Full research paper

ACTIONABLE LEARNING ANALYTICS: PREDICTING UNIVERSITY PERFORMANCE LEVELS WITH INTERPRETABLE MACHINE LEARNING

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ABSTRACT

Higher education institutions need timely, explainable tools to identify students at risk of low performance on large-scale examinations and to guide targeted academic support strategies. In response to this challenge, this study proposes an explainable machine learning framework to predict undergraduate students' performance levels in Colombia's SABER PRO examination. Using student background variables (e.g., gender, region, school type, parental education, and occupation) and SABER 11 standardised test scores (Critical Reading, Mathematics, Citizenship Skills, Science, and English), we formulate a binary classification problem that distinguishes desirable outcomes (levels 3–4) from non-desirable outcomes (levels 1–2). We benchmark baseline models against non-linear learners, including XGBoost, GLMNET, SVM, DT, and LDA, using a 10-fold cross-validation protocol with systematic hyperparameter tuning. Model performance is assessed through confusion matrices and AUC scores. To support educational decision-making, we complement predictive results with explainability analyses, including global feature importance and individual-level explanations via SHAP, enabling transparent identification of the key drivers behind performance levels. The proposed approach provides actionable learning analytics to guide early academic support, promote responsible and transparent educational decision-making, and improve the likelihood of desirable SABER PRO achievement.

KEYWORDS

Academic performance, explainable artificial intelligence, learning analytics

HOW TO CITE

De La Hoz E., Garcia-Yerena C., Torres-Rojas I. (2026) 'Actionable Learning Analytics: Predicting University Performance Levels with Interpretable Machine Learning', *Journal on Efficiency and Responsibility in Education and Science*, vol. 19, no. 1, pp. 15–27. http://dx.doi.org/10.7160/eriesj.2026.190102

Article history
Received
February 11, 2026
Received in revised form
March 24, 2026
Accepted
March 25, 2026
Available on-line
March 31, 2026

Highlights

- *The proposed framework supports actionable, interpretable, and responsible learning analytics for higher education.*
- *Combining prior academic achievement with socioeconomic context enables earlier and more equitable identification of students needing support.*
- *Explainability tools help institutions make transparent and auditable decisions when using predictive models.*
- *The proposed models show useful predictive performance and can support more efficient targeting of mentoring, tutoring, and academic reinforcement resources.*

INTRODUCTION

Predicting university learning outcomes has become a strategic priority for higher education systems that rely on standardised exit assessments to evaluate students' competencies near the end of undergraduate programs. In many countries, these assessments report results through ordered performance levels (e.g., four categories from low to high), which are directly used for institutional benchmarking, accreditation-related reporting, and the design of academic support strategies. This practical relevance aligns closely with the learning analytics agenda of converting educational records into actionable evidence to improve decision-making at scale (Long and Siemens, 2014). Therefore, beyond predictive accuracy, this study is positioned within a responsible learning analytics perspective. The purpose of the proposed framework is not merely to classify student performance but to support higher education institutions in making transparent, explainable, and contextually sensitive decisions. In this sense, the model's contribution lies in both its role in educational decision-making and its more efficient allocation of academic support resources, such as mentoring, tutoring, and reinforcement programs.

The academic variables are the most common predictors used in forecasting models, typically course grades, outputs from a learning management system, and standardised test results, because these indicators are closely related to academic management and are readily operationalised.

However, there is solid evidence that socioeconomic and contextual features, such as parental education and occupation, and economic resources, partially determine students' educational trajectories. Sirin (2005), in a systematic literature review, reveals a strong correlation between socioeconomic status and academic performance, suggesting the importance of contextual factors for both forecasting and classification. For instance, the international PISA tests integrate students' socioeconomic context through composite indices that represent parental education, employment status, and other factors, and serve as key variables for understanding and predicting learning outcomes (Lamichhane et al., 2021).

The main objective of a machine learning model is not only to predict a future value. The true value of machine learning modelling lies in the server as an objective support for decision-making, enabling the implementation of administrative and academic initiatives to improve educational quality in the long term. The philosophy of learning analytics has experienced rapid and sustained growth in recent years, leveraging diverse datasets and machine learning models to generate knowledge in the educational environment (Berens et al., 2019). However, there are common constraints in machine learning models applied to education, including difficulties in achieving generalizability across different scenarios and the need to include variables related to students' socioeconomic context (Delahoz-Domínguez and Hijón-Neira, 2025).

Consequently, one of the most common applications of learning analytics is the creation of early warning systems to identify students at risk of dropping out or being dissatisfied with the educational process. Previous research shows that predictive models can estimate a student's risk (Diaz Lema et al., 2024). However, they are not sufficiently self-explanatory to take effective action, since they do not seek to verify that the model correctly predicted a problem associated with the student, but rather to take actions to prevent the problem and to generalise the intervention scheme for future similar cases (Sušnjak, 2022). Multiple large-scale and meta-analytic studies find that socioecomic variables are a consistent predictor of academic performance, typically with moderate-to-medium effect sizes. Meta-analyses across primary/secondary education report strong correlations (Hasan et al., 2020). Consequently, machine learning models using socioeconomic and school-level variables (family income, parental education, school characteristics) achieve high accuracy in predicting success, with these SES-related features among the most important predictors (Sangsawang, 2025).

Based on the studies discussed above, predictive systems appear to be most valuable when they are (i) built from data available early enough to support action, and (ii) designed to produce outputs that can be operationalised within institutional processes. Motivated by these needs, this study develops a machine learning approach to predict students' performance levels in a final-year national standardised assessment using information available before graduation. Our feature set integrates two complementary sources: (i) student background variables and (ii) prior standardised test results from the end of high school. The background predictors include gender, region of residence, school sector (public/private), school calendar, and parental characteristics such as mother's/father's education and mother's/father's occupation. The academic preparation predictors correspond to competences assessed in the national exam in Colombia (critical reading, mathematics, citizenship skills, science, and English).

