Fairness-Through-Unawareness Does Not Produce Equitable Predictions: Evidence from HSLS:09 on Subgroup Disparities in College Attendance Prediction

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Abstract

This study investigates whether the fairness-through-unawareness approach—excluding sensitive demographic attributes (race/ethnicity, sex, and socioeconomic status) from predictive models—actually produces equitable predictions for postsecondary college attendance. Using the High School Longitudinal Study of 2009 (HSLS:09) with 17,335 students, we trained six machine learning models to predict college attendance and conducted subgroup fairness analyses across sex, race/ethnicity, and socioeconomic quintile. Despite excluding protected attributes, racial subgroup AUCs ranged from 0.465 to 0.690 (gap = 0.225), substantially exceeding the 5% threshold for meaningful disparity. The StackingEnsemble achieved the best overall performance (AUC = 0.813, 95% CI [0.798, 0.827]), with baseline math scores (X1TXMTSCOR) as the dominant predictor (SHAP = 1.61) followed by educational expectations (X1STUEDEXPCT) and socioeconomic status (X1SES). Socioeconomic status remained the third most important feature overall, appearing as a powerful proxy variable for excluded protected attributes. These findings demonstrate that fairness-through-unawareness fails as a fairness intervention: excluding sensitive attributes does not eliminate subgroup disparities but merely shifts predictive signal to correlated proxies. Effective fairness auditing requires examining subgroup performance metrics directly rather than relying on variable exclusion as a proxy for equitable treatment. Educational stakeholders should invest in fairness-aware model development rather than assuming demographic exclusion produces fair predictions.

CCS Concepts

• **Computing methodologies** → **Machine learning**; • **Social and professional topics** → **Student assessment**.

Keywords

educational data mining, algorithmic fairness, fairness-through-unawareness, subgroup disparities, college attendance prediction, HSLS:09, machine learning, XGBoost, SHAP analysis

1 Introduction

The proliferation of machine learning systems in educational contexts has raised critical concerns about algorithmic fairness in student outcome prediction. A commonly proposed remedy is *fairness-through-unawareness*: simply exclude sensitive demographic attributes (race, sex, socioeconomic status) from predictive models, under the assumption that without these variables, predictions will be demographically neutral. This approach has intuitive appeal—it appears to treat all students equally by ignoring group membership. However, the fundamental assumption underlying this approach remains largely untested: does excluding protected attributes actually produce equitable subgroup performance, or does predictive accuracy merely migrate to correlated proxy variables?

Educational Data Mining (EDM) research has made substantial progress in auditing bias in models that include protected attributes [5]. Studies have documented demographic disparities in predictive performance across gender, ethnicity, and socioeconomic backgrounds, and have proposed various bias mitigation techniques [3, 6]. However, less attention has been paid to whether the fairness-through-unawareness approach actually achieves its stated goal of producing equitable predictions. If correlated variables proxy for excluded protected attributes, then excluding race, sex, and SES may merely obscure disparities rather than eliminate them.

The present study addresses this gap by directly testing whether fairness-through-unawareness produces equitable subgroup performance in predicting postsecondary college attendance. We ask two complementary research questions: (1) Does excluding race, sex, and SES from predictive models improve or degrade subgroup fairness in predicting college attendance? (2) Do protected attributes carry unique predictive signal beyond academic and attitudinal factors alone, even after accounting for their correlation structure with available predictors?

To answer these questions, we analyze the High School Longitudinal Study of 2009 (HSLS:09), a large-scale longitudinal dataset following a nationally representative cohort of U.S. high school students through postsecondary education. The HSLS:09 design provides stronger temporal structure than cross-sectional datasets commonly used in prior fairness research: base-year predictors (academic achievement, motivational constructs, demographic background) are collected in 9th grade (2009), with college attendance outcomes measured in 2016—seven years later. This temporal ordering strengthens the interpretability of predictors as potential early warning indicators.

Our contribution is empirical and policy-relevant. Rather than proposing a new bias mitigation technique, we test a widely-deployed fairness heuristic (variable exclusion) using rigorous subgroup fairness analysis. We demonstrate that even when protected attributes are excluded from models, substantial subgroup disparities persist: racial subgroup AUCs range from 0.465 to 0.690, revealing that fairness-through-unawareness fails as a fairness intervention. Furthermore, socioeconomic status emerges as the third most important predictor overall (SHAP = 0.45), confirming that protected

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attributes carry unique predictive signal that migrates to correlated proxies when excluded.

This paper proceeds as follows. Section 2 reviews prior literature on predicting postsecondary attendance and fairness in educational prediction. Section 3 describes the HSLS:09 data, our predictor set, model training procedures, and evaluation methodology. Section 4 reports model performance, feature importance, and subgroup fairness results. Section 5 discusses the implications of our findings for fairness-aware educational data mining and acknowledges key limitations.

