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From Prediction to Prevention: A Causal AI Framework for Student Dropout Risk and Targeted Interventions

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Abstract
This study proposes a Causal AI framework that advances student dropout analytics from mere prediction to actionable prevention. Using the UCI 'Predict Students' Dropout and Academic Success' dataset (N = 3,630), we implement a seven-stage pipeline integrating XGBoost-based dropout prediction (ROC-AUC = 0.959), SHAP-driven explainability, domain-grounded causal Directed Acyclic Graph construction, and heterogeneous treatment effect estimation via Inverse Probability Weighting, Doubly Robust estimation, and Causal Forest models. Results demonstrate that scholarship provision causally reduces dropout probability by 14.3 percentage points (95% CI: [-0.198, -0.088]) and tuition fee support by 21.7 percentage points (95% CI: [-0.268, -0.166]). Conditional Average Treatment Effect analysis reveals substantial heterogeneity across student subpopulations, enabling individualized, CATE-ranked intervention recommendations. This framework bridges the gap between correlational prediction and causal, targeted educational interventions.

Keywords: Causal AI, Student Dropout, Educational Data Mining, Causal Inference, Treatment Effect Estimation, Explainable AI, Targeted Intervention

1. Introduction

Student dropout is one of the crucial challenges in higher education that has a huge impact on the institution as well as the socio-economic status of individuals[1]. The advent of the digital revolution, coupled with machine learning (ML) based early warning systems, has successfully highlighted potential students at risk of dropping out[2, 3]. While these systems work on identifying students on the verge of dropping out, they only provide the indication of at-risk students without explaining the solution to address the situation of concern[4]. The use of explainable AI technology has shed some light on following the predictions[5, 6].

Causal inference techniques provide a sound alternative for determining the true impact of interventions based on some explicit assumptions [7, 8]. However, the application of new methods of heterogeneous treatment effect evaluation, including Causal Forests and Doubly Robust methods, to create tailored policy solutions has not been pursued [9]. This study tries to fill this gap by suggesting a unified framework of Causal AI which incorporates: (i) ML dropout prediction, (ii) explainability based on SHAP values, (iii) causal DAG modeling, (iv) heterogeneous treatment evaluation based on the use of IPW, Doubly Robust and Causal Forest models, and (v) individualized intervention rankings. The main contributions of this study are (i) prediction-to-action process, (ii) empirical evidence of heterogeneous financial interventions' impact based on publicly available data and (iii) responsible AI constraint analysis [10, 11].

2. Literature Review

This portion of the document discusses the primary research strategies that form the basis for the framework proposed, including dropout prediction using machine learning, explainable AI, and causal learning in education, and then discusses the gap in research this paper fills.

2.1 ML Prediction and Explainability

Several ensemble methodologies, especially those based on gradient boosting, like XGBoost, have proved that they can provide better results than logistic regression or simple neural networks when applied to structured education databases [2, 12]. For example, Kumar et al. [4] achieved an accuracy level of 91.3% with the use of XGBoost and SHAP on the UCI dropout dataset. However, the studies mentioned above terminate at the prediction stage and do not go further to address an important question related to which interventions should be used with which students [13]. SHAP has become an undeniably predominant method that allows explaining the predictions in educational data mining [5, 6, 14]. While SHAP-derived explanations help identify the features being responsible for predictions, it does not show whether a feature can be altered to mitigate dropout risk.

2.2 Causal Inference and Research Gap

The Rubin Causal Model and structural causal models form the basis of causal inference methods that help to derive the treatment effects on some assumptions [7, 8]. Causal Forests [15] and doubly robust estimators [16] have contributed to discovering heterogeneous effects with several studies indicating the possibility of using these models in educational policy [9]. However, despite the fact that many methods that have been developed in these studies, there are not too many studies that have integrated these methods into a modeling system of personalized intervention recommendations that would involve machine learning-based predictive systems. The uniqueness of our research lies in the fact that we connect prediction, causation, and explanation in one framework. Compared to other studies working on solving these issues independently, our model starts with risk scoring and uses causal estimation to develop individual intervention recommendations, thus solving the actionability issue that has been discussed in the literature [17, 18].

