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Predicting K-12 Dropout

Ryan S. Baker[a,b], Andrew W. Berning[c], Sujith M. Gowda[d], Shizhu Zhang[a], and Aaron Hawn[b]

[a]University of Pennsylvania; [b]Teachers College, Columbia University; [c]University of Texas, Arlington; [d]Alpha Data Labs LLC

ABSTRACT
Dropout remains a persistent challenge within high school education. In this paper, we present a case study on automatically detecting whether a student is at-risk of dropout within a diverse school district in Texas. We predict whether a student will drop out in a future school year from data on students' discipline, attendance, course-taking, and grades, using a logistic regression framework. We discuss the predictive properties of the model, and the features that are predictive of dropout in this context.

Introduction

Teachers and school administrators have striven to reduce dropout for quite some time (Elliott & Voss, 1974), but it continues to persist in schools as a problem through the present day (Wiltz & Slate, 2016). Dropping out of high school is considered not just a serious educational problem but also a severe social problem, especially in recent decades when technology and societal developments have rendered more and more people without at least a college degree less likely to find a job (Rumberger, 1987; Statista, 2019). Apart from higher risk of unemployment or underemployment, students who drop out from high school are more likely to suffer from mental health problems such as depression, become involved in gang or other criminal activity, and to be incarcerated years later (Freeman et al., 2015; Peguero, 2011; Rumberger, 1987; Wiltz & Slate, 2016).

In recent years, efforts to intervene and prevent dropout have begun to leverage advances in predictive analytics, attempting to use mathematical models derived from data to identify students with a particularly high probability of risk of dropping out. This practice has developed alongside an increasing use of predictive analytics in education, referred to at times by the more general terms of learning analytics or educational data mining (EDM; Baker & Siemens, 2014), and has emerged as an approach to addressing a range of problems in education. Whereas traditional statistical methods attempt to determine if a relationship is statistically significantly more likely than chance, or attempt to determine if an intervention's impact is causal, EDM represents a range of methods that can be used to discover complex, unexpected patterns in data and to determine how broadly applicable those patterns are likely to be. Analytics

CONTACT Ryan S. Baker ryanshaunbaker@gmail.com 3700 Walnut Street, Philadelphia, PA 19104.

and data mining methods have been used in education to solve problems from understanding which math problems represent the same cognitive skills (Desmarais, 2011), to automatically detecting which students are bored during online learning (D'mello, Craig, Witherspoon, McDaniel, & Graesser, 2008), to understanding which students are effectively using course discussion forums (Romero, López, Luna, & Ventura, 2013). Increasing numbers of school districts are now deploying predictive analytics models, either developed in-house or provided by increasingly national vendors, such as the BrightBytes Early Warning Module (Singh, 2018). These models attempt to infer which students are at risk as well as which factors are associated with a student being at risk to provide information to schools that can be used in individualized interventions.

In this paper, we report on our work to predict dropout in a diverse Texas school district, focusing on these outcomes in line with the school district's plans for individualized intervention. In doing so, we leverage data mining techniques to examine relatively complex patterns in factors including student attendance, student grades (and their changes), student course-taking, and student disciplinary records. In this article, we first review how learning analytics or educational data mining models have historically been developed for the prediction of school dropout and the potential of these models for changing students' lives. Then we discuss the data mining procedure used to derive and validate our models. Thirdly, we report on the models themselves, their effectiveness at prediction, their properties for intervention (analyzing both the precision of their predictions and what proportion of at-risk students they capture), and which features play the largest role in prediction.

Why do students drop out?

The problem of high school dropout is highly complex, involving not only individual factors but also involving factors endemic to specific schools and the populations of students who attend those schools (Balfanz & Legters, 2004). There is clearly an interaction between individual factors and school factors; almost all schools experience some student drop out, and even the most troubled schools graduate some students.

At the individual level, family factors play a role in students' trajectories towards dropout (Alexander, Entwisle, & Kabbani, 2001). For example, family mobility plays a role—students who change schools more often are also more likely to drop out (Metzger, Fowler, Anderson, & Lindsay, 2015; Rumberger & Larson, 1998). Family socioeconomic status, structure, and stress levels as early as elementary school are also associated with eventual dropout (Alexander et al., 2001; Parr & Bonitz, 2015).

Other factors have been found to be relevant as well. One classic paper found that a range of different variables, including poor academic achievement, behavioral deviance (criminal actions or drug use), the choice of antisocial friends, and socioeconomic status are all independently associated with dropout (Battin-Pearson et al., 2000). However, the authors found that there was substantial variance in dropout not associated with any of these factors.

Indeed, across studies, a substantial number of factors have been found to be associated with dropout. Several reviews have been published on the causes of dropout (e.g. Rumberger, 1987; Schargel & Smink, 2014). While we will not review this extensive literature in full, we include a few examples: lower grades and poor academic achievement are associated with dropout (Balfanz, Herzog, & Mac Iver, 2007; Bowers, 2010; Suh, Suh, & Houston, 2007), as is the choice to take more nonacademic courses (Plank, DeLuca, & Estacion, 2008). Student behaviors within school are associated with dropout, from tardiness (Suh et al., 2007) to fighting (Suh et al., 2007) to disrupting or skipping class (Archambault, Janosz, Morizot, & Pagani, 2009). Correspondingly, discipline stemming from these behaviors, such as school suspensions, is associated with higher probability of dropout (Suh et al., 2007). More generally, being absent from class more often is associated with a higher probability of dropout (Balfanz et al., 2007; Finn & Rock, 1997).

Across these studies—and the many other studies of why students drop out that have been conducted over the last decades—the community of practitioners and scholars has accumulated a knowledge base that can provide insight into whether a specific student is at risk of dropping out. The challenge then becomes to find a way to use this knowledge to reduce the frequency of dropout and support specific students.

Dropout: the potential of predictive models to change lives

Despite the importance of reducing dropout, this problem has remained difficult to resolve (Christenson & Thurlow, 2004; Kennelly & Monrad, 2007), though there has been progress in recent years (DePaoli, Balfanz, Atwell, & Bridgeland, 2018). Broadly, attempts to reduce dropout have involved two paradigms: school-wide interventions and individual interventions.

The first paradigm, school-wide interventions, targets all students in a school across that school's contexts, and involves teachers, school administrators, and families (Sugai & Horner, 2006). School-wide positive behavior interventions and supports aimed at reducing dropout and other school-level problems have achieved very large scale, having been implemented in more than 26,000 schools in the United States (Pas, Ryoo, Musci, & Bradshaw, 2019). Among the 45 publications reviewed by Lehr, Hansen, Sinclair, and Christenson (2003), there are reports of programs attempting to create social bonding among students through service activities, school-wide cognitive skills training, systematic monitoring of engagement by teachers, re-designing the structure of the school day and the geography of the school, and many other programs. The number of school-wide interventions aimed at reducing dropout has continued to increase since then (Freeman et al., 2016).

However, despite the general success of many school-wide interventions, these programs face many challenges in terms of resources, funding, and available expertise (Archambault et al., 2009; Gottfredson et al., 2000; Noguera, 1995). There have also been reports of teachers who disagree with the principles of school-wide interventions choosing not to implement interventions, reducing the degree to which all students receive the support they need, and necessitating comprehensive programs to increase implementation fidelity (Bradshaw, Reinke, Brown, Bevans, & Leaf, 2008).