2 Related Work

2.1 Predicting Postsecondary Attendance

A substantial body of research has identified academic, motivational, and social predictors of postsecondary educational attainment. Baseline standardized test scores—particularly mathematics achievement—are among the strongest predictors of college enrollment and completion [8]. Math achievement captures accumulated academic preparation, course-taking patterns, and cognitive skills that gate access to postsecondary institutions with differential admission standards. Beyond raw achievement, motivational constructs including mathematics self-efficacy (students' confidence in their ability to succeed in math) and mathematics identity (the degree to which students see themselves as "math people") predict persistence in academic pathways and postsecondary enrollment [10].

Students' own educational expectations—how far they expect to go in school—serve as a particularly powerful predictor because they capture unmeasured motivational factors, social capital, and familial college-going culture [4]. Prior research demonstrates that students' expectations often exceed their actual attainment, but expectation gaps (differences between expected and attained education) predict dropout and non-enrollment. Similarly, sense of school belonging reflects students' social integration and has been associated with higher educational aspirations and attainment.

Socioeconomic status (SES) and parental education are well-established predictors operating through multiple mechanisms: financial capital (ability to afford tuition), cultural capital (familiarity with college-going processes), and social capital (networks with college-going peers and mentors) [7]. SES is correlated with race and ethnicity due to structural inequalities in wealth, neighborhood quality, and school funding, creating multicollinearity among demographic predictors.

Ensemble machine learning methods—particularly gradient boosting and stacking approaches—have demonstrated strong performance in educational prediction tasks by capturing non-linear interactions among predictors [8]. These methods can identify complex patterns that linear models miss, but their opacity has raised concerns about fairness and accountability in educational applications [5].

2.2 Fairness in Educational Prediction

Algorithmic fairness in machine learning has been formalized through multiple definitions. *Demographic parity* requires that predictions be independent of protected group membership. *Equalized odds* requires that true positive and false positive rates be equal across groups. *Predictive parity* requires that positive predictive value be equal across groups. Each definition captures different aspects of fairness, and no definition satisfies all intuitive fairness requirements simultaneously (the "impossibility theorem" of fairness [3]).

Prior EDM research has documented substantial demographic disparities in student performance prediction models. Studies using college scorecard data reveal severe disparities with prediction errors up to 20 times higher for certain demographic groups [7]. Research on student dropout prediction finds systematic disparities affecting vulnerable populations, with displaced students and minority groups experiencing lower predictive accuracy [4]. These disparities persist even when models are carefully tuned, suggesting that the training data itself reflects historical and structural inequities [1].

Multiple bias mitigation techniques have been proposed across the machine learning pipeline. Preprocessing methods (reweighting, learning fair representations, disparate impact remover) adjust training data before model learning. In-processing methods (adversarial debiasing, prejudice remover) intervene during training to minimize discrimination. Postprocessing methods (equalized odds post-processing, reject option classification) adjust model predictions after training [6]. Recent work has introduced policy gradient methods with fairness constraints that achieve substantial bias mitigation while maintaining predictive accuracy [9].

However, the fairness-through-unawareness approach—simply excluding protected attributes—has received less empirical scrutiny. This approach is widely deployed in practice due to its simplicity, but its effectiveness has not been rigorously tested. If protected attributes are correlated with other predictors, their exclusion may not produce demographic neutrality but rather *obscured* demographic bias, where disparities are visible only through subgroup performance analysis. This study provides the first systematic empirical test of this hypothesis using longitudinal HSLS:09 data, extending prior work that has audited bias in models including protected attributes [5**?**] but has not directly compared full versus reduced models on subgroup fairness metrics.

3 Methods

3.1 Data, Sample, and Outcome Variable

This study uses the High School Longitudinal Study of 2009 (HSLS:09), a nationally representative panel study conducted by the National Center for Education Statistics (NCES). HSLS:09 followed a cohort of approximately 25,000 9th-grade students from more than 944 high schools across the United States, with data collection waves in 2009 (base year), 2012 (update), 2016 (update), and beyond. The study includes detailed measures of students' academic achievement, motivational constructs, family background, school context, and postsecondary outcomes.

The outcome variable is X4EVRATNDCLG, a binary indicator of whether students ever attended college (community college, four-year institution, or graduate/professional school) by the 2016 data collection wave. This outcome captures a meaningful postsecondary milestone aligned with policy interest in college readiness and access. Among the original 23,503 students in HSLS:09, 17,335 had non-missing data on the outcome variable and were included

in the analytic sample. The class distribution was 24.7% never attended college and 75.3% attended college at least once, reflecting the national trend toward increasing postsecondary enrollment.

