explainability (SHAP Analysis)

Figure 3 illustrates the global feature relevance of the XGBoost model through SHAP values. Figure 3 depicts the global significance of features and their influence on academic risk prediction, with color representing feature value (high to low) and position along the x-axis indicating the size and direction of impact.

The SHAP analysis indicates that the model assigned the highest contribution to behavioral variables, particularly weekly study hours, assignment completion, class attendance, and sleep duration. These variables had stronger influence on model predictions than socio-demographic variables. This finding suggests that, within the synthetic dataset used in this study, the model primarily learned risk patterns from observable learning behaviors. Therefore, the interpretation should focus on how the model reads the structure of the synthetic data rather than making strong causal claims about real student behavior.

The explainability results also show that the contribution of learning-related indicators should be interpreted cautiously. If such variables are not among the dominant predictors, their role cannot be overstated. Instead, the results indicate that behavioral indicators provide the strongest predictive signal in the current dataset, while additional student-related variables may provide complementary contextual information.

Socio-demographic variables, such as part-time employment status, parental education, and internet access, demonstrate moderate yet significant contributions. A part-time employment correlates with heightened academic risk for certain students, perhaps due to time constraints that restrict learning opportunities. Parental education and internet access exhibit more intricate impacts, suggesting that although contextual factors affect academic achievement, their influence is typically subordinate to students daily learning behaviors.