The combination of academic and socioeconomic predictors aims to improve predictive performance by capturing both intrinsic and extrinsic student characteristics, thereby enabling more equitable and context-sensitive educational decision-making. In the present research, we consider a binary formulation that distinguishes desirable outcomes (upper levels, 3–4) from non-desirable outcomes (lower levels, 1–2). This dual framing supports operational decision rules, such as prioritising students for mentoring, tutoring, or targeted academic reinforcement. In this way, the proposed framework contributes not only to prediction but also to more responsible and effective educational action.

Methodologically, we follow the recommendation that comparative modelling is essential because no single algorithm consistently dominates across educational contexts and feature types (Domínguez-Jiménez et al., 2020). We therefore benchmark interpretable baselines against non-linear machine learning methods that are frequently reported as strong performers in student outcome prediction. To improve robustness and reduce overfitting risk, models are evaluated under cross-validation and systematic hyperparameter tuning, consistent with best practices discussed in the Learning Analytics (LA) and Educational Data Mining (EDM) (Durairaj and Vijitha, 2014). Finally, educational prediction requires more than accuracy: institutions need transparent explanations to justify interventions and build trust among stakeholders. This study, therefore, incorporates explainable AI methods to provide both global interpretability (which predictors matter most) and local interpretability (why a particular student is predicted to fall into a given level). Model-agnostic local explanations and Shapley-value-based attribution are widely adopted approaches for interpreting complex models, especially when predictions may trigger real academic decisions (Messalas et al., 2019; Parisineni and Pal, 2023). In this way, the proposed framework aims to deliver not only predictive performance but also actionable, auditable insights consistent with the goals of the ERIES special issue on predicting learning outcomes using machine learning.

LITERATURE REVIEW

Predictive learning analytics in higher education

The development of EDM/LA in higher education aims to identify early signals that help students succeed. The key idea behind learning analytics is translating educational data into valuable insights to support decision-making and improve student satisfaction (Siemens, 2019). Predictive models play a fundamental role in the development of learning analytics, implementing everything from descriptive statistical techniques to advanced supervised and unsupervised machine learning models.

In the literature, there is a recurring emphasis on aligning predictive models with institutional constraints and contexts. Specifically, models must work with the information and data available in the environment to facilitate effective interventions and achieve interpretable, actionable results. Accordingly, Predictive Learning Analytics (PLA) most often predicts course grades, pass/fail status, retention, and dropout, as well as learning outcomes and engagement levels (Sghir et al., 2022). Besides, Common data sources include Learning Management Systems (LMS) logs (clicks, submissions), video analytics, assessment scores, demographics, prior Grade Point Average (GPA), and sometimes emotions or self-reports (Hasan et al., 2020; Umer et al., 2021). Supervised ML dominates: decision trees, random forests, Support Vector Machines (SVMs), K-Nearest Neighbours (k-NNs), logistic regression, neural networks, and ensembles (Edmond et al., 2025; Yağcı, 2022). Accordingly, ensemble and hybrid models (bagging, boosting, Random Forest (RF), gradient boosting) generally achieve the best accuracy and robustness (Chen et al., 2025). Reported accuracies often range 70–90%+ (e.g., ~70–75% with simple features; ~88–98% in richer or smaller datasets), but generalizability across contexts is uncertain (Pali and Verma, 2024).

Academic Predictors and the Role of Previous Standardised Tests

Across higher education prediction models, prior standardised/entrance scores and institutional academic variables are typically integrated as complementary features in a single feature set, rather than as separate model stages (Rhaiem, 2017). In consequence, predictive higher-education models start from pre-admission data (e.g., high school grades, standardised entrance exams) and then add institutional academic variables, such as course grades, midterms, attendance, teacher quality, and program/department indicators, to form a single feature vector. These are fed simultaneously into ML models such as Random Forests, Gradient Boosting, SVMs, XGBoost, neural networks, or AutoML frameworks (Guevara-Reyes et al., 2025; Zeineddine et al., 2020). According to Ahmed et al. (2025), excluding entrance or standardised examination scores represents a missed opportunity, since the inclusion of university entrance exam data could further enhance predictive accuracy and robustness.

Accordingly, studies that quantify feature importance consistently find that historical academic performance (standardised/entrance exams, prior GPA, midterms) is a top predictor of later success, often alongside institutional variables such as attendance and parental education (Ahmed et al., 2025; Talajić et al., 2025) such as artificial intelligence (AI). However, some evidence warns that standardised test scores and highschool GPA are not universally reliable across diverse contexts, so models that also integrate institutional and contextual variables (teacher quality, infrastructure, student–teacher ratio) tend to generalise better and avoid overreliance on test scores alone (Guevara-Reyes et al., 2025).

Socioeconomic context as a key driver of educational outcomes

A substantial body of research in higher education consistently shows that family income, parental education, and parental occupation influence academic outcomes through multiple interrelated mechanisms involving resource availability, family support, and exposure to stress. In the Chinese context, mixed-method studies have found that higher parental education and greater family income are associated with better university GPA, as students from more affluent households tend to report stronger financial and emotional support, more favorable study environments, and, consequently, better academic performance; however, these studies also note that intrinsic motivation and institutional support play an important complementary role in shaping outcomes (Wang and Panicker, 2025). Similarly, research conducted in Türkiye shows that household income, need to work while studying, parental education, and region of residence significantly affect the chances of entering a desired university department and placement rank, indicating that regional economic disparities and the necessity of student employment channel inequality into selective higher education outcomes (Kutlu and Özer, 2024).