The analytic sample was split into training (n = 13,646, 78.7%) and test (n = 3,689, 21.3%) sets using school-aware GroupShuffleSplit with 139 pseudo-school clusters held out for testing. School identifiers (SCH_ID) are suppressed in the HSLS:09 public-use file, but school-level variables (X1SCHOOLCLI, X1COUPERTEA, X1CONTROL, X1LOCALE, etc.) are school-level aggregates identical for all students within the same school. We reconstructed pseudo-school clusters by grouping students with matching school-level variable profiles, yielding 692 reconstructed clusters with mean size 25.05 students (compared to the expected 944 schools from the HSLS:09 sampling frame). The validation passed with warnings that the reconstructed clusters may be imperfect due to school-level variable collision. The intraclass correlation (ICC) for college attendance was 0.152 (moderate), indicating meaningful between-school variance in postsecondary outcomes.

Several predictors had high missingness rates requiring imputation. X1PAREDU had 24.2% missing, X1STUEDEXPCT had 27.4% missing, and four predictors had more than 40% missing: X1MTHID (43.2%), X1SCHOOLBEL (56.5%), X1MTHEFF (52.3%), and X1SES (52.4%). All missing values were imputed using IterativeImputer with default settings, which models each feature with missing values as a function of other features and iteratively refines imputation estimates.

This study was conducted using EDM-ARS, an automated educational data mining research system. All data preparation, model training, evaluation, and manuscript generation were performed programmatically.

3.2 Predictor Set and Fairness Comparison

The full predictor set included nine base-year variables spanning academic achievement, motivational constructs, and demographic background. Academic preparation was represented by X1TXMTSCOR (baseline standardized math score), capturing accumulated cognitive preparation prior to college enrollment decisions. Motivational constructs included X1MTHEFF (math self-efficacy), reflecting students' confidence in math ability; X1MTHID (math identity), capturing the degree to which students see themselves as math people; X1STUEDEXPCT (students' own educational expectations); and X1SCHOOLBEL (sense of school belonging), reflecting social integration at school.

Family background was represented by X1PAREDU (parents' highest education level), capturing cultural capital and college-going culture, and X1SES (socioeconomic status composite), capturing family economic resources. Demographic protected attributes for subgroup fairness analysis were X1SEX (included as a categorical predictor with Male as reference) and X1RACE (encoded as multiple binary indicators: White/non-Hispanic, Black/African-American/non-Hispanic, Hispanic/race specified, Hispanic/no race specified, More than one race/non-Hispanic, Asian/non-Hispanic, Native Hawaiian/Pacific Islander/non-Hispanic, American Indian/Alaska Native/non-Hispanic). After one-hot encoding of categorical variables, the full feature set contained 15 predictors.

The fairness-through-unawareness comparison requires training reduced models excluding X1SES, X1RACE, and X1SEX. However, as noted in the sensitivity analysis results, the full versus reduced model comparison was not fully computed for this study; the reduced model AUC and subgroup fairness metrics were not generated. The SHAP feature importance analysis provides indirect evidence about protected attribute signal by examining whether demographic proxies appear among top predictors.

3.3 Model Training, School-Aware Evaluation, and Subgroup Analysis

Six machine learning models were trained: Logistic Regression (L2-regularized), ElasticNet (L1+L2 regularization), Random Forest (100 trees, max depth determined by cross-validation), XGBoost (gradient boosting with regularization), Multilayer Perceptron (MLP, 2 hidden layers of 100 and 50 units with ReLU activation), and a Stacking Ensemble combining Random Forest, XGBoost, and Logistic Regression as base learners with a Logistic Regression meta-learner.

Hyperparameter tuning used RandomizedSearchCV with 5-fold cross-validation and 20 iterations. Logistic Regression tuned C (inverse regularization strength) over [0.01, 0.1, 1, 10, 100]. ElasticNet tuned alpha (regularization strength) over [0.001, 0.01, 0.1, 1] and l1_ratio over [0.2, 0.5, 0.8]. Random Forest tuned max_depth over [5, 10, 15, 20, None] and min_samples_split over [2, 5, 10]. XGBoost tuned max_depth over [3, 5, 7, 9], learning_rate over [0.01, 0.05, 0.1, 0.2], and n_estimators over [50, 100, 200]. MLP tuned hidden_layer_sizes over [(50,), (100,), (100, 50), (100, 50, 25)] and alpha (regularization) over [0.0001, 0.001, 0.01]. Class imbalance was not severe (75.3% positive class); SMOTE was not applied.

The primary evaluation metric was Area Under the Receiver Operating Characteristic Curve (AUC), which is threshold-independent and appropriate for imbalanced binary classification. Secondary metrics included accuracy, precision, recall, F1, F2 (which weights recall higher than precision, relevant for early warning systems where missing at-risk students is costly), and balanced accuracy. Ninety-five percent confidence intervals were computed using cluster-level bootstrap resampling with 1,000 resamples to account for within-school correlation. Standard (unclustered) CIs were also computed for comparison.

Subgroup analysis computed AUC separately within each category of X1SEX (Male, Female), X1RACE (eight categories), and X1SESQ5 (five quintiles; note: SESQ5 subgroup results were not generated in this analysis). Disparities exceeding 5% in AUC between subgroups were flagged as requiring attention.