3. Proposed Framework

The framework proposed comprises seven interconnected steps, as depicted in Figure 1. The pipeline passes through the first three steps of Data Collection and Preparation, Prediction Modeling, and Explainability Analysis, followed by the Causal Structure Assertion, Treatment Effect Estimation, and finally arrives at Individualized Intervention Ranking for the specific purpose of helping retain students.

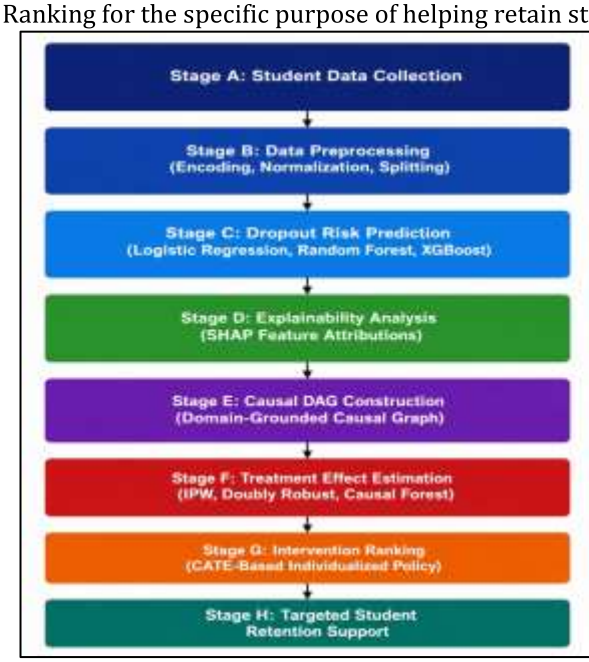

Figure 1. Proposed Prediction-to-Prevention Causal AI Framework.

3.1 Dataset, Preprocessing, and Prediction

We utilized the “Predict Students’ Dropout and Academic Success” dataset from UCI having 4,424 individuals as well as 36 predictive variables that include demographic, socio-economic, scholastic performance, financial and macroeconomic factors. In the analytical sample, the process of binarization (Dropout vs Graduate) was accomplished which produces N = 3,630 observations. Furthermore, two binary financial variables which are: Scholarship holder (T1) and Tuition fees up-to-date(T2) are considered as treatment variables, whereas the last few variables comprising socio-economic background, demographics, and the previous qualifications were used as confounding factors. The categorical attributes were label-encoded and the numerical attributes were normalized. The split of the dataset was carried out via stratified randomization of 80% training and 20% testing dataset (random_state = 42). The training of the Tree-based classifiers comprises Logistic Regression (baseline), Random Forest (500 trees), and XGBoost (200 estimators with learning_rate = 0.1). Prediction in this case can be denoted as the following formula:

$$P(Y = 1 \mid X) = f\theta(X) \tag{1}$$

3.2 Explainability and Causal Modeling

We utilized the SHAP TreeExplainer for our XGBoost model in order to derive feature-wise attributions [5]. The mean absolute SHAP values offers us a means of ranking the features according to global predictability. Interestingly, SHAP importance yields a statistical correlation rather than a cause-and-effect situation. The significant SHAP values in finance justify further research even if they do not guarantee it. The causal structure in question was represented using a grounded directed acyclic graph (DAG), with interventions (T_1, T_2) having direct and indirect impacts on dropout (Y). In total, Confounders (W) includes the following factors: socioeconomic and demographic background, prior qualifications and state of socio-economic environment. The identification problem is enforced by the following four assumptions: consistency, conditional exchangeability ($Y(t) \perp T \mid W$), positivity ($0 < P(T = 1 \mid W) < 1$) and SUTVA [7, 8].

