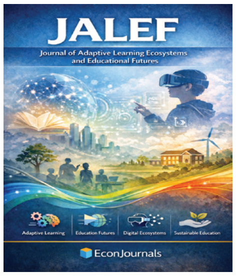

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From Prediction to Action: A Portfolio Framework for Student Performance Improvement Plans in Higher Education

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ABSTRACT

Higher education institutions increasingly seek student-success systems that move beyond descriptive monitoring and generate operationally usable improvement plans. The study develops and tests a portfolio-oriented analytics framework which uses multiclass academic outcome prediction to create student performance improvement plans. The study uses the UCI predict students' dropout and academic success dataset which contains data about 4424 students to assess three models: Multinomial logistic regression, random forest, and XGBoost for predicting student dropout, continued enrollment, and graduation. The random forest model achieves its best performance with a cross-validated macro-F1 score of 0.702 and a hold-out accuracy of 0.748 which includes a macro-AUC score of 0.889. The analysis of predictors shows that the model performance depends mostly on semester-level approved units and curricular-unit grades and academic evaluations and tuition status and admission-related variables. The paper develops a priority score with an action-mapping system which places students into managerial plans: Financial continuity, academic recovery, progression coaching, stabilization, and acceleration. The resulting portfolio yields distinct empirical for example, the continuity and academic recovery groups each contain dropout rates above 94%, whereas the acceleration portfolio exhibits a graduate rate above 95%. The study makes two main contributions. The part demonstrates that public higher-education records can support reproducible multiclass prediction with institutionally interpretable drivers. The second part provides an analytically based planning framework which assists organizations

Keywords: Higher Education Analytics, Student Success, Learning Analytics, Intervention Planning, Early Warning, Academic Improvement Plans, Educational Data Mining

JEL Classifications: D83, I21, I23

1. INTRODUCTION

Higher education institutions now treat student success as their top strategic priority because they need to meet rising accountability standards while dealing with budget limitations and diverse student needs. The current situation forces school administrators to better methods for evaluating student risk than their existing methods. Academic institutions must develop decision-making frameworks that translate performance indicators into speci action plans which enable academic departments and student support services to concentrate their resources on areas with the most potential for development.

The recent studies brought new measurement techniques to learning analytics which includes methods for interpreting dropout predictions and dashboard-supported self-regulation functions and engagement measurement tools and systems that forecast student behavior for learning interventions (Bergdahl et al., 2024; Johar et al., 2023; Lee and Kim, 2025; Nagy and Molontay, 2024; Paulsen and Lindsay, 2024). Researchers established a direct connection between prediction success and school performance but found that schools still needed actual prediction abilities to solve their problems. The existing ethical guidance with its prescriptive designs together with intervention frameworks has helped to solve this problem yet institutions still need to develop operational systems that connect prediction results to institutional improvement planning at the portfolio level (Alalawi et al., 2025; Dai et al., 2025; Liu et al., 2025; Rets et al., 2023).

The paper provides a solution to the existing research gap by presenting a business-focused analytical framework for higher education institutions which uses prediction results to create plans for improving student performance. The research analyzes a public higher education dataset which contains enrollment and data together with semester performance information to calculate the likelihood of three possible outcomes which include dropout and enrolled and graduate status and afterward creates distinct support plans based on these likelihoods.

The paper presents three main contributions to the of research. First, it provides a fully reproducible multiclass empirical analysis based on a public dataset which enables subsequent researchers to verify their results. Second, it develops a mathematically explicit planning logic that uses predictive probabilities together with operational indicators to determine which student support programs should receive priority. Third, it reframes learning analytics as a portfolio-management problem which is closer to institutional decision practice than isolated risk scoring.

The paper has its remaining content organized into sections. Section 2 reviews recent research and the paper's positioning. The decision problem gets presented in Section 3 together with its mathematical formulation and analytical framework. Section 4 describes the data and methods. The empirical results get presented in Section 5. Section 6 creates the improvement-plan portfolio while exploring its on management operations. The paper reaches its conclusion in Section 7.