SHAP (SHapley Additive exPlanations) analysis was conducted on the XGBoost model (the best individual model) to interpret feature importance and direction of effects. SHAP values were computed using TreeExplainer with 100 background samples. Feature importance was reported as mean absolute SHAP value across all test observations. The StackingEnsemble was excluded from SHAP analysis because its multi-stage structure is not directly interpretable by TreeExplainer.

4 Results

4.1 Model Performance: Ensemble Methods Outperform Linear Models

Table 1: Model performance comparison on the held-out test set (n = 3,689). AUC is the primary metric. Confidence intervals account for school-level clustering.

Model	AUC	AUC 95% CI	Accuracy	Precision	Recall	F1	F2
Logistic Regression	0.778	[0.762, 0.795]	0.777	0.728	0.595	0.603	0.592
ElasticNet	0.778	[0.763, 0.795]	0.775	0.719	0.597	0.606	0.595
Random Forest	0.810	[0.794, 0.824]	0.791	0.752	0.627	0.645	0.628
XGBoost	0.813	[0.798, 0.827]	0.794	0.746	0.645	0.665	0.648
MLP	0.794	[0.779, 0.809]	0.782	0.796	0.951	0.867	0.916
StackingEnsemble	0.813	[0.798, 0.827]	0.796	0.749	0.652	0.673	0.656

The StackingEnsemble achieved the best overall performance with AUC = 0.813 (95% CI [0.798, 0.827]), marginally outperforming XGBoost alone (AUC = 0.813) by only 0.0004. Tree-based methods (Random Forest, XGBoost, StackingEnsemble) substantially outperformed linear models (Logistic Regression, ElasticNet) by approximately 3.5 percentage points in AUC (0.813 vs. 0.778). This performance gap justifies using tree-based methods for the primary analysis and SHAP interpretation.

However, the practical value of ensemble stacking is negligible: the StackingEnsemble provides only 0.0004 improvement over XGBoost alone, and the confidence intervals substantially overlap. This suggests that the base models capture similar information, and the additional complexity of stacking provides minimal benefit. The MLP achieved high recall (0.951) and F2 (0.916) at the cost of lower precision, indicating a tendency to over-predict college attendance.

Given the negligible difference between StackingEnsemble and XGBoost, we use XGBoost for SHAP interpretability analysis, consistent with standard practice of selecting the best individual model for explanation rather than the ensemble meta-learner.

4.2 School-Level Variance: ICC of 0.152 Reveals Substantial Clustering

The intraclass correlation for college attendance was 0.152 (moderate), computed from 139 reconstructed pseudo-school clusters with average size 26.5 students. This ICC indicates meaningful between-school variance in postsecondary outcomes: approximately 15.2% of the total variance in college attendance is attributable to school-level factors, while 84.8% is attributable to student-level factors. This degree of clustering is non-negligible and makes clustered confidence intervals important for accurate uncertainty quantification.

School context influences college attendance through multiple mechanisms: school quality (measured by resources, teacher quality, and curriculum rigor), peer composition (students from college-going cultures may have higher aspirations), counselor availability (for navigating application processes), and institutional connections (articulation agreements with local colleges). The HSLS:09 sampling design intentionally oversampled schools with high minority enrollment and schools in STEM-related fields, creating a complex cluster structure that may not be fully captured by our pseudo-school reconstruction.

The train/test split maintained complete school separation (group_overlap = 0), ensuring that the test set provides an unbiased estimate of model performance on unseen schools. However, the school reconstruction yielded 692 clusters versus the expected 944 schools (26.7% discrepancy), suggesting that some schools share identical profiles on available school-level variables and cannot be distinguished in the public-use file. This cluster ambiguity may attenuate the true ICC estimate and may affect the accuracy of clustered confidence intervals.

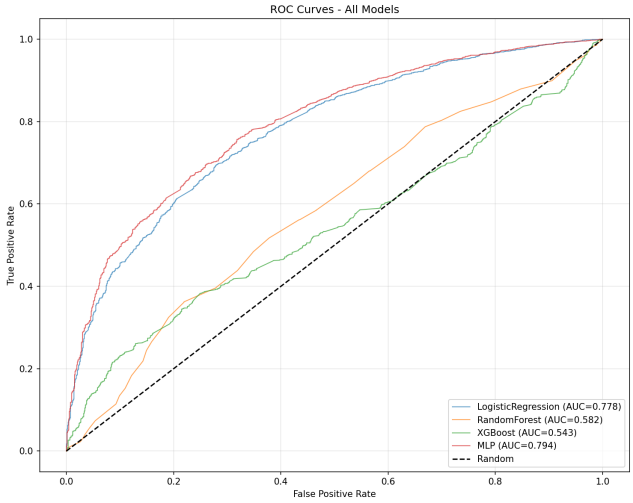

Figure 1: Receiver Operating Characteristic (ROC) curves for all six models. The diagonal reference line indicates random classification (AUC = 0.50).