This pattern is reinforced by evidence from other national settings. Among Sudanese medical students, higher family income is significantly associated with higher cumulative GPA, even after controlling for age and other relevant characteristics, highlighting the persistent influence of socioeconomic background in academically demanding programs (Jaber et al., 2024). Likewise, Cross-country panel analysis finds that household access to credit significantly increases higher education participation, especially in developing countries, whereas macroeconomic uncertainty expands university enrollment in developed economies but reduces it in developing ones; in addition, the combination of uncertainty and household credit particularly harms women's tertiary outcomes (Koirala et al., 2024). In the same vein, during the COVID-19 pandemic in Colombia, parental education and household technological assets (e.g., computers, internet) were positively associated with test scores both before and during the pandemic, with the importance of technology and high-quality institutions increasing under remote instruction, thus magnifying the academic impact of household and institutional resources (Mena and Bulla, 2022). Taken together, these findings support the view that socioeconomic status should be understood not as a simple one-step predictor of grades, but rather as a structural background condition that shapes access to resources, psychosocial support, and vulnerability to academic risk.

Additionally, Frameworks for academic research efficiency emphasise individual, organisational, and contextual drivers; efficiency cannot be meaningfully compared without modelling all three levels (Rhaiem, 2017). Consequently, academic productivity is a latent construct, dependent on disciplinary norms and institutional capacities; single, decontextualised outputs (e.g., publications only) are conceptually inadequate (Martinez-Daza et al., 2024). Therefore, comprehensive Higher Education Institutions (HEI) evaluation frameworks explicitly integrate context, inputs, processes, and products, arguing that context is a formal dimension of performance rather than a nuisance to be averaged out (Chinta et al., 2016). Besides, ignoring context yields biased productivity scores, high misclassification rates, and inequitable resource allocation, particularly penalizing less selective, less resourced, or disadvantaged institutions (Agasisti et al., 2022; Guo and Ye, 2025). Thus, Context-aware models—through value-added metrics, conditional efficiency estimation, or multi-dimensional Context Items Processess Products (CIPP)-style frameworks—are necessary to produce accurate, interpretable, and fair productivity assessments in higher education (Horn and Lee, 2019; Rhaiem, 2017).

Datasets and predictors

Across higher education analytics, data quality and class/group imbalance are central determinants of both accuracy and fairness. Therefore, large higher-education datasets often have substantial missing responses; how these are imputed can affect both performance and group disparities. Several studies on college success prediction show that common imputation methods can increase bias when test data reflect historical (unequal) distributions, even when headline accuracy is acceptable (Nezami et al., 2024). In the case of early warning, models are typically trained on heavily imbalanced pass/fail or on-time/late graduation labels. Without correction, models become biased toward the majority class, missing many at risk students and sometimes disadvantaging minority groups. In course and graduation prediction tasks, oversampling the minority class substantially improves minority-class recall and F1, sometimes with only a negligible loss in overall accuracy (Sha et al., 2023). Consequently, unequal representation of gender, race, or first-language groups yields distribution and hardness biases—models are trained more on majority groups and on "easier" examples. Studies on course success and forum classification show that such data characteristics are strongly associated with systematic performance gaps across demographic groups (Sha et al., 2022).
Considering the variability in the model's predictors, it is evident that educational machine learning models for predicting student success are highly sensitive to which predictors are used and how they are engineered. For El-kenawy et al. (2025), careful feature selection and engineering consistently improve accuracy, reduce overfitting, and enable good performance with less data or fewer features. The systematic review by Alsariera et al. (2022) emphasises that prediction quality is determined by the traits or features used. Accordingly, the Academic variables (GPA/CGPA, grades, and attendance), internal assessments, and demographic/family attributes are repeatedly identified as high value predictors (Ahmed, 2024; Alsariera et al., 2022). Also, adaptive or ensemble selection methods reduce dimensionality while maintaining competitive cross-validation accuracy, simplifying models and speeding up training (Malik et al., 2025).

Explainability and responsible prediction

Models in social contexts should be transparent and explainable, as the decisions they make impact people's futures. From this perspective, Explainable AI (XAI) emerges as a framework for explaining the outputs of machine learning models. Consequently, an example of a model-agnostic technique is local surrogate explanations, which was created to help users understand individual predictions (Alonso and Casalino, 2019). From another perspective, methodologies based on Shapley values enable us to evaluate each predictor's contribution to the responses (Melo et al., 2022).
In the study by Johora et al. (2025), they incorporate XAI directly into the modelling flow for academic performance predictions, thereby transitioning from a model based on accuracy to one driven by decision support. Consequently, explainable AI (XAI) techniques such as SHAP and LIME are used to clarify global feature importance and local, per-student predictions, enabling trust and legal compliance (Oyedotun et al., 2025; Sušnjak, 2022). Thus, Responsible LA is framed as relational and "responseable": institutions must act appropriately on predictions rather than merely generate them (Khalil et al., 2023; Rets et al., 2023) facilitate effective teaching, highlight aspects of course content that might be adapted, and predict a range of possible outcomes, such as students registering for more appropriate courses, supporting students' self-efficacy, or redesigning a course's pedagogical strategy. It will do all these things based on the assumptions and rules that learning analytics developers set out. As such, learning analytics can exacerbate existing inequalities such as unequal access to support or opportunities based on (any combination of. From an operational aspect, Practical recommendations include ethics protocols, stakeholder involvement, ongoing monitoring, and an explicit equitybydesign framework (Mathrani et al., 2021). Accordingly, in this study, responsibility is understood as the combination of interpretability, transparency, and context-sensitive use of predictions in educational settings. The aim is not to automate decisions about students, but to provide evidence that can support fairer and more accountable institutional actions. At the same time, these predictions may improve institutional effectiveness by helping universities prioritise limited support resources according to student needs.

MATERIALS AND METHODS

Anticipating which supervised model will optimally fit the data a priori is challenging; this principle is referred to as the No Free Lunch theorem. Algorithms with superior theoretical predictive capabilities may sometimes fail to elucidate the links between input and output variables. Consequently, in light of the performance disparities among various algorithms, five methods will be employed: Extreme Gradient Boosting (XGBoost), Generalised Linear Model – Elastic Net Regularisation (GLMNET), SVM with linear kernel, Decision Trees (DT), and Linear Discriminant Analysis (LDA).