A second paradigm, individual interventions, depends on accurately identifying students on a trajectory towards dropping out, and providing those students interventions specific to their situation (Lewis, Newcomer, Trussell, & Richter, 2006). Individual interventions are often part of a program of school-wide positive behavior interventions, forming a second or third tier of intervention for students not responsive to school-wide efforts (Sugai & Horner, 2006). Although individual interventions can be driven by informal or intuitive decision-making processes, doing so can be unreliable; teachers are not always correct as to which students are at risk (Alvidrez & Weinstein, 1999), and biases (implicit or explicit) can enter into these types of decisions (Alvidrez & Weinstein, 1999).

An alternate approach to individual interventions is for school leaders to select students for intervention by using a predictive model that identifies at-risk students. These models are increasingly used at scale. For example, the BrightBytes Early Warning Module (a widely-used commercial system) makes individualized dropout predictions based on a range of student variables, and provides them to school district with recommendations for preventing dropout (Singh, 2018). Since the State of West Virginia began use of BrightBytes, its dropout rate has reduced considerably (West Virginia Department of Education, 2016). It is impossible to conclude causality without a proper experimental study, but this type of finding suggests considerable potential promise. In another example, Chicago Public Schools uses students' middle grade information to predict which students are more likely to fail in high school in order to develop individualized intervention plans for specific high-risk students (Allensworth, Gwynne, Moore, & de la Torre, 2014). Again, while there is incomplete causal evidence, graduation rates have gone up considerably in Chicago during that time period (Heller et al., 2017).

Development of past predictive models

Perhaps the first work to attempt to predict whether specific students would drop out was Tobin and Sugai (1999), who predicted whether a student was on track to graduate as well as other outcomes from data on earlier school violence, suspensions, and disciplinary violations. This work was slow to scale up for many years, with only a small number of projects emerging over the successive decade (e.g. Allensworth & Easton, 2007; Fleming et al., 2005). However, in the last decade, a large number of projects have emerged which attempt to use statistical models and predictive analytics to determine in advance which students will drop out of high school and use these predictions as early warning indicators (EWIs) that help districts allocate resources towards those students most at risk of not completing high school (Allensworth, 2013; Allensworth, Moore, & de la Torre, 2014; Baltimore Education Research Consortium, 2011; Bowers, Sprott, & Taff, 2012; Carl, Richardson, Cheng, Kim, & Meyer, 2013; Kemple, Segeritz, & Stephenson, 2013; Kieffer & Marinell, 2012). Increasingly, data scientists have worked to make these predictions useable to a range of stakeholders, going beyond district-level administrators to include teachers, parents, and students (Bowers, Krumm, Feng, & Podkul, 2016).

Several districts and research groups have invested heavily in EWI initiatives, each district exploring variations on the theme of dropout prediction, and each with varying degrees of success. Overall, though, EWI predictors have been based on similar sets of student factors. In Chicago, for example, the public schools have implemented a dropout flag based on ninth grade course completion (Allensworth & Easton, 2007). In Baltimore, a similar flag is based on 9th grade student characteristics, course failure, absence, suspension, 8th grade achievement tests, and other 8th grade factors (Mac Iver & Messel, 2013). In Wisconsin, attendance, suspensions/expulsions, schools attended, achievement tests, and demographics (Knowles, 2015) have been used to build predictive models, and in New York City, 9th grade credits earned, Regents exams passed, attendance, and academic credits earned have been used to predict graduation (Kemple et al., 2013).

These models have typically attempted to leverage fairly simple features and combinations of factors in order to maintain interpretability and the appearance of legitimacy of the predictions made. This decision has typically not led to a sacrifice in predictive accuracy – as Bowers and colleagues (2012) note, many of these models achieve acceptable predictive power. However, their focus on straightforward indicators may reduce their usefulness in intervention: it is not a surprise that failing courses leads to failing to graduate, as failing courses is a direct cause of failing to graduate.

In contrast, predictions of other constructs, such as long-term learning, have tended to include a more diverse set of factors. When predicting 11th grade achievement test outcomes, for example, the Consortium on Chicago School Research explored relationships between middle school students' standardized testing performance, attendance, background characteristics, survey responses on grit and study habits, and discipline referrals (Allensworth et al., 2014). In another example of the prediction of long term learning outcomes, Fleming et al. (2005) predicted 10th grade academic achievement, in the form of standardized testing and self-reported grades, based on survey responses from 7th grade students, their parents, and their teachers in regard to a large number of student risk factors—attention and depression, social-emotional skills, substance use, antisocial behavior, school bonding, and peer relationships.

Educational data mining researchers have also predicted end-of-year learning outcomes, such as state test scores, based on students' interactions with instructional software over the course of school year. Pardos, Baker, San Pedro, Gowda, and Gowda (2014) predicted end-of-year state test scores from performance, affective, and behavioral indicators derived from students' interaction with the ASSISTments online tutoring system. In the context of a different online learning environment, Ritter, Joshi, and Fancsali (2013) predicted end-of-year state test scores and computer-adaptive test scores based on process variables derived from students' interactions with Carnegie Learning's Cognitive Tutor, as well as from demographic variables, such as sex, age, economic status, English proficiency, race, and special education status. Looking at longer-term outcomes (but not the outcomes traditionally focused on in early warning systems), other studies have predicted whether students attend college and major in STEM (science, technology, engineering, and mathematics) fields, using performance, affective, and behavioral indicators derived from students' interaction with ASSISTments during middle school (San Pedro, Baker, Bowers, & Heffernan, 2013; San Pedro, Baker, Heffernan, & Ocumpaugh, 2015).

Work to predict dropout and failure in higher education has also leveraged relatively rich feature sets, including somewhat non-intuitive factors such as dormitory card swipes (indicating a late return from some other activity, such as a late night study session) (Lane & Finsel, 2014). For example, Purdue University developed the Course Signals online system as an early intervention tool for faculty (Arnold & Pistilli, 2012). Based on student grades, demographics, past academic history, and LMS usage, Course Signals prompts university instructors as to which students may need intervention and facilitates faculty in providing assistance through personalized emails to students suggesting avenues for help. Feedback is provided to faculty and students through the image of a stoplight, showing either a green, yellow, or red light, based on the predicted success of the student. Results from the implementation of the Course Signals system point to improved grades and retention rates for students (Arnold & Pistilli, 2012). Positive results have also been seen for the multi-university Civitas Learning system in terms of course completion and persistence (Milliron, Malcolm, & Kil, 2014).

As such, in this paper, we investigate whether the richer forms of modeling that predictive analytics makes possible can shed additional light on the factors associated with high school dropout. Does this approach enable us to find new predictors? And does it enable us to find predictors that may represent an earlier stage in the process of student disengagement—predictors that therefore may be more actionable?