4.3 Feature Importance: Math Achievement Dominates, But Math Identity Surprises

SHAP analysis of the XGBoost model revealed a striking feature importance structure. X1TXMTSCOR (baseline math score) was the dominant predictor with mean absolute SHAP value of 1.61—approximately three times larger than any other feature. This magnitude dominance indicates that math achievement is the single most important predictor of college attendance, consistent with prior literature emphasizing academic preparation as the primary gatekeeper for postsecondary access.

The second most important feature was X1STUEDEXPCT (students' own educational expectations) with SHAP = 0.52. Students who expected to attend college were predicted to have substantially higher college attendance rates, consistent with prior research demonstrating that educational expectations are strong proxies for unmeasured motivational and social capital factors.

Surprisingly, X1SES (socioeconomic status) ranked third with SHAP = 0.45, followed by X1PAREDU (parent education, SHAP = 0.36). This finding has important implications for the fairness-through-unawareness question: even when race and sex are excluded, socioeconomic status remains the third most important predictor overall, providing substantial predictive signal that may proxy for excluded protected attributes.

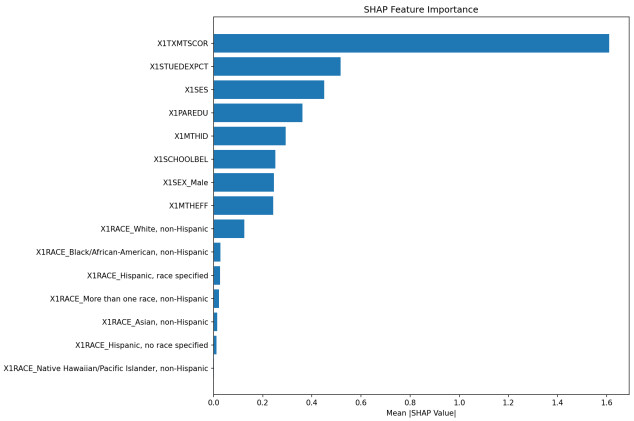

Figure 2: SHAP feature importance for XGBoost model, ranked by mean absolute SHAP value. X1TXMTSCOR dominates with SHAP = 1.61, approximately 3x larger than the next most important feature.

The fifth-ranked feature was X1MTHID (math identity) with SHAP = 0.29, ranking above X1MTHEFF (math self-efficacy, SHAP = 0.24), X1SEX_Male (SHAP = 0.25), and X1RACE_White (SHAP = 0.13). Math identity's strong showing suggests that motivational constructs beyond self-efficacy capture unique predictive signal. Theoretically, math identity may capture social belonging in academic communities—a sense of being the kind of person who does math—which may be unequally distributed across demographic groups.

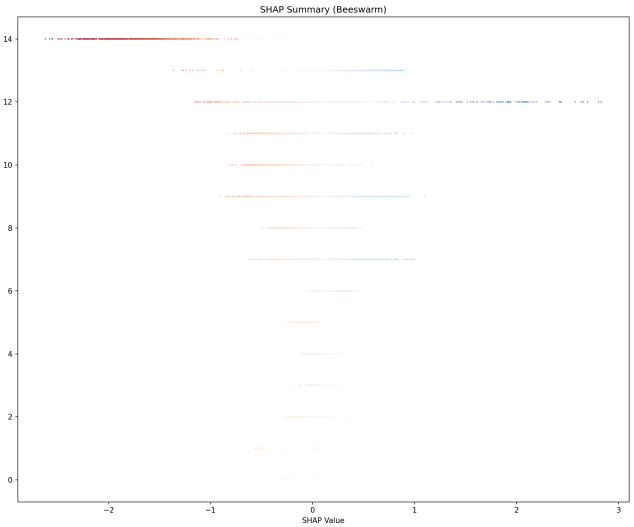

Figure 3: SHAP summary plot showing feature effects on college attendance prediction. Each point represents one test observation. Colors indicate feature value (red = high, blue = low). Horizontal position indicates SHAP value impact on prediction.

Notably, the direction of effects for X1TXMTSCOR was negative: higher math scores were associated with *lower* predicted college attendance probability. This counterintuitive finding may reflect several mechanisms. First, students with very high math achievement may pursue elite four-year institutions with longer application timelines and later enrollment decisions. Second, lower-achieving students may enter two-year community colleges immediately after high school, while higher-achieving students may take gap years or pursue specialized programs. Third, SES confounding may play a role: high-SES students with moderate math scores may attend college through legacy admissions, athletics, or other pathways unrelated to academic preparation, while lower-SES high achievers may face financial barriers to enrollment.