Proposed modeling structure

This study develops and evaluates five machine learning models for predicting university performance levels. The procedure begins by splitting the original dataset into 80% for training and 20% for testing (See Figure 1). Model training is conducted using a 10-fold cross-validation scheme, where the training set is randomly partitioned into 10 equal-sized folds. In each iteration, nine folds are used to train the model, and the remaining fold is used for validation, rotating the validation fold until all ten folds have been used once. The average predictive performance across the ten iterations is then reported as the overall evaluation of each model.

The model's input variables represent student information, grouped into three categories: high school standardised test results, high school socioeconomic data, and college standardised test results. The structure, category, and description of the variables are presented in Table 1.

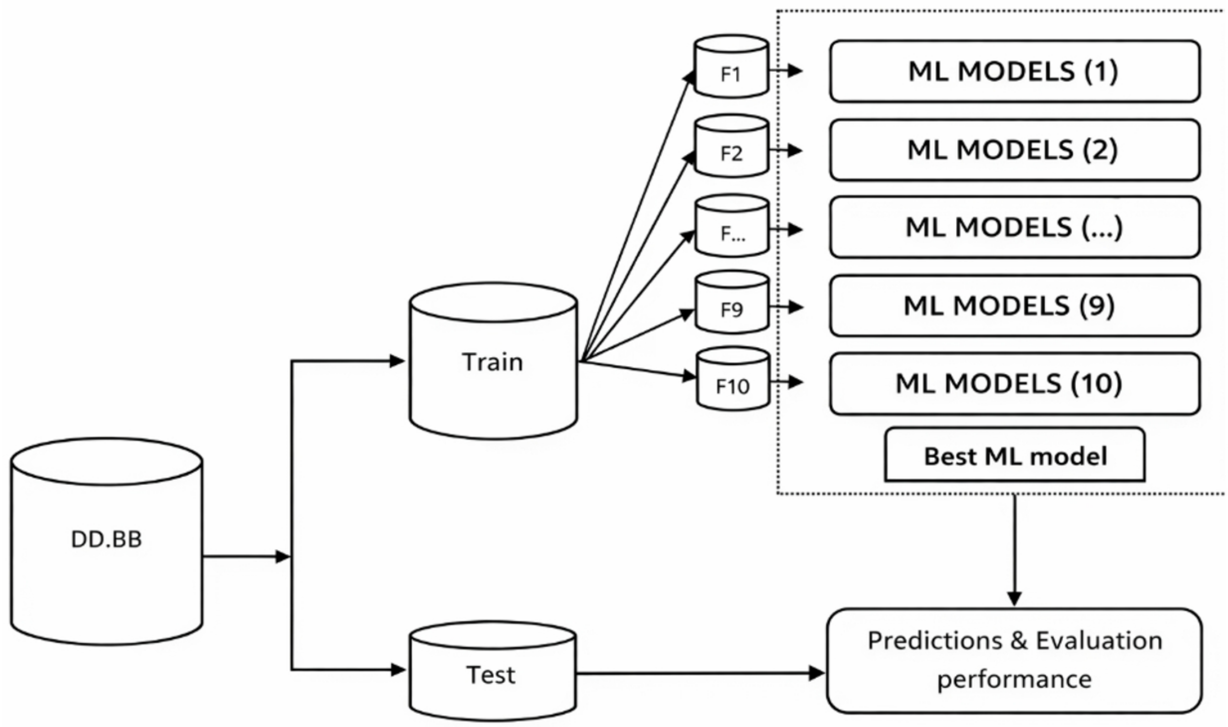

Figure 1: Machine Learning framework

Category	Name	Type	Levels/scale
Student Background	Gender (gen)	C	Male, female
	Department of Residence (dep.res)	C	Students' department of residence
	School type	C	Public, private
	School calendar (sch)	C	Calendar_A, Calendar_B
	Father's education (fedu) Mother education (medu)	C	Complete professional education, Incomplete professional education, None, Does not know, Postgraduate, complete secondary school, incomplete secondary school, complete Technical degree, incomplete technical degree.
	Father's occupation (focus) Mother's occupation	C	unemployed, general manager, auxiliary level employee, Domestic employee, businessman, Stay-at-home, day laborer, employee of a private company, government employee, Other activity or occupation, Little Businessman, Independent professional, Unpaid family worker, Self-employed, Worker without remuneration.
Standardised test at High School	Critical Reading (CR)	N	Score in the test (0-100)
	Math (Math)	N	Score in the test (0-100)
	Citizenship Skills (CS)	N	Score in the test (0-100)
	Science (sci)	N	Score in the test (0-100)
	English (ENG)	N	Score in the test (0-100)
Standardised test at University	Level of performance	N	1, 2, 3, 4

Table 1: Description of raw variables. In the Type column, the N denotes a numerical variable and C.

By feeding the model with a new student's social factors and academic performance on the Sabre Pro university exam, the model can operationalise predictions of which occupations the student is most likely to excel in. The operational flow of the recommendation system is depicted in Figure 2.