Methods

Educational data mining includes a large family of methods and algorithms; data mining is arguably more extensive than statistics, as a discipline, in terms of the variety and number of methods in use (Witten, Frank, Hall, & Pal, 2016). Within the predictive analytics approach we discuss below, the goal is to find a combination of features that effectively predict an aspect of the data (the predicted variable) from a set of other aspects of the data (predictor variables), typically referred to as "features" of the data (Baker, 2017). A data mining algorithm selects a set of features from an initial larger set, combines them in some fashion according to the algorithm's assumptions (referred to as a "model"), and then tests them on entirely new data separated out from the initial data set in some fashion. Unlike in statistical significance testing, the goal is not to determine whether specific features are significantly different than chance (technically, whether the data observed is unlikely given an assumption that there is no relationship between variables) but instead to determine whether the model's ability to predict the predicted variable from the features works for new data.

Because data mining algorithms are evaluated in terms of generalizability rather than traditional statistical forms of evaluation, there is no need to estimate statistical significance, standard errors, or posterior distributions. As generalizability measures how well the model can be generalized to new data sets, data mining can and typically does involve more complex functional forms than are seen in traditional statistical methods. However, many of the same functional forms are seen in data mining as statistics, including logistic and linear regression. Even in those cases, the different requirements of the data mining paradigm allow for the consideration of more complex models – for instance, rather than needing to avoid collinearity, it can be exploited to discover second-order effects.

There is no assumption that the relationships found in predictive analytics are causal in nature; we would argue that a similar disclaimer applies to most use of statistical analysis on non-experimental data as well (with an exception perhaps made for some quasi-experimental analysis methods). Instead, the goal is to identify features which can be the subject of intervention—eventually creating the types of data that could allow us to draw a principled conclusion as to whether a factor is indeed causal. In other words, while predictive analytics alone cannot establish causality, it can identify a broader range of factors that have potential to be causal, and which may be more amenable to intervention than the generally fairly obvious factors found in the types of straightforward risk identification models that are feasible to develop solely through human reasoning.

The results of such a model can then be used to drive intervention as follows. First, a practitioner or researcher might identify a factor from a predictive model that is associated with dropout. The second step is to identify a strategy for reducing dropout based on that factor. Finally, the predictive model is embedded into the school context (e.g. Singh, 2018) and used to drive the intervention strategy, after which a test is conducted to see if both the factor and the outcome of interest are impacted by the causal intervention. We return to this possibility, in concrete context, within the "Discussion and Conclusions" section.

Data

The data set we used to predict student dropout was generated using data from a medium-to-large public school district that included schools both within the city limits of a medium-sized city in Texas, as well as suburban areas nearby. The school district had a population of around 15,000 students, with about 18% White, 30% Hispanic, 44% Black, 3% Multiracial, 4% Asian, and 1% Native American students. Approximately 15% of students had limited English language proficiency and 60% were eligible for free or reduced-price lunch or other public assistance. As such, this school district captured considerable economic and racial diversity amongst its students.

We analyzed data from the 2013-2014 school year, from one cohort of students in this district, who were in 9th grade that year, and used it to predict whether they would drop out in the successive three school years. Data from 4,864 students was obtained for analysis. We collected data on these students' dropout status from district-level databases aligned to state-level data standards. District personnel provided data to the research team in fully de-identified fashion. We distilled dropout information from a school database relating to school withdrawal. Students who withdrew from the district for reasons other than dropout (e.g. changing schools, moving) were not counted as having dropped out. 173 students (3.56%) were identified as having dropped out after 9th grade.

Features used in prediction

We predicted dropout after 9th grade from variables in students' 9th grade experiences distilled from district databases on course-taking, course grades, attendance, and disciplinary incidents. We obtained data from an additional database on computer use but did not use this data as a source of variables for this analysis due to limitations in the information recorded. We distilled a total of 231 features (potential predictors for use in data mining) from the students' 9th-grade data, with data taken directly from the school district's data warehouse to increase the feasibility of use of our model by the district. We selected features based on a combination of presence in previously published models, and feasibility within the district's data systems (see Table A1 in the Appendix for a complete list of features with descriptive statistics).

The following categories of features were generated:

- Features based on the student's course grade information (11 features), including features such as average mid-term grade, lowest semester grade in any class, and highest final grade in any class. (Balfanz et al., 2007; Bowers, 2010)
- Features based on student attendance (101 features), including features such as how often a student was present or absent from class for specific reasons, including excused absences, unexcused absences, and in-school suspensions (e.g. Balfanz et al., 2007; Finn & Rock, 1997; Suh et al., 2007). The school district recorded this type of information within two distinct databases, and due to inconsistencies in the options available in the database designs (as well as data entry errors), the two databases contained non-identical information; both databases were considered in feature calculation.
- Features based on student course-taking (24 features), including features such as how many advanced courses a student had taken, and how many vocational courses the student had taken. (Plank et al., 2008; Sadler, Cohen, & Kockesen, 1997)
- Features based on the student's disciplinary record (60 features), including features such as the total number of disruptive behaviors recorded for a student, and the total number of dress code violations (Balfanz et al., 2007; Holloman, LaPoint, Alleyne, Palmer, & Sanders-Phillips, 1996; Suh et al., 2007).
- Features based on a combination of student course-taking and course grade information (35 features), including features such as the student's average grade for English as a Second Language (ESL) courses, and the student's highest semester grade in any Advanced Placement (AP) course.

Data mining approach

Our model of dropout was developed as a binary classifier (Witten et al., 2016): i.e., we attempted to predict whether the student would drop out of school (1) or would not drop out of school (0). We attempted to predict the outcomes using a small set of off-the-shelf classification algorithms, implemented in scikit-learn within the Python programing language (Pedregosa et al., 2011). In order to avoid over-fitting (fitting to noise rather than signal) through trying too many algorithms (Michalski, Carbonell, & Mitchell, 2013), we restricted ourselves to a small set of algorithms found to be successful for related classification problems and this general data set size: decision trees (Quinlan, 2014), JRip decision rules (Cohen, 1995), and logistic regression and step regression. A review of these algorithms' common usage for similar applications can be found in (Baker, 2017). In each case, we used standard packages within scikit-learn, with the algorithms set to default settings. For logistic and step regression, missing values in the data were replaced with the most frequent value in the data. For the decision trees and JRip, missing values in the data were replaced with an arbitrary out-of-bounds value that represented that this value was missing to the algorithm. While these types of simple imputation are often criticized in statistical settings due to violation of assumptions leading to inflated Type I error (e.g. Schafer & Graham, 2002), these assumptions are not relevant in the use of these models for the very different purpose of prediction modeling. Discussions of these issues and the tradeoffs involved can be found in (Acuna & Rodriguez, 2004; Grzymala-Busse & Hu, 2000). For brevity, we do not discuss the internal workings of each of these algorithms, but instead describe below the algorithm that performed best for predicting dropout.

We evaluated each algorithm using 10-fold cross-validation (Efron & Gong, 1983). In this process, students are split randomly into 10 groups. Then, for each possible combination, a model is developed using data from nine groups of students (the "training set") before being tested on the tenth "held out" group of students. By cross-validating, we can assess how well our models can be expected to function for entirely new students drawn from the same population as our sample. Students were divided into groups using scikit-learn's randomized process, using a single default random seed.