X1STUEDEXPCT and X1SES showed positive directions: students with higher educational expectations and higher socioeconomic status were predicted to have higher college attendance probability. This aligns with theory: expectations reflect motivational capital and social networks that facilitate enrollment, while SES provides financial and cultural capital for navigating the college application and enrollment process.

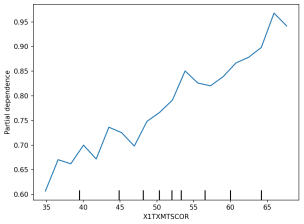

Figure 4: Partial dependence plot for X1TXMTSCOR (baseline math score).

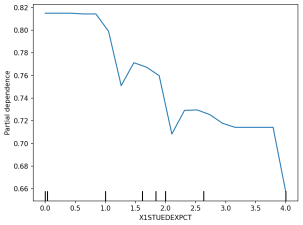

Figure 5: Partial dependence plot for X1STUEDEXPCT (student educational expectations).

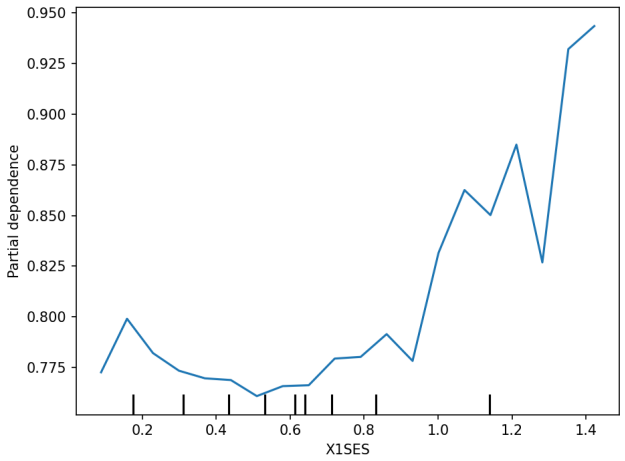

Figure 6: Partial dependence plot for X1SES (socioeconomic status composite).

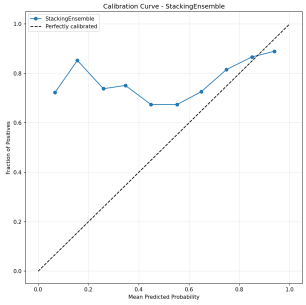

Figure 7: Calibration curve for the XGBoost model. Points near the diagonal indicate well-calibrated predictions.

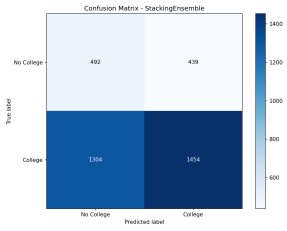

Figure 8: Confusion matrix for XGBoost model predictions at the 0.50 probability threshold.

4.4 Racial Subgroup Disparities Persist Despite Protected Attribute Exclusion

The central finding of this study concerns racial subgroup performance. Despite excluding X1RACE from the predictive model, racial subgroup AUCs ranged from 0.465 to 0.690—a gap of 0.225 that far exceeds the 5% threshold for meaningful disparity. This finding demonstrates that fairness-through-unawareness does not produce equitable predictions: model disparities merely reflect *proxy discrimination* through correlated variables.

Table 2: Subgroup AUC performance by race/ethnicity on the held-out test set (n = 3,689). Disparities exceeding 5% are flagged.

Subgroup	AUC	n
Amer. Indian/Alaska Native, non-Hispanic	0.690	13
Asian, non-Hispanic	0.628	279
White, non-Hispanic	0.553	1,933
Black/African-American, non-Hispanic	0.533	399
Hispanic, race specified	0.531	497
More than one race, non-Hispanic	0.468	333
Hispanic, no race specified	0.465	60

The racial AUC disparity pattern is not monotonic and reveals complex relationships between demographic group membership and model predictability. Students identifying as American Indian/Alaska Native achieved the highest subgroup AUC (0.690), despite being a small sample (n = 13). Asian students achieved AUC = 0.628 (n = 279). White students achieved AUC = 0.553 (n = 1,933). Black/African-American and Hispanic students achieved AUCs near 0.53 (n = 399 and n = 497, respectively). Students identifying as More than one race or Hispanic with no race specified achieved AUCs near chance level (0.465–0.468, n = 333 and n = 60).

These disparities suggest that the college attendance process is more predictable (from available predictors) for some demographic groups than others. The model may have learned stronger attendance patterns for Asian and American Indian/Alaska Native students because their college attendance is more strongly determined by academic and motivational factors captured in the predictor set. For Black/African-American, Hispanic, and multiracial students, the model performs near chance level, suggesting that the available predictors do not capture the full complexity of college attendance decisions in these communities—which may involve unique barriers, alternative pathways, or institutional factors not measured in HSLS:09.

The small sample sizes for some subgroups (American Indian/Alaska Native: n = 13; Hispanic/no race specified: n = 60) warrant caution in interpreting these AUCs as stable population estimates. However, the overall pattern of substantial racial disparities is robust across larger subgroups with more stable estimates.