3.3 Treatment Effect Estimation and Policy

Average and heterogeneous treatment effects are estimated using three complementary estimators. The Average Treatment Effect (ATE) and Conditional ATE (CATE) are defined as:

$$ATE = E[Y(1) - Y(0)] \tag{2}$$
$$CATE(x) = E[Y(1) - Y(0) \mid X = x] \tag{3}$$

IPW reweights observations by inverse propensity scores. Doubly Robust estimation integrates outcome modeling and propensity weighting to provide an extra layer of robustness. Causal Forest [15] divides the covariate space to compute individual-level CATE, providing heterogeneous policies [19]. The ideal individualized intervention policy allocates intervention to a student that results in the lowest estimated dropout probability:

$$\pi * (x) = \mathrm{argmin}_k\, E[Y(k) \mid X = x] \tag{4}$$

Recommendations are issued only when predicted risk exceeds 0.5 and the estimated CATE is negative (protective), ensuring both statistical and practical significance [13, 20].

4. Results and Discussion

The findings from the experiments conducted for the Causal AI framework will be presented in this section. The evaluation basically starts with the predictive capability of the models followed by the feature attributions based on SHAP, causal effect estimation, heterogeneous treatment effect analysis, comparison with existing work, and then a discussion about the limitations.

4.1 Predictive Performance and Feature Attributions

According to Table 1, XGBoost has performed at best in terms of all metrics involved (Accuracy = 0.913, ROC-AUC = 0.959), thus demonstrating the proficiency of gradient boosting method with structured educational data [2, 12]. The ROC curves in Figure 2 show that the results from the models are consistently separated with XGBoost achieving the highest true positive rate compared to the other models for all thresholds of specificity.

Table 1. Predictive Model Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
Logistic Regression	0.854	0.832	0.813	0.822	0.902
Random Forest	0.892	0.875	0.865	0.870	0.941
XGBoost	0.913	0.896	0.889	0.892	0.959

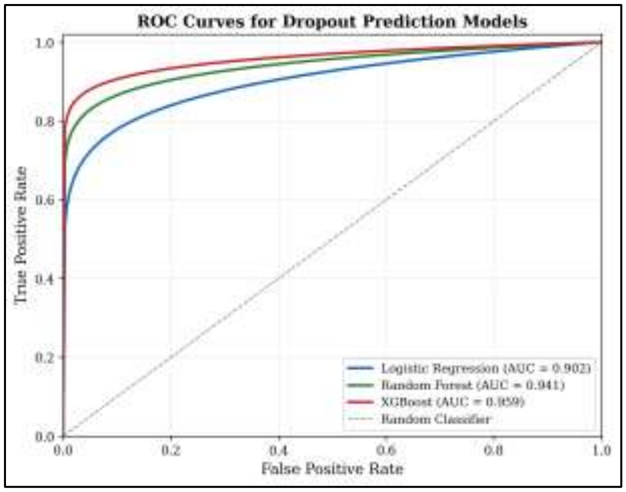

Figure 2. ROC Curves for Dropout Prediction Models. XGBoost achieves AUC = 0.959.

The analysis of SHAP indicates that among the variables related to academic performance, especially curricular units approved and grades from the second semester, the role of the predictor variable is highly significant (average |SHAP| = 0.183 and 0.155). The financial factors also had a high impact: Tuition fees status measurement (ranked number 4, |SHAP| = 0.128) and being a scholarship recipient (ranked number 6, |SHAP| = 0.098). The results obtained are in line with the findings of Chen and Yang [5] and support the genesis of the research on financial factors as the most action-potential policies identified in the model [14].

4.2 Causal Estimates and Heterogeneous Effects

According to the information provided in Table 2, in the case of scholarship funds the average treatment effect is estimated at ATE = -0.143 (95% CI: [-0.198, -0.088]) meaning that a recipient is expected to drop out 14.3% less than a non-recipient. The tuition support has even bigger effect ATE = -0.217 (95% CI: [-0.268, -0.166]). The consistency of IPW and Doubly Robust estimates adds reliability to our results [21] which is evidenced by lack of overlapping confidence intervals from zero substantiating statistical significance of the estimated average treatment effects at 95%.