Given the significant "class imbalance" (where one category is much more common than the other – in this case, only a small proportion of students dropped out), we used re-sampling (also called over-sampling) to adjust our training sets. Re-sampling (Ganganwar, 2012) is a procedure where data points in the rarer category (in this case, students who dropped out) are duplicated several times; specifically, we selected the number of duplications that best equalized the number of data points in the rarer and more common categories. Re-sampling was only used on the training sets; all calculations of model goodness took place in unmodified test sets, as discussed in the previous paragraph.

In order to control for the large number of features distilled from the data, we selected which features to input into our algorithms using forward selection (Liu & Yu, 2005), where the feature that most improves model goodness is added repeatedly until adding additional features no longer improves model goodness. This relatively simple procedure can function better for limited data than more sophisticated approaches; it also yields more interpretable models than, for example, multi-algorithmic ensemble selection methods (e.g. Liu & Yu, 2005).

The primary metric used to evaluate the model was the Area Under the ROC Curve (AUC ROC, or AUC for short) (Bowers et al., 2012). AUC, also referred to in many cases as A', is equivalent to W, the Wilcoxon statistic (Hanley & McNeil, 1982). The Wilcoxon or A' interpretation of this statistic indicates that it represents the proportion of the time where, if you randomly select one student who will eventually drop out, and randomly select one student who will not drop out, the model can accurately identify which is which. As such, AUC ROC is robust to highly imbalanced data distributions (as is seen in our dropout data set) (Jeni, Cohn, & de la Torre, 2013). AUC ROC is one of the most popular metrics in machine learning in general and has been explicitly recommended for at-risk prediction models in education (e.g. Bowers et al., 2012). A model with an AUC of 0.5 performs at chance, and a model with an AUC of 1.0

performs perfectly. AUC was computed within scikit-learn. During feature selection, we applied AUC to the original (e.g. non-resampled) training data set to decide if the model was improving. Later, to evaluate the model's final quality, we used cross-validation to repeatedly build the model on one subset of resampled data and evaluate the AUC on a different subset of non-resampled data, averaging our AUC estimate across subsets.

We used AUC to assess overall model quality; two other metrics were used to assess specific cutoffs for decision-making using these models. While each of the models used here provide a probability of dropout for each student, intervention is ultimately dependent on choosing a cutoff, above which a student is considered to be at-risk and a target for intervention, and below which a student is not a target for intervention. It is, of course, also feasible to select multiple interventions and choose different cutoffs for different interventions. While it might seem intuitive to simply choose a 50% probability as the cutoff, there are multiple reasons why this choice is not optimal. The most important practical reason is that the cost of an incorrectly applied intervention and the benefit of a correctly applied intervention are seldom equal (Baker, 2017); some interventions such as automated suggestions are "fail-soft" and can be safely given even when confidence is low (Michalski et al., 2013), other interventions such as an hour-long conversation with a school counselor are costly to apply, and some interventions may upset or concern students when misapplied. In terms of technical reasons, re-sampling methods (including the method used in this paper) tend to distort model confidences somewhat, making 50% seldom the optimal threshold for intervention even when costs and benefits are equal. As such, we evaluate the models' precision and recall at different cutoffs to better understand the models' potentials for intervention (Davis & Goadrich, 2006). A model's recall is the proportion of target cases correctly identified by the model at a given cutoff, i.e. of the 173 students who will drop out, what percentage of them are correctly identified? A model's precision is the proportion of cases identified by the model at a given cutoff who are genuinely target cases; if the model indicates that 173 students will drop out, what percentage of them is the model correct about? For any given model, there is generally a tradeoff between precision and recall: setting a lower cutoff leads to correctly identifying more of the students who will eventually drop out, but it also leads to incorrectly indicating that students will drop out when they will not. We can view this tradeoff in a precision-recall curve (Davis & Goadrich, 2006) – see Figure 1 below.

Results

The goodness of the algorithm best predicting dropout, logistic regression, is shown in Table 1. For brevity, only the performance of the best algorithm is given. The model predicting dropout achieved an AUC of 0.76, indicating that it could distinguish a student who would drop out from a student who would not 76% of the time for entirely new students (i.e. different students were used to develop the model than were used to test the model). AUC ROC values in this range are used in medical decision-making with major real-world impact, such as the choice of which anti-retroviral therapy to use for HIV patients (e.g. Revell et al., 2013).We can further understand the

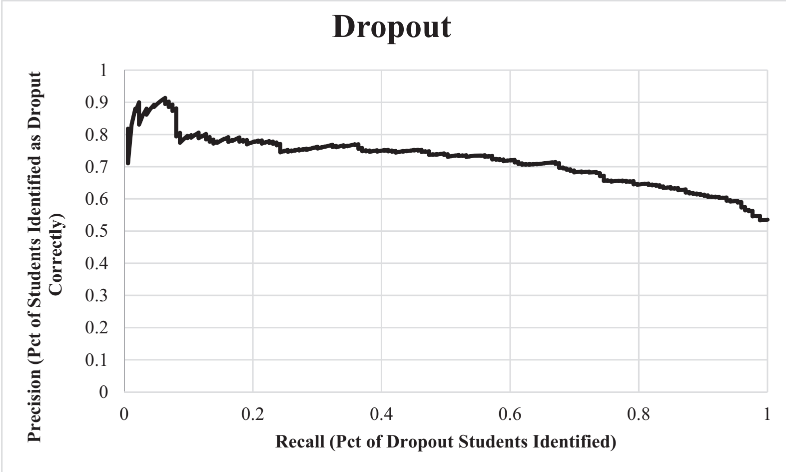

Figure 1. Precision-recall curve for logistic regression model identifying dropout.

performance of the model through the use of precision-recall curves, as discussed above. Figure 1 shows the tradeoff between precision (how often our predictions of student risk are correct) and recall (how many of the students at risk are identified) for the model predicting dropout. For this model, precision remains good along a range of values of recall. At a recall of 78.0%—approximately 80% of students who will drop out are identified—precision remains at 65.6%, indicating that the model is correct two thirds of the time when it indicates that a student will drop out. Alternatively, precision around 75% can be achieved if one is willing to identify just under half of the students who will drop out.

Understanding which features are important to prediction

Models developed using data mining are notoriously difficult to interpret; even relatively interpretable models such as logistic regression involve understanding the interrelationships of several variables (in this case 23), which are themselves inter-correlated. Baker (2017) provides an example of how this type of interpretation is highly challenging even for linear models consisting of only two correlated variables. As such, we present the model for use in replication but will focus on understanding which features are important to prediction in a different way.

The logistic regression model for dropout prediction has the form $\mathrm{logit}(Y) = \ln(\frac{p}{1-p}) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \ldots$ (Peng, Lee, & Ingersoll, 2002). In this model, Y is the outcome of interest (dropout), p is the probability of Y, α is the intercept, β is the coefficient or weight for each feature, and X is the feature.

Table 1 shows that many factors are associated with whether students eventually drop out. The three strongest predictors were how many non-correctible dress code violations the student had, the number of in-school suspensions the student had, and the standard deviation for the student's grades in the current semester. We can compute probabilities for changes in individual variables by taking a model where the sum of all weighted features is 0 (corresponding to a probability of 50% for school dropout) and then

Table 1. The logistic regression model predicting dropout.