Table 1: Selected studies published after 2022 relevant to higher-education learning analytics and intervention design

Study	Context	Main analytical focus	Method/design	Main contribution for the present study
Rets et al. (2023)	Distance education	Ethical predictive analytics	Recommendations grounded in literature and practice	Shows that prediction must be paired with design.
Johar et al. (2023)	Online higher education	Engagement and performance	Systematic review	Demonstrates the importance of multidimensional engagement indicators for performance improvement.
Xing et al. (2023)	Collaborative higher education learning	Multifaceted engagement	Learning analytics on collaborative traces	Shows that behavioral traces can be linked to richer engagement constructs.
Nagy and Molontay (2024)	Higher education dropout prediction	Interpretable modelling	Explainable AI approach	Supports the need for interpretable outputs when assigning personalized support.
Paulsen and Lindsay (2024)	Student-facing dashboards in higher education	Dashboard design and pedagogy	Systematic review	Indicates that analytics should be learningoriented rather than merely descriptive.
Chen (2024)	Blended university course	Feedback and achievement	Quasiexperiment with learning analytics feedback	Provides evidence that analytics-based feedback can improve course outcomes.
Bergdahl et al. (2024)	Higher education learning analytics	Student engagement	Systematic review	Highlights the conceptual breadth of engagement and the overreliance on behavioral proxies.
Alalawi et al. (2025)	Higher education courses	Prediction and intervention framework	Framework plus predictive infrastructure	Moves from performance prediction toward actionable intervention support.
Lee and Kim (2025)	Asynchronous online higher education	Motivationaware dashboards	Design and evaluation study	Shows that analytics tools become more useful when grounded in motivational theory.
Kleimola et al. (2025)	Higher education students	Self-regulated learning support	Qualitative study	Indicates that students value analytics when linked to self-monitoring and control of study progress.
Ngulube and Ncube (2025)	Higher education LMS environments	User experience and analytics	Systematic review	Extends learning analytics beyond prediction to the quality of digital learning environments.
Wong et al. (2025)	Course evaluation in higher education	Quality evaluation	Systematic review	Demonstrates the managerial use of analytics for course improvement and institutional decision making.
Jung and Wise (2025)	Online undergraduate course	Student use of message based analytics	Trace-based empirical study	Shows that access and action-taking behaviors mediate the value of student-facing analytics.
Seo et al. (2025)	Online university	Prescriptive analytics	Learning-tailored support design	Directly motivates the prescriptive orientation adopted in the present study.
Dai et al. (2025)	At-risk student	Prediction plus feedback intervention	Predictive model with relational communication support	Demonstrates the importance of coupling risk detection with relational support.
Liu et al. (2025)	Multiple educational settings	Intervention	Meta-analysis	Provides evidence that analytics-based interventions
Chang et al. (2025)	Taiwanese higher education	Early warning and intervention cycle	Socio-technical early-warning design	Shows the value of linking algorithmic prediction with personalized intervention processes.
Dixon et al. (2025)	UK higher education	Institutional uses of analytics	Case-based institutional analysis	Reinforces the managerial and organizational relevance of analytics use.

2. RECENT RESEARCH AND POSITIONING

Recent research conducted after 2022 demonstrates three major research paths which scholars follow to study higher education analytics. The research direction establishes how researchers conceptualize student engagement. The research shows that learning analytics systems use student behavioral data to measure engagement but they fail to capture complete cognitive and emotional states of students (Bergdahl et al., 2024; Johar et al., 2023). The second research pathway investigates student analytics which includes dashboards that help students with their
and motivational and self-regulated learning activities (Kleimola et al., 2025; Lee and Kim, 2025; Paulsen and Lindsay, 2024). The third research area establishes intervention and feedback design as a that uses predictive analytics to develop personalized feedback systems which assist students at risk of dropping out from their courses (Chang et al., 2025; Chen, 2024; Dai et al., 2025). The fourth research direction investigates three main areas which include explainability and fairness and ethical system deployment (Nagy and Molontay, 2024; Rets et al., 2023). The direction extends managerial control of learning analytics to evaluate course quality and student learning management system use and university educational operations (Dixon et al., 2025; Ngulube and Ncube, 2025; Wong et al., 2025).

Two gaps exist which continue to a ct institutional operations despite the present advancements in educational research. The existing literature reaches its endpoint at prediction and interpretation and reflection support because it lacks a compact planning architecture which managers need to distribute resources according to their needs. The majority of research studies at the course or platform level whereas actual student outputs should be transformed into a set of improvement plans which advising and retention and
able 1).