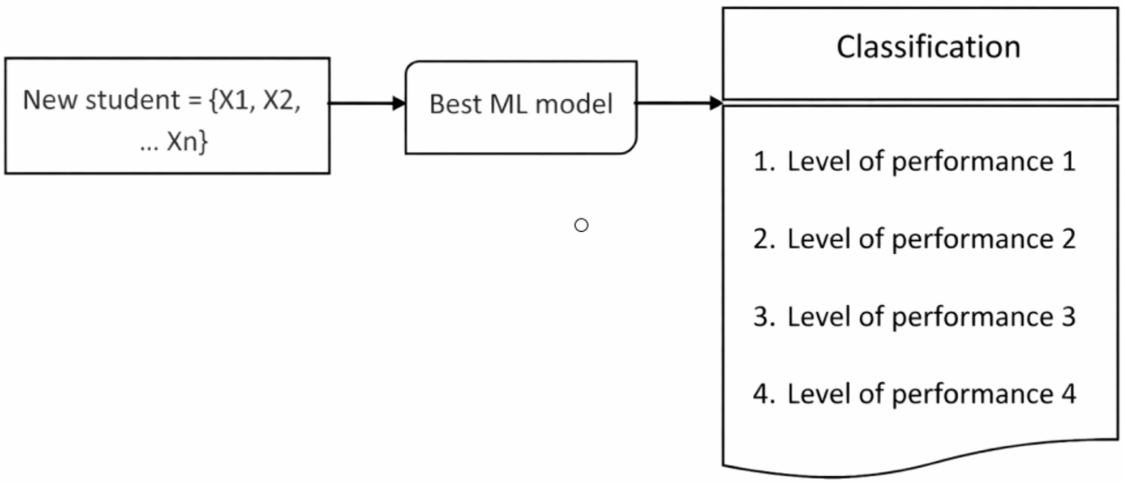

Figure 2: Predictions development

Dataset

Data were collected from the Colombian Education Institute (ICFES) and included the records of undergraduate students who had participated in at least one national academic exam from 2008 to 2022. In total, 921,041 records containing the results of standardised tests for high school and university are present in the data. There are 102 degree focus options across multiple categories, including engineering, literature, science, and art. In addition, some socioeconomic information is included, such as parents' education and occupation, type of school, academic calendar, gender, and department of residence. Consequently, for each student, fourteen variables were defined, as described in Table 1. Eight of them are categorical variables derived from students' demographic information and school background. The above information was gathered from the ICFES repository. These variables were taken as inputs of the prediction model. The result of the standardised test at the university stage was defined as the target variable. Before analysis, the dataset was anonymised to protect any private or sensitive information.

Descriptive data analysis

Table 2 presents the descriptive analysis results for the 921,041 records in the database, adjusted by gender, over the 14 years of the study. As shown in Table 2, the gender distribution is 58% female and 42% male. Additionally, the median and mean values for all evaluated modules are higher in men than in women.

Variable	gender	*n*	Min	*q1*	Median	Mean	*q3*	Max	*sd*	IQR
CR	F	548046	0	47.1	53.0	53.5	59.3	102.6	9.5	12.1
	M	372995	0	47.3	53.2	54.1	60.0	113.2	9.6	12.7
	all	921041	0	47.2	53.0	53.7	59.4	113.2	9.5	12.2
MATH	F	548046	0	45.0	51.0	51.8	58.1	120.4	10.8	13.2
	M	372995	0	47.7	55.0	56.0	63.0	121.5	12.1	15.4
	all	921041	0	45.4	53.0	53.5	60.0	121.5	11.5	14.6
SCI	F	548046	0	45.6	51.0	52.0	57.8	122.2	9.6	12.2
	M	372995	0	47.5	53.2	54.5	61.0	123.0	10.7	13.5
	all	921041	0	46.3	51.9	53.0	58.6	123.0	10.1	12.3
CS	F	548046	0	45.9	52.0	52.4	58.2	108.3	9.7	12.3
	M	372995	0	47.7	54.0	54.1	60.3	107.0	10.3	12.6
	all	921041	0	46.1	53.0	53.1	59.8	108.3	10.0	13.6
ENG	F	548046	0	43.0	49.0	52.4	58.4	117.3	13.6	15.4
	M	372995	0	43.5	50.9	54.5	61.7	117.3	14.6	18.2
	all	921041	0	43.5	50.0	53.3	59.7	117.3	14.0	16.2
average.pro	F	548046	0	10.6	131.2	99.6	155.4	265.0	69.3	144.8
	M	372995	0	10.9	135.4	103.3	162.0	268.8	72.0	151.1
	all	921041	0	10.7	132.6	101.1	158.0	268.8	70.4	147.3

Model evaluation and Performance metrics

Table 2: Descriptive Statistics

The efficacy of the classification procedure is established by analysing the divergence between predicted outcomes and ground truth labels. This relationship is quantified using the fundamental metrics True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) (Fawcett, 2006). To provide a comprehensive assessment of the model's performance, we utilise the Correct Classification Rate (C) alongside the Receiver Operating Characteristic (ROC) curve analysis. The ROC curve serves as a graphical representation of the trade-off between the True Positive Rate (Sensitivity) and the False Positive Rate (1-Specificity) across a continuum of discrimination thresholds. The diagnostic utility of this curve is summarised by the Area Under the Curve (AUC) (Hanley and McNeil, 1982). Numerically, an AUC value of 1.0 denotes a model with flawless categorisation and perfect separability. In contrast, an AUC of 0.5 indicates a model with no predictive power, performing no better than random chance.

RESULTS

This section presents the 10-fold cross-validation results (See Table 3). Table 4 shows the tuning hyperparameters for all the models and the selected ones. Table 3 reports the AUC–ROC results across validation iterations for the five models. Overall, XGBoost achieved the strongest and most consistent discriminative performance, with a mean AUC of 0.85 and a relatively narrow range (0.77–0.92), indicating robust generalisation across data splits. GLMNET ranked second (mean AUC = 0.77; range: 0.66–0.85), suggesting that a regularised linear decision boundary captures part of the signal but does not reach the performance of the non-linear boosting approach. In contrast, the SVM model exhibited substantial variability, with a mean AUC of 0.66 and values ranging from 0.44 to 0.88, suggesting sensitivity to the specific training/ validation partitions and potentially to hyperparameter settings or class distributions within folds.