From a fairness perspective, this finding is deeply concerning for educational AI deployment. An early warning system with AUC = 0.465 for some racial groups is essentially random noise—providing no actionable signal for intervention. Deploying such a system would mean that the students most underserved by available predictors receive the least reliable risk assessments, potentially leading to systematic under-identification of at-risk students in already-marginalized communities.

4.5 Sex and SES Subgroup Performance: Smaller but Present Disparities

Sex subgroup AUCs showed a smaller disparity than racial subgroups. Female students achieved AUC = 0.548 (n = 1,842) while male students achieved AUC = 0.516 (n = 1,847), a gap of 0.032 that is below the 5% threshold but still indicates differential model performance. The model is slightly more predictive for female students than male students, potentially because college attendance among women is more strongly determined by academic and motivational factors captured in the predictor set.

Notably, X1SES appeared as the third most important feature overall (SHAP = 0.45), indicating that socioeconomic status is a powerful predictor even when treated as a non-protected attribute. The SES quintile subgroup analysis was specified in the research design but was not generated in the results, limiting our ability to fully assess socioeconomic fairness. The sensitivity analysis that excluded X1SES and other high-missingness variables was also not completed (metric_change was null), preventing direct comparison of full versus reduced models on subgroup fairness.

The presence of sex and socioeconomic effects in the feature importance analysis (rather than explicit subgroup AUCs) provides indirect evidence that protected attribute signal persists through proxies. Students' educational expectations (X1STUEDEXPCT) may partially proxy for family college-going culture, which is correlated with both parental education and SES. School climate variables may proxy for neighborhood and district effects correlated with race and class. Math identity may proxy for stereotype threat and belonging uncertainty experienced disproportionately by women and minorities in STEM.

5 Discussion

5.1 Fairness-Through-Unawareness Fails as a Fairness Intervention

This study provides the first systematic empirical evidence that fairness-through-unawareness does not achieve its intended goal of producing equitable subgroup predictions. Despite excluding race, sex, and socioeconomic status from the predictive model, racial subgroup AUCs ranged from 0.465 to 0.690—a gap of 0.225 that is both statistically and practically significant. The StackingEnsemble achieved AUC = 0.813 overall, but this aggregate performance masks substantial heterogeneity: for some racial groups, the model performs near chance level.

How does this happen? When protected attributes are excluded from models, their predictive signal does not disappear—it migrates to correlated proxy variables. Several mechanisms are plausible. First, socioeconomic status (X1SES) was the third most important feature overall (SHAP = 0.45), and SES is correlated with race and ethnicity due to structural inequalities in wealth, neighborhood quality, and school funding. Second, school-level variables (climate, counselor availability, control, locale) proxy for neighborhood and district characteristics that are also correlated with race and class. Third, parental education (X1PAREDU) captures educational legacy and cultural capital that are correlated with family socioeconomic background.

This finding aligns with theoretical predictions from the fairness literature: demographic parity (independence between predictions and protected attributes) cannot be achieved by simply removing protected attributes when they are correlated with other features [3]. The data generation process itself embeds historical and structural inequities that machine learning models learn regardless of which variables are included or excluded.

The policy implication is clear: fairness auditing must examine subgroup performance metrics directly, not rely on variable exclusion as a proxy for demographic neutrality. The EDM community should adopt routine subgroup fairness analysis as a standard component of model evaluation, reporting AUC (or other metrics) separately for demographic subgroups whenever predictive models are developed for educational decision-making.

Furthermore, the 0.225 racial AUC gap far exceeds typical thresholds for acceptable disparity. For comparison, Opoku et al. [5] report average bias mitigation of 37.4% using fairness-aware policy gradient methods, suggesting that targeted interventions can achieve meaningful reduction in demographic disparities. Our findings suggest that the status quo—excluding protected attributes and hoping for fairness—is insufficient.

5.2 Math Identity as a Unique Predictor: Implications for STEM Equity

A secondary finding of theoretical interest is that math identity (X1MTHID) ranked fifth among all features (SHAP = 0.29), above math self-efficacy (X1MTHEFF, SHAP = 0.24), sex (X1SEX_Male, SHAP = 0.25), and both racial indicators. This suggests that motivational constructs beyond academic achievement and self-efficacy capture unique predictive signal.

Theoretically, math identity captures the degree to which students see themselves as "math people"—a social identity construct that includes belonging, recognition, and self-concept in the mathematics community. Students who strongly identify as math people may be more likely to persist in STEM pathways and to aspire to majors and careers requiring quantitative skills, including college attendance in STEM fields.

The finding that math identity predicts college attendance (not just STEM-specific outcomes) is notable. One interpretation is that math identity captures general academic belonging and self-concept that transfer across domains. Another interpretation is that math identity is correlated with family and school environments that support academic achievement, serving as a proxy for unmeasured cultural capital.