The current research establishes itself as an operational analytics study. The research project does not attempt to achieve the highest level of novel predictive results. The system develops an action-oriented framework which uses multiclass probabilities as part of its structured decision logic system that creates support plans based on student academic performance and financial situation. Learning analytics serve as a basis for decision design which enables institutions to create plans that support student performance enhancement.

3. DECISION PROBLEM AND ANALYTICAL FRAMEWORK

3.1. Institutional Decision Problem

The institutional problem addressed in this paper can be stated as follows. Let each student i be represented by a feature vector $x_i \in R^p$ derived from admission records, demographic information, financial status, and semester-level academic progress. The institution observes one of three mutually exclusive terminal states:

$$y_i \in Y = \{\text{Dropout, Enrolled, Graduate}\}.$$

The managerial objective is not only to estimate the probability of each state, but also to assign students to an improvement plan that supports intervention prioritization.

3.2. Predictive Formulation

$$\pi_{ik} = P(y_i = k \mid x_i), \qquad k \in y.$$

For the multinomial logit benchmark, the class probabilities are written as

$$\pi_{ik} = \frac{\exp(ß_k^T xi)}{\sum_{h \in Y} \exp(ß_h^T xi)}$$

Tree-ensemble models replace the parametric logit structure with nonlinear partitions of the feature space. For a random-forest with T trees, the estimated probability of class k for student i can be written as

$$\hat{\pi}_{ik}^{RF} = \frac{1}{T}\sum_{t=1}^{T} \mathrm{I}(ft(xi) = k)\ ,$$

Where $f_t(.)$ denotes the prediction from tree t. The selected class is

$$\hat{y}_i = \arg\max_{k \in y} \hat{\pi}_{ik}$$

Model quality is assessed using accuracy, macro-precision, macro-recall, macro-F_1, and one-versus-rest macro-AUC. For example,

$$F_{1,\,\text{macro}} = \frac{1}{|y|}\sum_{k \in y} \frac{2 \cdot \text{Precision}_k \cdot \text{Recall}_k}{\text{Precision}_k + \text{Recall}_k}$$

3.3. From Prediction to Improvement Planning

Prediction alone is for intervention design. Therefore, a second-stage priority function is constructed:

$$S_i = 0.45\hat{\pi}_{i,D} + 0.25F_i + 0.20A_i + 0.10G_i,$$

Where $\hat{\pi}_{i,D}$ is the predicted dropout probability, F_i is a binary indicator, A_i captures shortfall in second-semester approved units, and G_i captures shortfall in second-semester
,

$$F_i = \mathrm{I}(\text{tuition not up to date or debtor}),$$

$$\mathrm{A_i} = \max\left(0, \frac{T_A - \mathrm{a_i}}{T_A}\right), G_i = \max\left(0, \frac{T_G - \mathrm{g_i}}{\mathrm{T_G}}\right),$$

Where a_i is second-semester approved units, g_i is second-semester grade, $\tau_A = 5$, and $\tau_G = 12$. The portfolio mapping is operationalized through decision rules:

- Financial continuity plan: $\hat{\pi}_{i,D} \geq 0.45$ and $F_i = 1$.
- Academic recovery plan: $\hat{\pi}_{i,D} \geq 0.45$ and $F_i = 0$.

- Progression coaching plan: $\hat{\pi}_{i,E}$ ≥0.35 and $\hat{\pi}_{i,D}$ <0.45.
- Acceleration plan: $\hat{\pi}_{i,G}$ ≥0.55 and academic momentum >0.25.
- Stabilization plan: all remaining cases.

This structure allows the institution to distinguish students who need nancial continuity support from those who require academic remediation, continued coaching, or acceleration opportunities (Figure 1).

4. DATA AND METHODS

4.1. Dataset

The study uses the public UCI Predict Students' Dropout and Academic Success dataset, which contains 4,424 student records and 36 predictive attributes plus the multiclass target outcome. The available variables cover admission history, demographic attributes, parental background, ncial indicators, and - and second-semester academic performance. The target variable has three classes: Dropout, enrolled, and graduate.

The dataset is suitable for the present objective because it combines academic progress, exposure, and enrollment outcomes within a single student-level table, making it possible to operationalize both prediction and improvement planning with reproducible data.