Feature (X)	Coefficient (β)
Total number of non-correctible dress code violations	+0.527
Number of in-school suspensions	+0.065
Standard deviation of grades in current semester	+0.052
Number of times student was absent from specific class	+0.028
Average midterm grade in current semester within Vocational classes	+0.020
Number of times student absence was corrected to present	+0.019
Student variance in grades across the course of the year	−0.003
Average final grade in current semester within Vocational classes	−0.029
Lowest final grade in any class	−0.037
Largest shift between midterm and final grade in any AP class in the current semester	−0.053
Lowest average grade across the semester in any ESL class	−0.167
Total number of advanced classes taken	−0.314
Was student ever marked as tardy to class	−0.468
Total number of bullying or harassment disciplinary incidents	−1.307
Number of times student was absent due to participating in compensatory activities due to pregnancy	−2.002
Number of times student was absent due to influenza	−2.130
Total number of dress code third/fourth offense violations	−2.256
Number of times student was disciplined for theft, possession, or sale of an item with value under $50	−2.295
Total number of disciplinary incidents for tobacco use	−2.362
Number of times student was absent due to attending citizenship ceremony	−2.544
Total number of disciplinary incidents involving persistent low-level "level 1" infractions	−2.740
Total number of disciplinary incidents involving prohibited electronic device	−2.787
Number of times student was absent due to district-approved weather excuse	−2.931
Intercept (α)	+2.586

adjusting a single feature variable. For example, with a coefficient of 0.527, a student who would otherwise have a probability of 50% of dropout rises to a probability of 62.9% if they have a non-correctible dress code violation. With a coefficient of 0.065, a student who would otherwise have a probability of 50% of dropout only rises to a probability of 51.6% if they are sent to in-school suspension a single time; however, if they are sent to in-school suspension four times, the probability of dropout rises to 56.4%, and if they are sent to in-school suspension fifteen times (18 students had 15 or more in-school suspensions), the probability of dropout rises to 72.6%. The feature standard deviation of grades in the current semester has a seemingly low coefficient of 0.052, but with values for that feature ranging as high as 40 (for a student who aced some classes and failed other classes), this feature could have a substantial impact. A student with a standard deviation of 40 would rise from a 50% probability of dropout (if all other features were average) to an 88.9% probability of dropout.

We can further understand the relationships captured in this model by examining the relationship between some of the key variables and student outcomes, looking at the actual data rather than running the model forward. For example, students who never had a non-correctible dress code violation had, in the actual data, a 3.4% chance of dropping out, whereas students who had one or more non-correctible dress code violations had a 9.1% chance of dropping out. By comparison, students who had one or more in-school suspensions had a 7.0% chance of dropping out. Even after one in-school suspension, the probability of dropout rises to 4.3%; students who had five or more in-school suspensions dropped out 12.0% of the time. In terms of the standard deviation for students' grades in the current semester, the average standard deviation was 8.27 points (just under one letter grade). Students below this cutoff (with less variance in their grades than average) dropped out 2.6% of the time. Students above this cutoff (with more variance in their grades than average) dropped out 5.1% of the time.

Discussion and conclusions

Within this paper, we have presented a logistic regression model predicting dropout in the context of a Texas school district. We find that this model achieves reasonable predictive power, combining values of AUC ROC considered sufficient for medical decision-making (e.g. Revell et al., 2013) while being capable of identifying over three quarters of students who will drop out and capable of achieving precision over 75% in its predictions. This predictive power is achieved through a combination of features drawn from past accounts of the factors associated with dropout and related constructs, combined with the ability of machine learning algorithms to search through a wide range of potential models.

The goal of our predictive model is to identify students who are at risk, to drive intervention. To this end, we examine the exact constructs that predict students' future risk within the models; by focusing on a specific student's pattern of features associated with risk, we can identify potential factors and opportunities for intervention for each student.

The model shows that a range of factors are predictive of student outcomes, in combination. Our model predicting dropout incorporates 23 features, finding a broad range of factors are associated with dropout in this district: dress code violations, in-school suspensions, high variance in grades, grades shifting across the course of the year, and absences. This wide range of factors associated with dropout corresponds to the many reasons that students drop out of school (Stearns & Glennie, 2006). Past dropout prediction approaches such as the approach used by Allensworth and colleagues (2014) in the Chicago Public Schools have used middle school grades and attendance as indicators of high school grades. Our model also finds that some of the same factors are predictive. However, we find a particularly strong relationship to dress code violations, a feature previously found to be related to school violence but not to dropout (Brunsma & Rockquemore, 1998; Suh et al., 2007). In contrast to our model, many previous early warning systems explored a smaller range of early warning signs. Focusing on a larger number of often more subtle indicators creates a greater potential for intervening while there is still an opportunity to create positive change.

In interpreting these factors, it is important to recognize that the models presented here give no evidence with regards to causality. For example, the factor most strongly predictive of dropout within the model is non-correctible dress code violations. It is doubtful that wearing inappropriate clothing directly causes students to drop out of school, and a range of factors govern a student's choice of what to wear (see, for instance, the classic ethnographic account in Garot & Katz, 2003 for why students choose clothing in an alternative school). As such, non-correctible dress code violations may be predictive for several reasons. One possibility is that this type of dress code violation is indicative of a student no longer caring about school norms or expectations. In particular, if a student adopts negative peer norms instead of school norms, they are more likely to drop out of school (Shin, Daly, & Vera, 2007), and changing clothing can be a key part of a student's adoption of these norms (Axelman, 2006). Alternatively, a dress code violation can also represent a strategy for provoking teachers or administrators or for being sent home (Garot & Katz, 2003).

Another possibility is that these dress code violations are a proxy for problems in the student's home. If the student does not have clean appropriate clothing available, other issues may be going on at home that may lead to the student dropping out. While some schools have purchased washers and dryers for students (Lumsden & Miller, 2002), this addresses the symptom (inability to wash clothes) without addressing the underlying problem creating risk.

As such, if a seemingly unusual predictor such as this one is particularly relevant for a given student, it may provide an opportunity for further probing and problem-solving on the part of school personnel. We cannot expect to observe all potentially meaningful factors, but a good model can help us to identify factors that can be followed up on in an individualized intervention. By identifying unexpected factors that are associated with outcomes that matter, a data mining approach such as the one used here can create openings not only to intervene, but also to better understand why students are at risk in a specific context, enriching our understanding of how phenomena play out in a specific context such as the district studied here.

One clear limitation to our findings is the fact that this paper was developed based on the data in a single district. School districts (and schools within them) often vary considerably in terms of both populations and policies. As such, the findings obtained here may be specific to this district. For example, this district's policies around dress code and dress code violations (normal within Texas but not necessarily representative of dress code policies nationwide) likely influenced the somewhat unexpected finding that dress code violations predicted dropout. Similarly, characteristic aspects of the district's population may have influenced the impact of factors such as teen pregnancy differently than might be seen in other settings. While this is a limitation to the broad application of this paper's findings, it argues for the importance of building models in a range of venues and investigating the specific factors associated with dropout in specific districts. A model developed elsewhere might not find the same relationships, and using such a model in the current district might miss opportunities for intervention that could have significant positive effects.