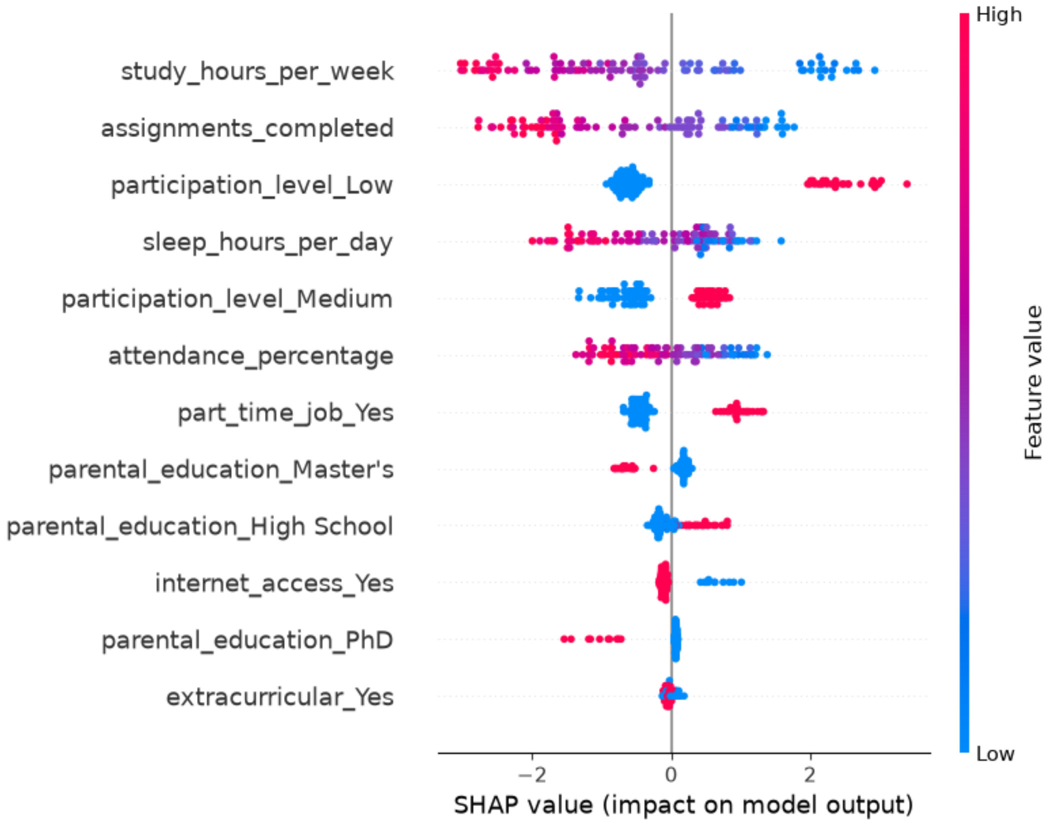

Figure 3. SHAP Summary graphic Illustrating Feature Contributions

The SHAP-based explainability improves the transparency of the predictive model by elucidating both the significance of variables and their impact on individual predictions. This interpretability enables educators to convert model outputs into implementable interventions. Because the dataset is synthetic, the findings should not be interpreted as direct evidence of real student behavior in a specific higher education institution. Instead, the results demonstrate how interpretable machine learning models identify patterns among available predictors and translate these patterns into explainable outputs. In practical implementation, the proposed framework should be validated using real institutional data before being used to support academic advising or student intervention programs.

3.4. Practical Implications for Early Warning Systems

The findings indicate that Logistic Regression achieved the highest accuracy and F1-score, while XGBoost obtained the highest AUC value. Random Forest and XGBoost also produced the lowest false negative values, indicating their usefulness in detecting at-risk students. In practical academic contexts, this result suggests two complementary deployment strategies: Logistic Regression can be used as a transparent decision-support model, while XGBoost or Random Forest can be considered when the priority is minimizing false negative cases.

The main practical value of interpretable machine learning lies in its ability to provide transparent explanations rather than only prediction labels. For lecturers, counselors, and academic advisors, knowing that a student is predicted to be at risk is not sufficient. They also need to understand which factors contribute to the prediction. Logistic Regression coefficients and SHAP values can help identify whether the prediction is mainly influenced by study hours, attendance, assignment completion, or other available indicators. This explanation can support the design of more targeted academic guidance in future institutional applications. However, because the current dataset is synthetic, the proposed use should first be validated using real student data before being implemented in actual academic advising or counseling systems.

4. CONCLUSIONS AND RECOMMENDATIONS

This study developed an interpretable machine learning framework for the early detection of academically at-risk students using behavioral, socio-demographic, and learning-related variables from a synthetic educational dataset. The results show that machine learning models can classify academic risk with promising performance, with Logistic Regression achieving the highest accuracy and F1-score, while XGBoost achieved the highest AUC value. However, the findings should be understood as methodological validation using synthetic data rather than direct evidence from a real student population.

The SHAP-based explainability analysis revealed that behavioral indicators, particularly weekly study hours, assignment completion, class attendance, and sleep duration, were the most influential predictors in the model. Socio-demographic and other learning-related variables provided additional information, but their contribution was less dominant. Therefore, the conclusion of this study emphasizes the importance of observable learning behaviors in the model’s prediction process, while avoiding overgeneralization regarding psychological constructs. These findings emphasize that academic risk is influenced by a confluence of learning behaviors and contextual factors, which can be effectively represented by explainable machine learning models.

The proposed framework facilitates the creation of human-centered early-warning systems in higher education from a practical standpoint. Employing interpretable models allows educators and academic advisers to comprehend the fundamental aspects influencing students' risk status and to formulate targeted solutions, including academic coaching, time-management assistance, and learning plan help. The synergistic application of XGBoost for efficient screening and Logistic Regression for clear decision-making provides a balanced implementation strategy for institutional early-warning systems.

This study has several limitations. First, the dataset was synthetically generated and obtained from a public Kaggle repository; therefore, it does not represent direct observations from a real university population. Second, the findings cannot be generalized to actual student behavior without further validation using institutional or primary survey data. Third, this study did not use validated psychological instruments to measure constructs such as learning motivation, academic anxiety, or self-regulated learning. Therefore, the contribution of psychological constructs should not be overinterpreted. Future research should validate the proposed framework using real longitudinal student data, standardized psychological scales, and ablation analysis to examine whether the integration of psychological variables improves prediction performance.

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