Model	AUC		
	Min	Mean	Max
XGBOOST	0.77	0.85	0.92
GLMNET	0.66	0.77	0.85
SVML	0.44	0.66	0.88
DT	0.33	0.56	0.77
LDA	0.22	0.62	0.77

Table 3: Cross-validation scores for AUC-ROC

The single Decision Tree yielded lower average performance (mean AUC = 0.56; range: 0.33–0.77), consistent with the limited generalisation of un-ensembled trees, while LDA showed a moderate mean AUC of 0.62 but the widest instability at the lower end (0.22–0.77), suggesting that linear-discriminant assumptions may not hold uniformly across folds. Taken together, these results identify XGBoost as the most reliable model for predicting university performance levels in this setting, while GLMNET offers a competitive, more parsimonious alternative.

Model	Tuning parameters
XGBOOST	n.trees = 500, max_depth = c(1,4), eta = c(0.01; 0.1)
GLMNET	alpha = c(0,1), lambda = seq(0.001; 0.1 by 0.001)
SVML	cost = 2^c(0,5)
DT	cp = 2^c(-30, -22, -14, -8, -2)
LDA	NA

Table 4: Hyperparameters tuning

As explained in the materials and methods section, 20% of the data was reserved for the validation phase of the supervised learning models used. Figure 3 shows the ROC results for data that the algorithms did not previously know. In the model comparison, XGBoost shows the best performance, with an ROC value of 0.91. Thus, the ROC values of the five algorithms implemented are above 0.65. Those results indicate that these four models perform well at classifying academic performance. However, XGBoost outperforms the other models (XGBoost vs GLMNET, RF, KNN), achieving an ROC value of 0.91.

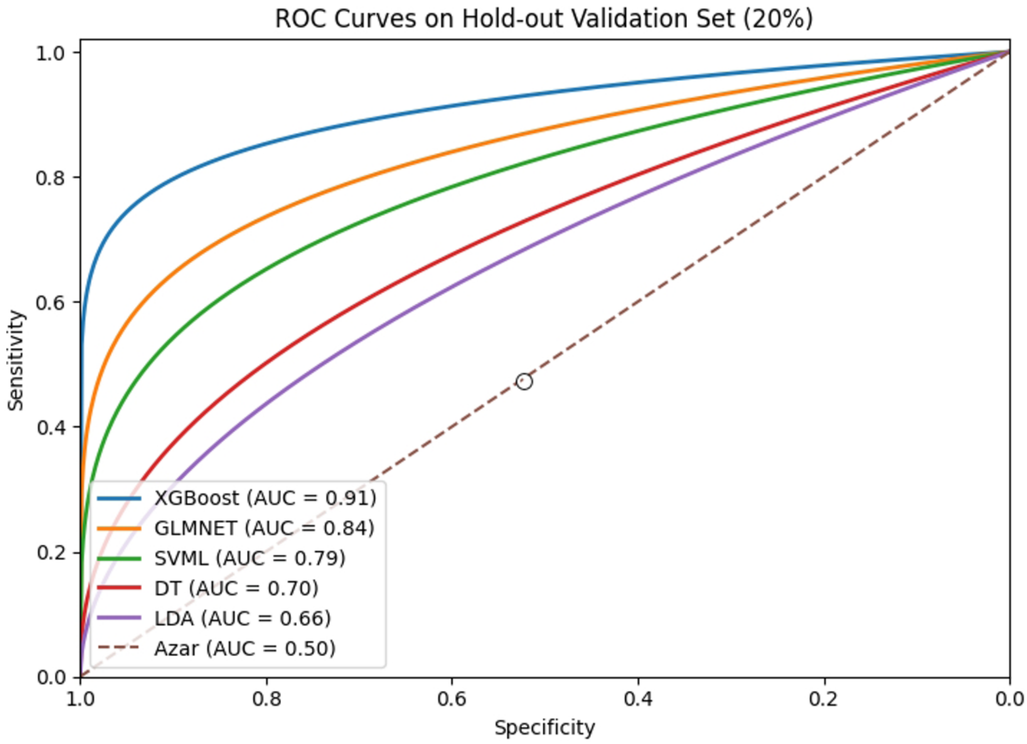

Figure 3: ROC curve for the validation set

Explainability through Global SHAP results

The Global SHAP results show that the most influential predictors of university performance are the prior academic competencies measured in SABER 11. In particular, Mathematics emerges as the strongest predictor, followed by Critical Reading, English, Science, and Citizenship Skills. This pattern indicates that university performance levels are primarily associated with the academic foundations students bring from secondary education. The direction of the effects is also consistent across these variables: higher prior scores are systematically associated with a greater probability of achieving higher performance levels. Among these predictors, Mathematics and Critical Reading stand out as the most decisive, suggesting that quantitative reasoning and academic literacy constitute the core competencies underpinning later achievement.

A second relevant finding is that importance values decrease gradually after the first five variables, suggesting a clear distinction between the predictive weight of prior academic preparation and that of background characteristics. While the standardised test competencies dominate the model, family-related variables still provide meaningful explanatory value. In particular, mothers' and fathers' education rank among the most important non-academic predictors, indicating that household educational capital shapes later academic outcomes. These variables likely capture differences in home-based academic support, expectations, and familiarity with educational trajectories. Therefore, the results suggest that performance is not explained exclusively by prior test scores, but also by the broader educational environment in which students develop before entering higher education.

The SHAP results also show that school type, department of residence, and school calendar contribute additional predictive information, even if their global importance is lower than that of academic competencies and parental education. These variables point to structural and territorial differences in students' pre-university trajectories. For example, school type may reflect variation in institutional quality and access to academic preparation. At the same time, the department of residence may capture geographic inequalities linked to educational opportunity, infrastructure, or socioeconomic conditions. Similarly, the school calendar may signal differences in school organisation and cohort composition. Although these variables are not the principal drivers of prediction, their presence confirms that educational performance is shaped not only by individual ability, but also by contextual conditions that precede university entry.