Our next step with this model is to deploy it in a school on an ongoing basis and see whether its predictions can form the basis of meaningful intervention. We intend first to develop reports, building on earlier work that attempted to derive general design principles for creating reports on student at-risk status (Ocumpaugh et al., 2017). We will use the co-design method (Penuel, Roschelle, & Shechtman, 2007) to develop these reports, working with the users (school personnel such as principals) to determine how best to communicate what the model has determined for use in intervention. We will deploy and iteratively enhance these reports in partnership with school personnel, seeing how to improve the information available and seeing what practices work most effectively with these reports. Beyond simply providing an end-of-semester risk estimate, this model can also be used to identify key situations, previously less focused on by school personnel, where probing to determine what is happening may be particularly helpful, such as when a student commits a non-correctible dress code violation. We will then work with school personnel to develop an intervention strategy. In the specific case of dress code violations, it may make sense for a trusted teacher or counselor to discuss with the student why the dress code violation is occurring, with an eye towards determining whether the student may benefit (for instance) from support for a difficult home situation or whether the student is trying to be sent home (and why). Especially when a relationship is not likely to be directly causal (as in this situation), it is appropriate to use an indicator of risk as a starting point for a deeper investigation of the factors that may be creating risk for a student. Finally, we intend to conduct a study to evaluate whether our data-driven intervention approach can be successful at concretely reducing dropout.

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Appendix

Table A1. Complete feature list with descriptive statistics and model coefficients.

Student Feature Description	Min	Max	*M*	*SD*	Total Events	*β*
Average mid-term grade current semester	0	99	45.32	24.91		
Average grade current semester	0	100	51.28	24.18		
Lowest grade current semester	0	100	72.79	13.65		
Highest average semester grade	0	100	57.00	21.21		
Lowest average semester grade	0	100	48.43	24.25		
Lowest final grade in any class	6	100	75.65	11.35		−0.037
Average change between midterm and final grades across all semesters	−43	157	23.14	21.79		
Largest change between midterm and final grades for any class in any semester	−18	100	64.67	39.76		
Standard deviation of the change between midterm and final grades across all semesters	0	59	27.13	15.58		
Student variance in grades across the course of the year	0	1264	46.96	80.62		−0.003
Standard deviation of grades in semester so far	0	40	8.27	4.17		0.052
Average mid-term grade in the current semester across all ESL classes	0	98	55.02	34.83		
Average final grade in current semester within ESL classes	0	100	61.15	38.05		
Lowest final grade in any ESL course	56	100	85.80	10.47		
Highest average grade across the semester in any ESL class	0	100	70.47	32.55		
Lowest average grade across the semester in any ESL class	0	100	57.31	38.14		−0.167
Average change between midterm and final grades in ESL classes across all semesters	−112	188	4.47	55.66		
Largest change between midterm and final grades for ESL classes in any semester	−46	98	1.62	36.74		
Average mid-term grade in the current semester across all AP classes	0	100	55.52	31.33		
Average final grade in current semester within AP classes	0	100	59.42	32.38		
Lowest final grade in any AP course	47	100	82.83	8.89		
Highest average grade across the semester in any AP class	0	100	68.35	27.63		
Lowest average grade across the semester in any AP class	0	100	56.10	32.47		
Average change between midterm and final grades in AP classes across all semesters	−119	124	10.54	31.66		
Largest shift between midterm and final grade in any AP class in the current semester	−42	100	12.34	32.65		−0.053
Average mid-term grade in the current semester across all advanced classes	0	100	54.29	30.74		
Average final grade in current semester within advanced classes	0	100	57.66	31.10		
Lowest final grade in any advanced course	0	100	79.59	10.74		
Highest average grade across the semester in any advanced class	0	100	65.96	26.79		
Lowest average grade across the semester in any advanced class	0	100	53.91	31.33		

(*continued*)

Table A1. Continued.

Student Feature Description	Min	Max	M	SD	Total Events	β
Average change between midterm and final grades in advanced classes across all semesters	−119	182	10.35	29.63		
Largest change between midterm and final grades for advanced classes in any semester	−47	100	14.67	32.86		
Average midterm grade in current semester within Vocational classes	0	100	39.54	39.70		0.020
Average final grade in current semester within Vocational classes	0	100	39.66	40.43		−0.029
Lowest final grade in any vocational course	0	100	87.16	10.14		
Highest average grade across the semester in any vocational class	0	100	65.13	34.39		
Lowest average grade across the semester in any vocational class	0	100	18.07	32.15		
Average change between midterm and final grades in vocational classes across all semesters	−89	200	52.48	41.62		
Largest change between midterm and final grades for vocational classes in any semester	−46	100	32.66	41.72		
Average mid-term grade in the current semester across all basic classes	0	100	51.87	34.72		
Average final grade in current semester within basic classes	0	100	50.92	37.10		
Lowest final grade in any basic course	20	100	82.02	10.69		
Highest average grade across the semester in any basic class	0	100	62.72	31.68		
Lowest average grade across the semester in any basic class	0	100	45.61	37.00		
Average change between midterm and final grades in basic classes across all semesters	−59	178	30.92	50.28		
Largest change between midterm and final grades for basic classes in any semester	−48	100	29.14	40.01		
Total number of AP classes taken	0	9	0.44	1.07	2154	
Total number of advanced classes taken	0	13	1.38	1.83	6705	−0.314
Total number of vocational classes taken	0	12	0.88	1.46	4278	
Total number of basic classes taken	0	6	0.07	0.45	327	
Total number of ESL classes taken	0	3	0.01	0.09	31	
Total number of distinct AP classes taken	0	9	0.42	1.01	2049	
Total number of distinct advanced classes	0	11	1.24	1.61	6030	
Total number of distinct vocational classes taken	0	5	0.51	0.74	2491	
Total number of distinct basic classes taken	0	6	0.06	0.41	302	
Total number of distinct ESL classes taken	0	1	0.01	0.07	26	
Total number of science classes taken	0	5	1.22	0.71	5936	
Total number of social studies classes taken	0	5	1.22	0.64	5949	
Total number of foreign language classes taken	0	5	0.69	0.73	3337	
Total number of fine arts classes taken	0	7	0.64	0.77	3097	
Total number of elective classes taken	0	14	2.13	2.17	10340	
Total number of middle school-level classes taken	0	14	0.42	0.91	2041	
Total number of speech classes taken	0	4	0.30	0.54	1435	
Total number of physical education classes taken	0	14	1.60	1.96	7760	

(*continued*)

Table A1. Continued.