4.2. Variables

The empirical design includes all non-target variables available in the dataset. Categorical variables are encoded through one-hot transformation, while continuous variables are median-imputed and standardized when required by the model pipeline. Variables with direct operational relevance include tuition status, debtor status, age at enrollment, admission grade, and semester counts of enrolled, evaluated, approved, and credited curricular units.

4.3. Analytical Procedure

The dataset is split into 80% training and 20% hold-out test partitions using strati d sampling. Three predictive models are compared: multinomial logistic regression, random forest, and XGBoost. Three-fold cross-validation is used on the training partition to reduce computational variance while maintaining reproducibility.

After selecting the best model, the study reports hold-out performance, class-level precision, recall, and F_1, one-versus-rest ROC curves, and feature-importance values. The selected model's predicted probabilities are then used to compute the improvement priority score and assign each student to one of the

5. EMPIRICAL RESULTS

5.1. Descriptive Evidence

Table 2 reports the main descriptive patterns across the three observed outcomes. Graduates show stronger semester progression, higher average grades, lower age at enrollment, and lower pressure than the dropout group. Students in the dropout class average only 1.94 approved units in the second semester, compared with 6.18 among graduates. The gradient is similarly visible in semester grades and tuition status (Figure 2).

5.2. Model Comparison

Cross-validated results show that the random forest model the strongest balance across the multiclass performance metrics (Table 3, Figure 3). Its mean cross-validated accuracy is 0.773 and its macro-F_1 is 0.702, marginally outperforming XGBoost on the macro-F_1 criterion and clearly exceeding the logistic benchmark on recall. These results suggest that nonlinear relationships and interaction

5.3. Hold-out Performance of the Selected Model

The selected random-forest model achieves 0.748 accuracy on the hold-out partition, with macro-precision of 0.694, macro-recall of 0.679, macro-F_1 of 0.685, and macro-AUC of 0.889 (Table 4, Figure 4). Class-wise performance is strongest for graduates and dropouts, while the enrolled class is more to classify because it captures transitional cases between persistence and completion.

5.4. Predictor Importance

The most uential variables are second-semester approved units, second-semester grades, approved units, first-semester grades, second-semester evaluations, first-semester evaluations, age at enrollment, admission grade, previous quali ation grade, and tuition status. This pattern is substantively coherent: academic momentum and academic quality dominate the signal, but continuity remains a powerful

6. IMPROVEMENT-PLAN PORTFOLIO AND DISCUSSION

6.1. Portfolio Composition

The probability outputs and priority score are translated into a plan portfolio. Table 5 and Figure 6 show that the acceleration plan contains the largest group (1,703 students) and is associated with a graduate rate above 97%. In contrast, the academic recovery and continuity plans each exhibit dropout rates above 94%. The progression coaching group occupies the middle ground: These students are not dominated by immediate dropout risk but display continuing-enrollment that merit structured support to improve completion prospects.

7. DISCUSSION

Several require special attention. First semester-level academic progression variables represent the most powerful research indicators which determine student performance outcomes. The current research shows that both behavioral indicators and progress indicators deliver better results than static background characteristics for student success analytics (Johar et al., 2023; Jung and Wise, 2025). The institutional decision makers must use momentum-based variables for their

Figure 1: Operational analytical framework for student-performance improvement planning

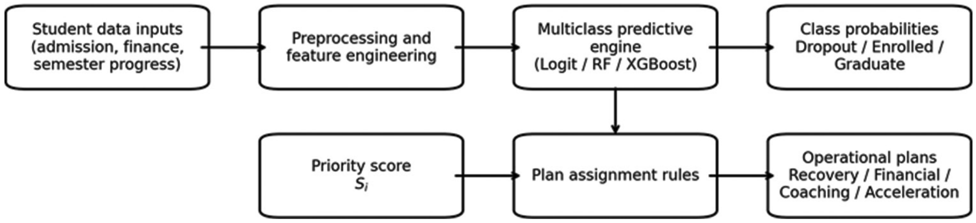


Figure 2: Diagnostic evidence on outcome distribution, tuition status, approved units, and semester grades