Finally, the lower-ranked variables, such as mother's occupation, father's occupation, and gender, should not be interpreted as irrelevant, but rather as factors with smaller average global effects than the dominant academic predictors. In particular, the relatively low global importance of gender suggests that it is not a primary determinant of overall prediction in the full sample. However, it may still be relevant for subgroup analysis and fairness monitoring. Taken together, the Global SHAP results support an explainable view of student success in which prior academic achievement is the central driver. At the same time, family background and contextual conditions provide complementary information that improves prediction and enriches the educational interpretation of the model. From a practical perspective, these findings justify interventions focused on strengthening quantitative reasoning, reading comprehension, and language skills, as well as supporting mentoring and context-sensitive institutional strategies for students from less advantaged backgrounds.

Rank	Feature (original variable)	Type	Mean |SHAP|	Typical direction toward higher performance*	Interpretation for decision-making
1	Math (SABER 11)	N	0.182	Higher Math -> higher level	Quantitative preparation is the strongest driver; it supports early reinforcement in quantitative reasoning.
2	Critical Reading (CR, SABER 11)	N	0.164	Higher CR -> higher level	Reading competence strongly differentiates levels; it points to academic literacy interventions.
3	English (ENG, SABER 11)	N	0.121	Higher ENG -> higher level	Language skills contribute to higher performance; they support strengthening English/academic language.
4	Science (sci, SABER 11)	N	0.107	Higher sci -> higher level	Scientific reasoning helps separate mid/high levels; indicates need for reasoning-focused support.
5	Citizenship Skills (CS, SABER 11)	N	0.093	Higher CS -> higher level	Civic competencies add signal beyond Math/CR; supports broad competency-building strategies.
6	Mother education (medu)	C	0.071	Higher education categories -> higher level	Proxy for educational capital; informs mentoring and structured academic guidance.
7	Father's education (fedu)	C	0.064	Higher education categories -> higher level	Similar to medu, it indicates differential support structures outside the university.
8	School type	C	0.058	Context-dependent	Captures pre-university institutional differences; suggests the need for differentiated onboarding.
9	Department of Residence (dep. res)	C	0.045	Context-dependent	Geographic disparities may reflect unequal opportunity; supports territory-sensitive support strategies.
10	School calendar (sch)	C	0.033	Context-dependent	Signals structural differences in prior schooling; helps interpret cohort heterogeneity.
11	Mother occupation (mocu)	C	0.028	Context-dependent	Socioeconomic proxy; may indicate time/resources available for academic support.
12	Father's occupation (focus)	C	0.024	Context-dependent	Socioeconomic proxy complements parental education as a background signal.
13	Gender (gen)	C	0.017	Context-dependent	Lower global impact; mainly relevant for subgroup monitoring and fairness diagnostics.

Table 5: Global SHAP summary for the XGBOOST model

DISCUSSION

This study aimed to determine whether early availability of academic and socioeconomic information can predict university performance in a final-year standardised exit assessment, under the premise that incorporating contextual variables should enhance the practical value of predictions for institutional decision-making. Thus, our development is aligned with the principles of Learning Analytics, which emphasise transforming educational data into knowledge to support timely interventions and continuous improvement (Long and Siemens, 2014). The results indicate that the selection and parameterisation of the model are critical, particularly for adjusting the nonlinear predictors and balancing discrimination and robustness.

In the cross-validation, XGBoost consistently achieved the best discriminative performance, with the highest mean AUC (0.85). This pattern suggests that the relationships between predictors and outcomes probably involve non-linearities and interactions that are not well captured by strict linear decision boundaries. This interpretation aligns with the established strengths of boosting methods for varied tabular datasets, where decision rules often depend on thresholds and complex feature combinations (Kolo et al., 2015). In comparison, GLMNET achieved a competitive but clearly lower performance level (mean AUC = 0.77), suggesting that a regularised linear model can capture some of the signal but might not fully capture the complex relationships between prior academic preparation and contextual factors.

Our results indicate that the model effectively predicts students' probability of belonging to higher or lower performance levels in the final-year standardised assessment, rather than academic success in a broad or undefined sense. This distinction is important because the dependent variable is operationalised as performance-level membership, and the Learning analytics interventions that explicitly predict actionable targets show improved pass rates, grades, and retention when educators use these outputs for targeted support (Alalawi, 2024a; Alalawi et al., 2024b). At the same time, the present results extend that perspective by showing that performance-level prediction can be meaningfully supported using information available before graduation, reinforcing the argument that actionable educational prediction depends on temporal usefulness as much as statistical precision (Pelima et al., 2024).

Among the predictors, Mathematics and Critical Reading are the most influential, followed by English, Science, and Citizenship Skills. This ordering suggests that later performance in the final-year assessment depends primarily on a broad academic preparation profile, with quantitative and literacy-related competencies occupying a central role. These findings are consistent with studies showing that prior academic achievement and standardised test competencies tend to be among the strongest predictors of subsequent university outcomes (Cerdeira et al., 2018). More specifically, the prominence of Mathematics and Critical Reading aligns with research emphasising that quantitative reasoning and academic literacy often structure performance not only in discipline-specific settings but also in general higher education assessments (Delahoz Dominguez et al., 2025). In contrast, some studies have suggested that institutional variables such as attendance, course grades, or early-semester assessments may dominate predictive models once university trajectory data are available (Parker et al., 2012). In the present case, however, the strong contribution of SABER 11 scores suggests that pre-university competencies remain highly informative even at later stages of the academic pathway.

