Predicting and Minimizing Student Behavioral Disruptions

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Abstract

In this study, we merge bus conduct logs, in-school disciplinary referrals, family engagement survey results, and local weather data to build a predictive pipeline that flags students at elevated risk for future disruptions. Exploratory analyses revealed clear temporal patterns where referrals peak in September and again during March–April testing seasons, referrals occur the most midweek, hotter days correspond to higher incident rates, and younger grades drive most events. We engineered features capturing previous incidents, semester periods, time-of-day slots, and parent engagement scores, then train logistic regression, random forest, and a multilayer perceptron (MLP) neural network - achieving the highest F_1 and ROC AUC with the MLP. We conclude with actionable recommendations for risk monitoring, seasonal planning, and weather contingencies.

Introduction

Behavioral disruptions in classrooms represent a pervasive challenge across K–12 education, leading to significant instructional time loss and negative impacts on both student learning and classroom climate. This project leverages data-driven methods to proactively identify students at higher risk of causing disruptions. By uncovering hidden behavioral patterns and building predictive models, we aim to shift school discipline approaches from reactive to preventative, ultimately supporting a healthier learning environment for all students.

Data Overview

The project integrated three district-provided datasets: Bus Conduct Data (transportation behavioral records), Family Engagement Survey (parental feedback metrics), and Disciplinary Referrals (in-school behavioral events).

Data cleaning involved removing duplicates, imputing missing demographics where possible, and aligning temporal fields across sources. Weather data (temperature and pressure) were appended externally. Only six schools provided consistent referral reporting, limiting sample size.

Feature engineering created flags for prior referrals, bus incidents, academic semester periods, and survey-derived engagement scores.

Methods

Exploratory Data Analysis (EDA) employed histograms, cross-tabulations, trendlines, and heatmaps to uncover behavior trends over time, by grade, and by setting. Hypotheses around monthly, grade-level, and daily variations were tested via one-way ANOVA and chi-square.

Modeling workflows included logistic regression (baseline), linear regression (quantity prediction), Random Forest (non-linear ensemble), and a multi-layer perceptron (MLP) neural network. All pipelines used a SMOTE step to correct class imbalance, followed by 5-fold cross-validation and grid-search hyperparameter tuning. DBSCAN clustering identified latent student segments, and permutation feature importance highlighted the most actionable predictors.

Findings

Monthly Trends

Figure 1 illustrates referral counts by month. September accounted for 400 incidents (20.5% of the year's total), followed by November (309; 15.8%) and October (216; 11.0%). During March and April, coinciding with standardized testing, referrals surged to 197 (10.1%; +77.5% vs. January) and 187 (9.6%; +68.5% vs. January), respectively.

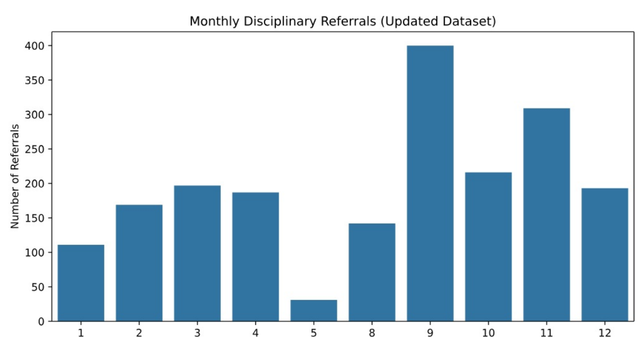

Figure 1: Monthly disciplinary referrals as a percentage of total incidents.

Weekly Trends

Midweek days exhibit the highest referral volumes, with Wednesday registering 435 incidents (22.3% of the school-week total), compared to Tuesday (397; 20.3%) and Thursday (393; 20.1%).

Daily Referrals & Temperature

Hotter days systematically correspond to elevated referral rates, supporting the hypothesis that heat stress contributes to behavioral incidents.