Student Feature Description	Min	Max	M	SD	Total Events	β
Total number of locally developed classes taken	0	6	0.25	0.60	1213	
Total number of English classes taken	0	5	1.23	0.69	5993	
Total number of math classes taken	0	6	1.31	0.73	6352	
Total number of health classes taken	0	2	0.01	0.09	39	
Total number of economics classes taken	0	4	0.26	0.53	1250	
Total number of special education classes taken	0	4	0.02	0.20	81	
Number of excused absences	0	143	4.77	6.17	23197	
Number of absences due to behavioral special education student being placed in disciplinary alternative education program	0	90	0.05	1.83	237	
Number of absences due to student being placed in disciplinary alternative education program	0	170	0.75	5.08	3652	
Number of absences due to student being expelled	0	3	0.00	0.05	5	
Number of in-school suspensions	0	30	0.53	1.78	2585	0.065
Number of absences due to being tardy to specific class	0	66	6.33	8.41	30789	
Number of absences due to out-of-school suspension	0	23	0.33	1.42	1624	
Number of times student absence was corrected to present	0	169	8.99	10.53	43722	0.019
Number of absences due to being tardy	0	34	0.50	1.22	2409	
Number of unexcused absences	0	59	0.98	2.34	4757	
Number of absences due to weather, health or safety	0	0	0.00	0.00	0	
Number of absences from specific class	0	137	8.23	13.10	40029	0.028
Number of absences due to student being in juvenile justice alternative education program	0	91	0.02	1.34	120	
Was student ever absent due to excused absence	0	1	0.79	0.41	3833	
Was student ever absent due to being a behavioral special education student placed in a disciplinary alternative education program	0	1	0.00	0.04	7	
Was student ever placed in disciplinary alternative education program	0	1	0.04	0.19	187	
Was student ever absent due to being expelled	0	1	0.00	0.02	3	
Was student ever absent due to being in special education in the home	0	0	0.00	0.00	0	
Was student ever in in-school suspension	0	1	0.19	0.39	937	
Was student ever absent due to being tardy to specific class	0	1	0.76	0.43	3683	
Was student ever absent due to out-of-school suspension	0	1	0.09	0.29	440	
Was student ever marked absent and then corrected to present	0	1	0.86	0.35	4191	
Was student ever absent due to being tardy	0	1	0.28	0.45	1347	
Was student ever absent due to an unexcused absence	0	1	0.38	0.49	1859	
Was student ever absent due to weather, health or safety	0	0	0.00	0.00	0	
Was student ever absent due to being absent from specific class	0	1	0.81	0.39	3928	

(*continued*)

Table A1. Continued.

Student Feature Description	Min	Max	*M*	*SD*	Total Events	*β*
Was student ever absent due to being in a juvenile justice alternative education program	0	1	0.00	0.02	3	
Number of absences due to influenza	0	6	0.01	0.16	53	−2.130
Number of times student was excused as absent due to parent phone call	0	44	0.91	2.09	4440	
Number of times student was excused as absent due to doctor's note	0	112	1.48	3.13	7184	
Number of times student was excused as absent due to early dismissal	0	13	0.74	1.37	3609	
Number of times student was excused as absent due to being in special education in the home	0	45	0.06	1.27	276	
Number of times student was excused as absent due to illness in family	0	24	0.77	1.59	3749	
Number of times student was excused as absent due to parent note	0	34	0.79	1.90	3829	
Number of times student was excused as absent due to other factors	0	17	0.22	0.77	1047	
Number of out-of-school suspensions	0	23	0.36	1.49	1728	
Number of absences due to district-approved weather excuse	0	1	0.01	0.10	50	−2.931
Number of times student was excused as absent due to death in family	0	6	0.09	0.45	438	
Number of times student was excused as absent due to visit to higher education institution	0	6	0.07	0.35	320	
Number of times student was excused as absent due to taking off-campus dual-credit course	0	0	0.00	0.00	0	
Number of times student was excused as absent due to log in nurse's office	0	4	0.07	0.31	330	
Number of times student was excused as absent due to serving as election clerk	0	1	0.00	0.02	3	
Number of times student was excused as absent due to participating in off-campus extracurricular activity	0	30	1.57	2.88	7638	
Number of times student was excused as absent due to serving jail time	0	10	0.01	0.18	31	
Number of times student was excused as absent due to on-campus activity	0	15	0.57	1.10	2763	
Number of times student was excused as absent due to making a court appearance	0	5	0.04	0.24	200	
Number of absences due to being in special education in the home	0	169	0.15	3.69	736	
Number of absences due to being at children's environmental health activity	0	2	0.00	0.06	18	
Number of absences due to being at alternative school	0	170	0.81	5.40	3935	
Number of times student was present despite early dismissal	0	18	0.83	1.54	4048	
Number of absences due to being on field trip	0	12	0.66	1.39	3206	
Number of absences due to religious holiday	0	5	0.01	0.15	45	
Number of absences due to in-school suspension*	0	34	0.67	2.12	3240	
Number of partial-day absences due to medical appointment*	0	8	0.11	0.44	537	

(*continued*)

Table A1. Continued.

Student Feature Description	Min	Max	M	SD	Total Events	β
Number of absences due to attending citizenship ceremony*	0	4	0.01	0.12	54	−2.544
Number of times student was excused from class absence due to being in school office*	0	17	0.37	1.00	1810	
Number of absences due to mandatory Medicaid screening appointment*	0	5	0.00	0.07	5	
Number of absences due to performing music at military funeral*	0	4	0.00	0.09	16	
Number of times student was excused as absent due to log in nurse's office*	0	7	0.06	0.31	284	
Number of times student was marked as absent but was actually tardy*	0	6	0.09	0.42	456	
Number of unexcused absences*	0	59	0.95	2.32	4609	
Number of absences due to extenuating circumstances*	0	71	0.09	1.19	435	
Number of absences due to voluntary juvenile justice alternative education program*	0	0	0.00	0.00	0	
Number of absences due to mandatory juvenile justice alternative education program*	0	91	0.02	1.34	120	
Number of absences due to family vacation*	0	0	0.00	0.00	0	
Number of absences due to influenza symptoms without clear diagnosis*	0	1	0.01	0.08	30	
Was student excused as absent due to parent phone call	0	1	0.34	0.47	1635	
Was student excused as absent due to doctor's note	0	1	0.48	0.50	2332	
Was student excused as absent due to early dismissal	0	1	0.37	0.48	1790	
Was student excused as absent due to being in special education in the home	0	1	0.00	0.06	19	
Was student excused as absent due to illness in family	0	1	0.35	0.48	1701	
Was student excused as absent due to parent note	0	1	0.29	0.45	1396	
Was student excused as absent due to other factors	0	1	0.14	0.34	658	
Was student recorded as being in out-of-school suspension	0	1	0.09	0.29	460	
Was student absent due to district-approved weather excuse	0	1	0.01	0.10	50	
Was student excused as absent due to death in family	0	1	0.05	0.23	263	
Was student excused as absent due to visit to higher education institution	0	1	0.04	0.21	214	
Was student excused as absent due to taking off-campus dual-credit course	0	0	0.00	0.00	0	
Was student excused as absent due to log in nurse's office	0	1	0.06	0.23	270	
Was student excused as absent due to serving as election clerk	0	1	0.00	0.02	3	
Was student excused as absent due to participating in off-campus extracurricular activity	0	1	0.39	0.49	1900	
Was student excused as absent due to serving jail time	0	1	0.00	0.05	11	
	0	1	0.34	0.47	1630	

(*continued*)

Table A1. Continued.