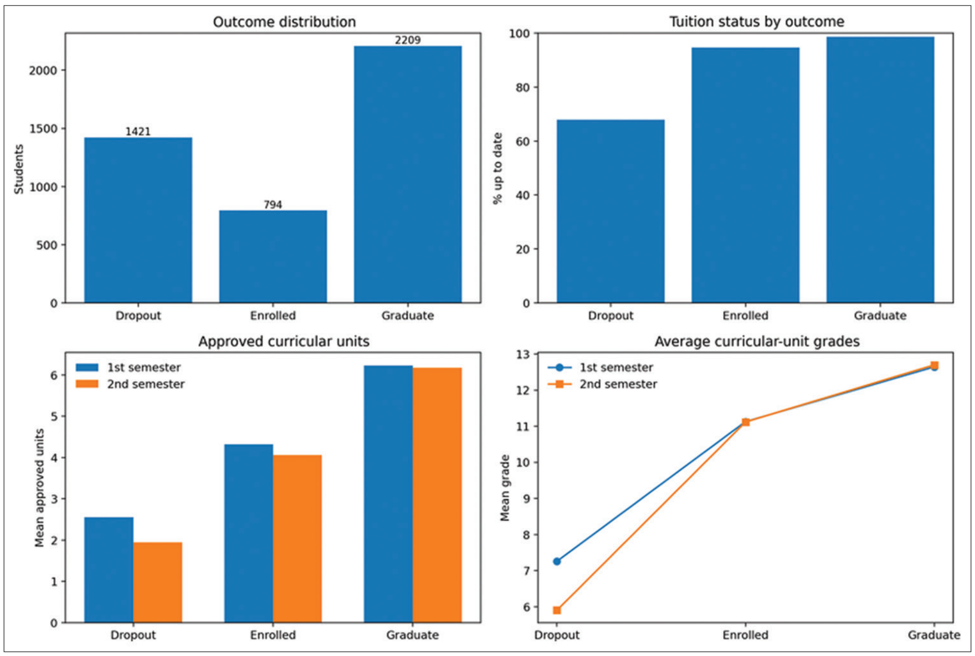


Table 2: Descriptive characteristics by observed outcome

Outcome	Students	Age	Admission	Tuition up-to-date	Debtor	Approved 1	Approved 2	Grade 2
Dropout	1421	26.07	124.96	0.73	0.36	2.55	1.94	5.90
Enrolled	794	22.37	125.53	0.93	0.10	4.39	4.06	11.12
Graduate	2209	21.78	128.79	0.98	0.03	5.75	6.18	12.70

Table 3: Cross-validated model comparison

Model	Accuracy	Macro-precision	Macro-recall	Macro-F_1
Random forest	0.773	0.728	0.702	0.702
XGBoost	0.776	0.729	0.691	0.691
Logistic regression	0.776	0.720	0.686	0.686

Table 4: Hold-out performance of the selected random-forest model

Class	Precision	Recall	F_1	Support
Dropout	0.796	0.701	0.745	284
Enrolled	0.477	0.453	0.465	159
Graduate	0.808	0.885	0.844	442
Macro average	0.694	0.679	0.685	885

improvement planning process because admission and

Strategic importance continues to attach to continuity requirements. Tuition arrears and debtor status emerge as operationally meaningful indicators not because they displace academic momentum but because they help distinguish students whose performance problems are intertwined with institutional a bility and continuity constraints. The current situation shows that prediction systems need more than prediction because prediction systems need additional resources to achieve optimal results. Students who have the same dropout risk exhibit requirements for their educational improvement strategies.

Third, the enrolled class functions as an analytically ambiguous middle state. The weaker class-level metrics for this group suggest that managerial attention should not be limited to clear dropout cases. Students who possess intermediate will achieve their best results through coaching and advising together with structured study-planning support until their risk of failure or withdrawal becomes evident. This observation resonates with recent work on prescriptive analytics and early warning systems which argues for intervention designs that act before poor outcomes become irreversible (Chang et al., 2025; Dai et al., 2025; Seo et al., 2025).