The results also show that performance is not explained exclusively by prior academic scores. Variables such as mother's education, father's education, school type, department of residence, and school calendar provide additional predictive information, even if their global importance is lower than that of the academic competencies. This finding aligns with the literature, which shows that socioeconomic and contextual factors shape academic outcomes by shaping educational capital, resource availability, prior school quality, and territorial opportunity structures (Wang and Panicker, 2025). In particular, the contribution of parental education is consistent with studies linking family educational background to stronger academic guidance, higher expectations, and more supportive learning environments (Guerra and Braungart-Rieker, 1999). Similarly, the effects of school type and department of residence are compatible with research showing that institutional and regional inequalities influence students' preparation before entering higher education (Kutlu and Özer, 2024).

These findings are especially relevant when viewed through the lens of efficiency and responsibility in education. From an efficiency standpoint, the model can help institutions allocate limited academic support resources more strategically by identifying, before graduation, students who are more likely to fall into lower performance levels and the competency domains in which reinforcement may be most needed. This interpretation is consistent with prior studies arguing that predictive models create institutional value when they support earlier, more targeted, and more cost-conscious interventions (Delahoz-Domínguez and Hijón-Neira, 2024). From a responsibility standpoint, the use of an interpretable framework such as SHAP is essential because it enables universities to justify predictions, communicate the basis of model outputs, and reduce the risks associated with opaque algorithmic decision-making (Guevara-Reyes et al., 2025). Importantly, lower-ranked predictors such as gender should not be interpreted as irrelevant, but rather as variables whose role may be more visible in subgroup analysis, fairness monitoring, or interaction effects than in pooled global importance rankings (Delahoz-Domínguez and Hijón-Neira, 2025). In this sense, the present results also support recent calls for responsible learning analytics that combine predictive performance with transparency, contextual sensitivity, and attention to potential differential effects across student populations (Sangsawang, 2025).

Prior work emphasises that predictive tools are most useful when they identify students early enough for meaningful support and when evaluation reflects the real-world costs of false negatives and false positives (Mathrani et al., 2021). Complementary frameworks for identifying at-risk students further argue that models should be aligned with educators' decision-making needs rather than treated as purely technical forecasting tools (Pali and Verma, 2024). In our case, defining the target both as a binary "desirable vs non-desirable" outcome enables flexible operationalisation: the binary framing supports actionable triage under limited support capacity. Importantly, predicting performance levels rather than only continuous scores enhances practical adoption because they are easier to communicate to stakeholders.

Simultaneously, the application of predictive analytics in educational contexts requires a focus on both operational effectiveness and ethical considerations. Efficiency is demonstrated through the generation of precise and consistent predictions, leveraging readily accessible data from administrative and assessment platforms while avoiding the imposition of supplementary data-acquisition requirements (Oyedotun et al., 2025). Conversely, responsibility mandates preventing model outputs that exacerbate existing disparities or validate diminished expectations for marginalised populations. Because socioeconomic factors can be both predictive and ethically sensitive, their responsible use requires subgroup auditing and careful interpretation. Recent studies highlight the need to incorporate fairness assessments into student performance prediction systems and to examine the trade-off between accuracy and fairness across different groups (Valdivia et al., 2021). Therefore, a key implication of this research is that results should be reported not only as overall metrics (such as AUC) but also for specific groups (e.g., gender, school type, and region) to identify differences in error patterns that could affect the fairness of intervention strategies. Consequently, the strong performance of complex models such as XGBoost increases the importance of explainability. Educational stakeholders typically require transparent reasoning, particularly when predictions may influence support allocation or advising decisions. Explainable AI methods help bridge this gap by providing global and local interpretations—showing which variables drive overall predictions and why a specific student is predicted to fall into a given outcome category (Alonso and Casalino, 2019). In applied terms, interpretability enables institutions to move from "prediction as labeling" toward "prediction as guidance," supporting targeted academic actions. Accordingly, from an institutional perspective, these findings show that interpretability is not an accessory component of the model, but a necessary condition for responsible application in educational settings.

By identifying the predictors most strongly associated with lower performance levels, the framework can help universities design interventions that are both more transparent and more efficiently targeted, particularly when academic support resources are limited.

Finally, several limitations should be acknowledged. First, the study relies on administrative and testing variables; psychosocial constructs such as belonging, engagement, or institutional climate—often linked to achievement—are not included and may explain additional variance if consistently measured. Second, predictive performance may shift across cohorts due to curriculum changes or assessment redesign, necessitating temporal validation and periodic recalibration. Third, as with most LA/EDM prediction studies, the results are correlational rather than causal; models identify patterns useful for forecasting but do not establish causal mechanisms. Future work can extend this approach by incorporating explicit ordinal-learning objectives, probability calibration, and systematic fairness auditing under realistic intervention constraints.

CONCLUSION

The present research develops a predictive framework in learning analytics. Consequently, integrating standardised test scores with student socioeconomic variables. The proposed methodology facilitates the early identification of students at risk of low performance and those who could benefit from timely academic assistance. This approach addresses the shortcomings of prediction systems that rely solely on academic indicators, thereby neglecting broader contextual factors that influence university learning outcomes.

A significant contribution of this research lies in the empirical evaluation of diverse model families, conducted within a robust validation framework. Furthermore, this research highlights the practical value of modelling results as ordered performance levels, and also as a binary classification that distinguishes between good and poor achievement. This approach mirrors the typical ways institutions share assessment results and the threshold-based decision-making processes often used in academic support programs. Within this framework, predictive capabilities act as a decision-support tool, potentially improving early-warning systems by enabling universities to allocate resources for mentoring, tutoring, and targeted intervention programs where they are most needed. In conclusion, the proposed methodology demonstrates that incorporating prior test performance alongside socioeconomic and contextual variables enables precise, practically useful forecasting of university achievement. Beyond predictive accuracy, this study contributes to the development of responsible learning analytics by promoting explainable, auditable, and context-sensitive use of machine learning in higher education. In practical terms, the framework can support more effective early-warning systems and a more efficient allocation of academic support resources, helping institutions direct mentoring, tutoring, and reinforcement efforts to students most likely to benefit.

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