Student Feature Description	Min	Max	*M*	*SD*	Total Events	*β*
Was student excused as absent due to on-campus activity						
Was student ever recorded as being in a court appearance	0	1	0.03	0.18	166	
Was student ever absent due to being in special education in the home	0	1	0.00	0.06	17	
Was student ever absent due to being at children's environmental health activity	0	1	0.00	0.06	17	
Was student ever absent due to being at alternative school	0	1	0.05	0.22	239	
Was student ever present despite early dismissal	0	1	0.37	0.48	1813	
Was student ever absent due to being on field trip	0	1	0.29	0.45	1412	
Was student ever absent due to religious holiday	0	1	0.00	0.07	24	
Was student ever absent due to in-school suspension*	0	1	0.22	0.41	1064	
Did student ever have partial-day absence due to medical appointment*	0	1	0.08	0.27	389	
Was student ever marked as absent due to attending citizenship ceremony*	0	1	0.01	0.10	49	
Was student ever excused from class absence due to being in school office*	0	1	0.21	0.41	1036	
Was student ever absent due to mandatory Medicaid screening appointment*	0	1	0.00	0.01	1	
Was student ever absent due to performing music at military funeral*	0	1	0.00	0.04	9	
Was student ever excused as absent due to log in nurse's office*	0	1	0.05	0.21	223	
Was student ever marked as tardy to class*	0	1	0.07	0.25	326	−0.468
Was student ever absent due to an unexcused absence*	0	1	0.37	0.48	1786	
Was student ever absent due to extenuating circumstances*	0	1	0.04	0.20	202	
Was student ever absent due to mandatory juvenile justice alternative education program*	0	1	0.00	0.02	3	
Total number of types of nonviolent behaviors leading to discipline	0	12	0.63	1.36	3075	
Total number of nonviolent behaviors leading to discipline	0	28	0.90	2.27	4376	
Total number of disciplinary incidents involving alcohol possession, use, or sale	0	2	0.00	0.05	6	
Total number of incidents of insubordination to authority	0	6	0.08	0.42	407	
Total number of bullying or harassment disciplinary incidents	0	2	0.00	0.04	6	−1.307
Total number of disciplinary incidents on a school bus	0	2	0.00	0.04	7	
Total number of disciplinary incidents in the school cafeteria	0	0	0.00	0.00	0	
Total number of disciplinary incidents involving cell phone or ipad	0	2	0.01	0.12	57	
Total number of cheating or plagiarism incidents	0	1	0.00	0.05	11	
	0	4	0.02	0.15	73	

(*continued*)

Table A1. Continued.

Student Feature Description	Min	Max	*M*	*SD*	Total Events	β
Total number of disciplinary violations involving other aspects of school code of conduct						
Total number of disciplinary incidents involving possession, use, or sale of controlled substance	0	6	0.02	0.23	98	
Total number of criminal mischief incidents involving under $50 in damages	0	1	0.00	0.04	7	
Total number of criminal mischief incidents involving over $50 in damages	0	1	0.00	0.02	3	
Total number of disorderly conduct offenses	0	4	0.03	0.22	166	
Total number of incidents involving derogatory terms with verbal abuse	0	6	0.02	0.19	113	
Total number of disruptive behavior incidents	0	10	0.17	0.66	835	
Total number of disruptive behavior incidents of a gross nature	0	4	0.05	0.29	253	
Total number of dress code third/fourth offense violations	0	3	0.00	0.06	12	−2.256
Total number of non-correctible dress code violations	0	2	0.03	0.17	137	0.527
Total number of persistent dress code violations	0	2	0.01	0.13	63	
Total number of dress code second offense violations	0	2	0.01	0.08	31	
Total number of dress code offenses	0	2	0.01	0.07	25	
Total number of disciplinary incidents involving violation of extracurricular activity rules	0	1	0.00	0.02	2	
Total number of incidents where student failed to attend detention or in-school suspension	0	9	0.10	0.54	495	
Total number of false fire alarm incidents	0	0	0.00	0.00	0	
Total number of disciplinary incidents involving gambling	0	1	0.00	0.03	4	
Total number of incidents involving gang activity	0	1	0.00	0.02	2	
Total number of disciplinary incidents involving participation in a group demonstration	0	1	0.00	0.05	14	
Total number of disciplinary incidents involving harassment	0	2	0.00	0.04	7	
Number of absences due to participating in compensatory activities due to pregnancy	0	3	0.00	0.04	3	−2.002
Total number of disciplinary incidents involving persistent low-level "level 1" infractions	0	2	0.00	0.08	18	−2.740
Total number of disciplinary incidents involving loitering	0	5	0.04	0.24	171	
Total number of disciplinary incidents involving possession of prescription medicines without a prescription	0	1	0.00	0.03	5	
Total number of disciplinary incidents involving possession of obscene literature or photo	0	1	0.00	0.01	1	
Total number of disciplinary incidents involving loitering in out-of-bounds area	0	3	0.01	0.10	33	

(*continued*)

Table A1. Continued.

Student Feature Description	Min	Max	*M*	*SD*	Total Events	*β*
Total number of disciplinary incidents whose type was not identifiable due to data entry error	0	1	0.00	0.01	1	
Total number of disciplinary incidents involving parking car at school without permit	0	2	0.00	0.04	4	
Total number of disciplinary incidents involving lack of hall pass	0	3	0.00	0.07	18	
Total number of disciplinary incidents involving profane or vulgar language to another student	0	3	0.01	0.08	26	
Total number of disciplinary incidents involving prohibited electronic device	0	2	0.01	0.08	29	−2.787
Total number of disciplinary incidents involving public display of affection	0	2	0.00	0.06	15	
Total number of disciplinary incidents involving retaliation towards school official	0	2	0.00	0.03	2	
Total number of disciplinary incidents involving refusal to show school ID	0	1	0.00	0.05	10	
Total number of disciplinary incidents involving safety violations	0	1	0.00	0.01	1	
Total number of disciplinary violations marked as multiple violations of other school policy	0	2	0.01	0.13	65	
Total number of times student sold merchandise on campus without permission	0	1	0.00	0.02	2	
Total number of incidents of sexual misconduct towards another student	0	3	0.00	0.04	3	
Total number of physical threats towards another student	0	0	0.00	0.00	0	
Total number of persistent tardies	0	12	0.06	0.34	275	
Total number of tardies	0	9	0.05	0.34	230	
Total number of terroristic threats	0	2	0.00	0.03	2	
Total number of theft violations involving value between $50 and $1500	0	3	0.00	0.09	23	
Number of times student was disciplined for theft, possession, or sale of an item with value under $50	0	2	0.00	0.08	24	−2.295
Total number of disciplinary incidents for tobacco use	0	2	0.00	0.07	19	−2.362
Total number of truancy incidents not filed with police	0	7	0.09	0.44	457	
Total number of truancy incidents lasting over 10 days	0	1	0.00	0.02	3	
Total number of truancy incidents lasting at least 3 days	0	1	0.00	0.02	3	
Total number of teacher referrals of student to office	0	4	0.04	0.24	188	
Total number of disciplinary incidents involving use of unauthorized computer	0	1	0.00	0.02	3	
Total number of disciplinary incidents involving vulgar language or obscene gesture	0	2	0.01	0.11	47	

*Secondary database record.