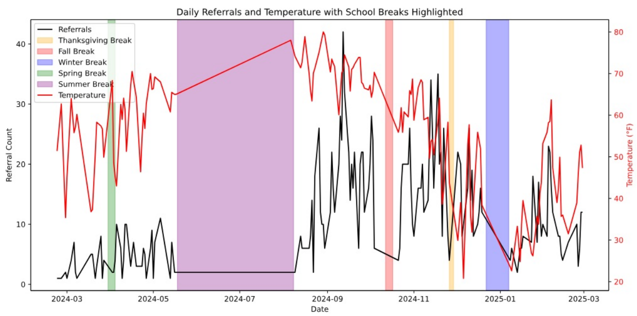

Figure 2: Daily referrals and temperature across the academic year (breaks highlighted).

Time of Day & Grade Level

Morning slots generate 51.5% of referrals, early afternoons 31.4%, and late afternoons 12.4%, with after-school incidents at 2.3%. Elementary grades (1–5) account for 78.2% of events, middle school (6–8) for 9.6%, and high school (9–12) for 12.3%.

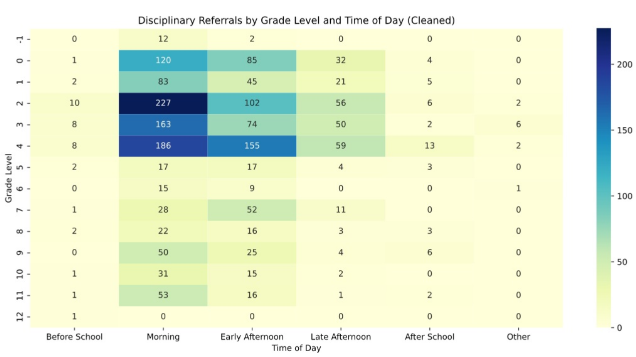

Figure 3: Heatmap of referrals by grade level and time of day.

Weather Impact

Binning days into Cold (<50°F), Mild (50–70°F), and Hot (>70°F) yielded mean referrals of 9.1, 11.8, and 14.0, respectively—a roughly 18.3% increase on hot days. Pearson's $r = 0.16$ (p=0.045) confirms a weak but significant temperature effect.

Bus Referrals

We noted a strong negative correlation to bus referrals and in-class referrals within the dataset. We believe this is due to bus referrals being used as a predictive indicator for early interventions already by the client, and these students are possibly being removed from the system, and thus not gaining in-class referrals, resulting in the negative correlation. As logically, both of these should show a positive correlation.

Summary

Our analysis confirmed strong temporal, weekly, and environmental drivers of referrals: September and March–April testing months saw spikes of 10–20%, Wednesdays accounted for 22% of weekly incidents, and hot days produced an 18% increase in incidents. Of our four models, the SMOTE-balanced MLP neural network performed best (F_1=0.71, ROC-AUC=0.78) by automatically learning complex patterns such as how heat and grade level combine to influence behavior that simpler models would miss. Instead of just saying "yes" or "no," it outputs a risk score between 0 and 1, so administrators can focus resources (extra counseling, bus monitoring, etc.) on students most likely to need help.

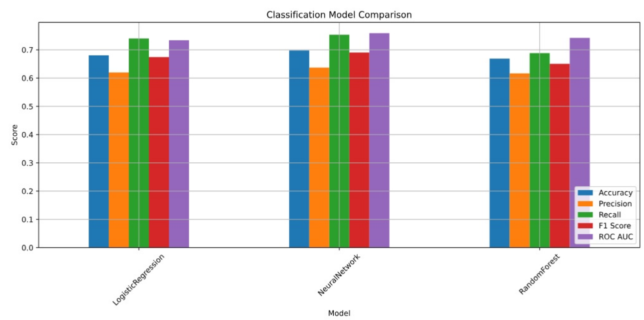

Figure 4: Overview of the three classification models performance for each target score.

Recommendations

Based on these findings, we advise:

- **Weekly Risk Monitoring:** Generate an automated list of students whose MLP-predicted referral probability exceeds 0.6 for counselor review each Monday.
- **Testing-Season Support:** Deploy stress-relief workshops, peer mentoring, and flexible scheduling programs in March–April to preempt test-related spikes.
- **Heat-Day Mitigations:** On forecasted >80°F days, incorporate structured cooling breaks, indoor activity rotations, and increased supervision during peak heat hours.
- **Client Model Selections**: Prioritize the Neural Network for referral prediction, as it provided the best overall performance and ability to discover non-linear patterns within predictive behaviors.