Table 5: Improvement-plan portfolio summary

Plan	Students	Dropout rate	Graduate rate	Mean p_D	Tuition overdue	Approved 2
Acceleration plan	1703	0.021	0.972	0.024	0.009	6.75
Progression coaching plan	864	0.066	0.339	0.129	0.033	4.50
Academic recovery plan	736	0.947	0.011	0.824	0.000	1.68
Financial continuity plan	570	0.949	0.005	0.797	1.000	1.85
Stabilization plan	551	0.163	0.657	0.205	0.047	4.59

Figure 3: Cross-validated performance comparison

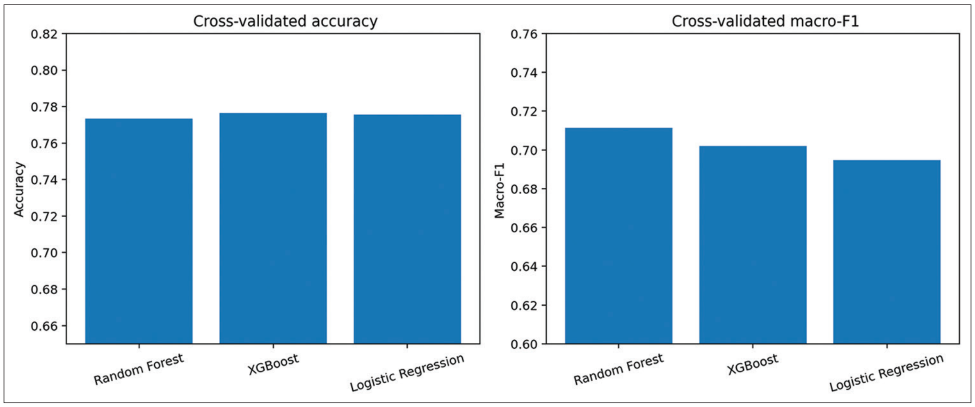


Figure 4: Hold-out confusion matrix and one-versus-rest ROC curves

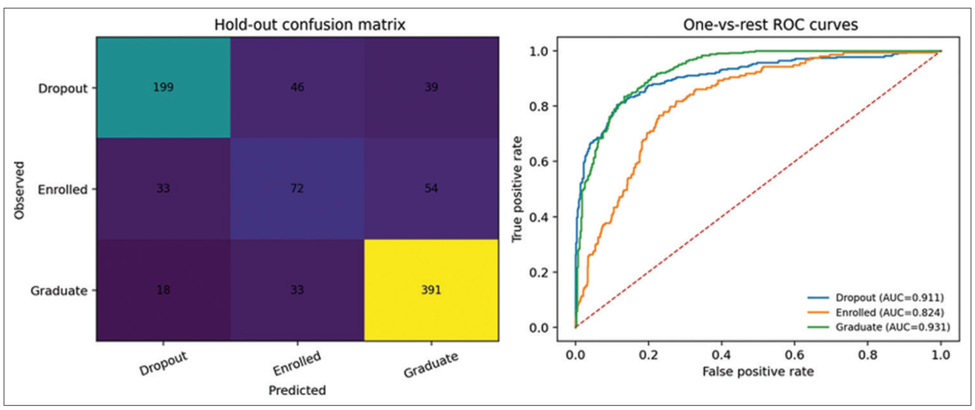
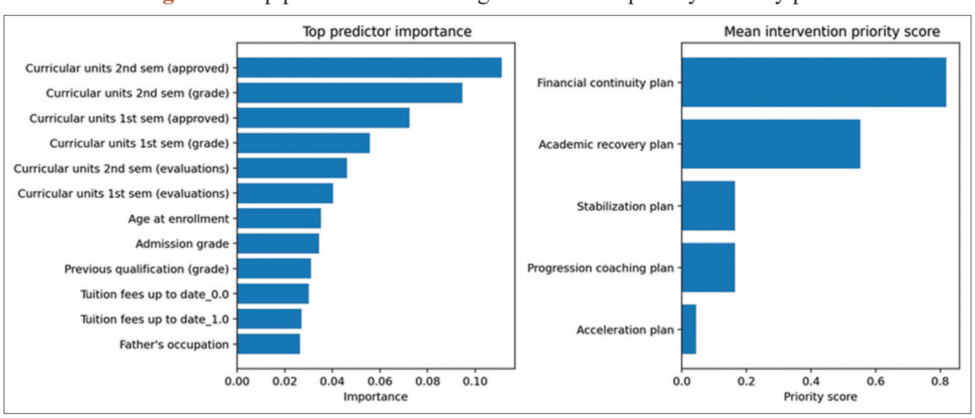
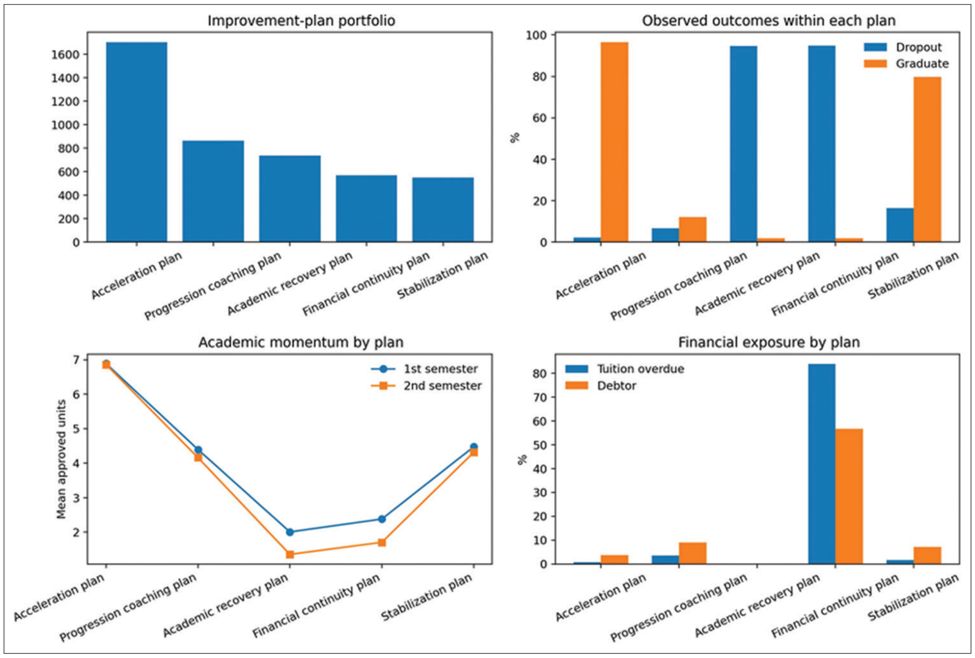