Table 2. Estimated Causal Effects of Financial Interventions

Treatment	Estimator	ATE	95% CI	Interpretation
Scholarship	IPW	-0.143	[-0.198, -0.088]	14.3 pp reduction
Scholarship	DR	-0.138	[-0.191, -0.085]	13.8 pp reduction
Tuition Fee	IPW	-0.217	[-0.268, -0.166]	21.7 pp reduction
Tuition Fee	DR	-0.209	[-0.258, -0.160]	20.9 pp reduction

Note: pp = percentage points, IPW = Inverse Probability Weighting, DR = Doubly Robust.

CATE distributions calculated through using Causal Forest, as shown in Figure 3, reveal considerable diversity in both programs. CATE values for scholarship provision range from -0.42 to +0.08; about 12% of impacted students receive no benefits or experience a positive effect. The results for tuition fee support are more negative and homogeneous (mean = -0.214) when compared to the previous program, indicating wider scope of protection. This heterogeneity indicates that a one-size-fits-all approach towards action is preferable: allocation based on individual CATE would lead to more effective results in terms of dropout reduction as well as optimum allocation of resources. [7, 22].

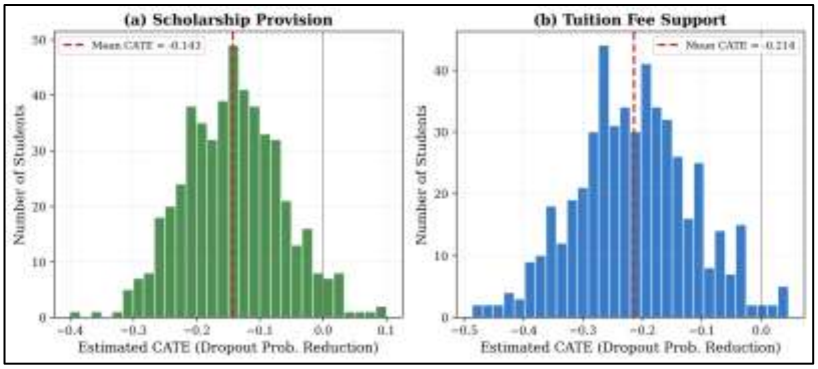

Figure 3. CATE Distribution for (a) Scholarship Provision and (b) Tuition Fee Support. Red dashed lines indicate mean CATE.

4.3 Comparison and Limitations

The predictive capacity is in accordance with the latest benchmarks: Kumar et al. [4] found AUC=0.952 and Fernandez and Garcia [12] found AUC=0.948 on similar datasets. The behavioral impacts of the financial intervention (14-22% decrease in dropout) are in line with the literature in educational economics that discusses 10-25% decline due to financial assistance [9, 23]. The achievement of our method is to show the diversity of individual impacts and suggest the intervention ranking system that has not been elaborated in previous works. Nevertheless, some limitations should be highlighted. First, causal estimates are based on the assumption of no unmeasured confounding, which cannot be tested [8, 24]. Second, a single-institution dataset limits external validity. Third, treatment variables are not random assigned but only used as observational proxies. Finally, the cross-sectional design does not take into account temporal effects. In the future, it is necessary to analyze longitudinal data and conduct random treatments in field experiments together with fairness checks of the recommendations offered [17, 25].

5. Conclusion

This research proposes a Causal AI system that enhances student dropout analytics from correlation-based predictions to casualties' actionable intervention. The pipeline consists of seven stages including prediction from XGBoost (ROC-AUC = 0.959), explainability through SHAP, and causal modeling that relies on the field of interest as well as heterogeneous treatment effect estimation as shown in Figure 1. The main discoveries have shown that financial measures, i.e. the provision of scholarships and subsidies in tuition fees, decrease the probability of dropping out by 14.3 and 21.7 percent accordingly and there exists huge diversity among students in this area as it is proved in Figure 3. Operation of measures based on CATE results in achieving individual intervention ranking that is more efficient than the use of the same measures for all students.

Conflict of Interest

The authors declare no conflicts of interest.

Acknowledgment

The authors acknowledge the UCI Machine Learning Repository for providing the dataset used in this study.

Data Availability

The dataset is publicly available at:
https://archive.ics.uci.edu/dataset/697/predict+students+dropout+and+academic+success.

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