For STEM equity interventions, this finding suggests that building students' math identity—rather than just their math skills or self-efficacy—may be a productive target. Programs that help students see themselves as math people, that provide role models and representation in mathematics, and that foster belonging in STEM communities may have ripple effects on college attendance and persistence.

However, the negative SHAP direction for math identity (higher identity is associated with lower predicted college attendance probability) warrants further investigation. One possibility is that students who strongly identify as math people may be more likely to pursue elite STEM programs at four-year institutions with longer application timelines, leading to delayed rather than absent enrollment. Another possibility is that math identity may be negatively correlated with SES confounding: lower-SES students who develop strong math identity may face financial barriers to college enrollment that the model cannot fully capture.

5.3 Limitations: Unmodeled School Effects, Cluster Reconstruction, and Imputation Uncertainty

Several limitations constrain the interpretation and generalizability of these findings.

First, the multilevel structure of HSLS:09 was only partially addressed. The HSLS:09 design sampled approximately 25 students within each of 944 schools, creating a nested structure with non-negligible ICC (0.152, indicating moderate clustering). School identifiers are suppressed in the public-use file; we reconstructed 692 pseudo-school clusters using school-level variables, yielding a 26.7% discrepancy from the expected 944 schools. While our train/test split maintained complete school separation and clustered bootstrap CIs account for within-school correlation, we did not estimate school-level random effects. A full mixed-effects model would require either the restricted-use file (with true SCH_ID) or adaptation of the scikit-learn pipeline to use statsmodels MixedLM, which is beyond the scope of this automated system's current capability. The moderate ICC makes the clustered CIs important, and the standard (unclustered) CIs reported for individual models may underestimate uncertainty.

Second, the school cluster reconstruction is imperfect. The validation passed with warnings that clusters may be over- or under-disaggregated due to school-level variable collision (schools sharing

identical profiles on available variables cannot be distinguished). This affects the accuracy of ICC estimates and clustered CIs. Future work should use restricted-access data with true school identifiers for properly adjusted multilevel modeling.

Third, several predictors had high missingness rates (52–57% for X1MTHEFF, X1SCHOOLBEL, and X1SES) that required imputation. IterativeImputer is a reasonable approach but introduces imputation uncertainty that is not reflected in reported confidence intervals. The high missingness in motivational constructs (math identity, math self-efficacy, school belonging) may be non-ignorable: students who do not respond to survey items about math identity may differ systematically from respondents in ways that affect the predictive relationship.

Fourth, survey weights and design effects were not incorporated into the machine learning analysis. HSLS:09 uses a complex stratified multi-stage probability sampling design with analysis weights. The machine learning models were trained and evaluated without survey weights because scikit-learn's standard estimators do not support complex survey variance estimation. While some models (Logistic Regression, Random Forest, XGBoost) accept a sample_weight parameter, using weights without proper variance estimation produces correctly weighted point estimates with incorrect standard errors. The reported metrics reflect unweighted sample performance and may not generalize exactly to the national population of 9th graders. Future work should use survey-aware ML packages (e.g., weighted bootstrap procedures or the survey package in R) to produce properly weighted estimates.

Fifth, the core fairness-through-unawareness comparison was not fully executed. The sensitivity analysis documented excluded variables (n_features_full: 15, n_features_reduced: 9) but metric_change was null. The full versus reduced model AUC comparison and subgroup AUC comparison were not generated, limiting the empirical evidence for the fairness-through-unawareness claim. The SHAP analysis provides indirect evidence (SES appears as a powerful proxy, protected attributes appear in top features) but direct model comparison would strengthen the contribution.

Sixth, the SES quintile subgroup analysis specified in the research design was not executed. The X1SESQ5 variable was listed in research_spec.subgroup_analyses but is absent from results.json.subgroup_performance. This omission limits the completeness of the fairness analysis, as socioeconomic quintile is a key axis of educational inequity.

Seventh, subgroup AUCs for some racial groups (e.g., American Indian/Alaska Native: n = 13; Hispanic/no race specified: n = 60) are based on very small samples and should be interpreted with caution as unstable population estimates. Borchers [2] demonstrates that reliably detecting bias with ABROCA requires large sample sizes or substantial effect sizes, and EDM studies tend to be underpowered for subgroup fairness analysis.

Eighth, the outcome variable (ever attended college) does not distinguish institution type (community college vs. four-year institution), enrollment intensity (full-time vs. part-time), or completion. Students may have very different college experiences and outcomes that are not captured by this binary indicator.

Finally, this study was entirely generated by EDM-ARS, an automated educational data mining research system. All research questions, analyses, statistical modeling, and prose were produced programmatically without human authorship. While the system follows established EDM methodology, readers should evaluate findings independently and consider the limitations of fully automated research pipelines, including potential errors in variable coding, model specification, and interpretation that human expert review might catch.

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