Figure 5: Top predictors and average intervention priority score by plan



Fourth, the portfolio lens is useful because it matches institutional practice. Universities rarely intervene with students one by one using bespoke models. The organization distributes advisors together with tutoring resources and emergency assistance and curriculum support throughout various student groups. The plan architecture developed here is therefore designed as a decision support artifact: it makes the transition from prediction to segmented action explicit.

Figure 6:



7.1. Managerial Implications

The framework enables three distinct functions which managers can use to their advantage. First, the system enables retention governance through its ability to create intervention team priorities. The system enables organizations to enhance their operational through its ability to identify two types of academic cases. The system enables institutions to monitor their performance by tracking their results through complete plan portfolios instead of individual score assessments.

Institutions need to avoid using standardized support methods which do not consider their unique requirements. The continuity plan needs immediate administrative and assistance for all students who have been assigned to it. Academic recovery students need remediation together with tutoring and learning-support services to succeed. Progression coaching students receive guidance that assists them in reaching their educational goals while acceleration students receive direction toward enrichment programs and honors pathways and advanced progression opportunities.

8. CONCLUSION

This paper introduced an analytical framework which focuses on portfolio development to help students improve their academic performance in higher education. The study demonstrated that a random-forest model can produce accurate multiclass predictions of student dropout and continuous enrollment and graduation through its testing of a public dataset and reproducible code. The research established that the prediction results can be transformed into distinct im provement strategies through two methods which include a transparent priority scoring system and a rule-based portfolio mapping system.

The main value of the study lies in its operational orientation. The paper used prediction as a decision-making tool which educational institutions could use to establish their operational priorities and develop their institutional activities. The results show that academic momentum variables are the strongest empirical drivers, while exposure remains essential for plan

The study has limitations. The dataset represents a single institutional context and does not include direct measures of intervention uptake, psychosocial support, or qualitative advising records. The framework requires future research which will integrate institutional data with learning management system data and advanced temporal analysis methods and documented intervention results.

9. DATA AVAILABILITY

The dataset used in this study is publicly available from the UCI Machine Learning Repository:

https://archive.ics.uci.edu/dataset/697/predict+students+dropout+and+academic+success.

A copy of the CSV used for the analyses is included in the replication package accompanying this manuscript.

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