INEQUALITIES IN EDUCATION: A CLOSER FOCUS ON SCHOOL DISCIPLINE

by

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ABSTRACT

TAYLOR FURUKAWA. Inequalities in education: a closer focus on school discipline. (Under the direction of DR. ANTHONY FERNANDES and DR. ELIANA CHRISTOU)

Disproportionalities in school discipline have become a popular research topic in recent decades, particularly at the school-, district-, and state-level. While there are a handful of reports using nationally representative data, this study provides a closer look into factors affecting out-of-school suspensions in 41,339 K-12 U.S. schools. The public-use data file for the 2017-2018 school year used in this study was obtained from the Civil Rights Data Collection conducted by the U.S. Department of Education's Office for Civil Rights. This study utilizes two machine learning methods, logistic regression for classification and random forest, to determine which factors raise the risk of disciplinary action such as out-of-school suspensions. Our results indicate that random forest outperforms logistic regression in terms of classification accuracy. Moreover, both methods indicate that the number of counselors as well as retention rates and the number of harassment and bullying allegations have significant predictive power in this classification problem.

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CHAPTER 1: INTRODUCTION

The problem of inequalities in school discipline in K-12 education has been well documented and thoroughly researched over the decades. Major findings include that students of color, students with disabilities, and LGBT students are at high risk for disproportionate discipline [1, 2]. In particular, Black students and students with disabilities are at higher risk for facing exclusionary discipline or discipline that "involves removing students from the classroom through punishments such as suspensions and expulsions" [3].

An analysis by the Center for Public Integrity, using data from the Civil Rights Data Collection, found that more than 30 states referred Black students to law enforcement more than twice as often as White students [4]. A 2019 working paper focusing on Charlotte-Mecklenburg Schools found that students attending schools with a higher suspension rate were 15 to 20 percent more likely to face arrest or incarceration as adults [5]. Further, research also shows that having police presence on school campuses in the form of school resource officers unnecessarily involves students with the justice system and does not necessarily improve safety. Students are more likely to be referred to law enforcement for offenses such as fights or theft if there are law enforcement officers present on campus at least once a week [6]. Depending on the severity of the misconduct, it may or may not be reasonable to allow an officer to help investigate, but the simplicity of this referral for school administrators and teachers may encourage referrals for even lower-level offenses. Allowing school resource officers to participate in discipline for lower-level offenses like disruptive behavior or dress code violations, rather than letting such things be resolved by capable administrators, counselors, teachers, or principals of schools, escalates the misconduct into something so criminal it requires a discussion with a sworn police officer [4, 7, 8].

A November 2011 report from the Justice Policy Institute poses an argument against police officer presence on school grounds, as it contributes to the school-to-prison pipeline [6, 7, 9]. Many school districts currently have contracts with local law enforcement agencies, which has led to teachers and staff relying on the police to help administer discipline [7]. As current data and news continue to provide evidence for racial inequalities in arrests and police brutality, this is particularly concerning. A meta-analysis by [10] found a significant relationship between the presence of school resource officers and increased instances of exclusionary discipline.

Referrals, suspensions, and expulsions remove students from classrooms, which can increase negative emotions related to the school environment and can foster disengagement, especially when discipline practices are not applied fairly to all students [7]. In the case of out-of-school (OOS) suspension, students are required to spend time away from school and are often forbidden from participating in any school-related activities until the suspension period is finished, further disenfranchising these students. Solutions such as restorative practices, positive behavior interventions and supports, social-emotional learning, and peer-to-peer counseling have been suggested by research and explored by many states to reduce punitive disciplinary measures, and yet researchers, policymakers, and school teachers alike continue to find and recognize inequalities even in these alternative approaches [11, 12].

In 2014, the U.S. Department of Education released a letter calling for nondiscriminatory administration of discipline in schools, offering data and legalities and outlining a process for the Department and school districts to collaborate on remedies for uneven application of discipline [13]. Regardless, there are still anecdotes and news reports released each month documenting the continued problems with applying discipline fairly.

There are a wide range of articles and studies that detail these inequalities in school discipline, including disability, racial, gender, and sexuality bias. Additionally, it is crucial to recognize the underpinnings of these biases that are in large part systemic, embedded in current educational policies and practices.

Additionally, [9] found that being suspended was associated with decreased odds of taking advanced mathematics courses, which is associated with decreased odds of participation in higher education. Their study demonstrates that suspensions can have a long-term, disruptive effect on students' lives, leading them to a "punishment track", which can result in more suspensions, dropping out, and incarceration, rather than an "achievement track". However, in schools where minorities make up the majority, advanced mathematics courses are less likely to be offered. Similarly, a school-district-level study in Denver, Colorado, found that participating in a gifted and talented program was associated with reduced odds of facing disciplinary action, echoing the idea that access to achievement pathways may lower the chance of discipline [14].

The shortcomings of policies affecting current discipline systems should also be recognized. Zero-tolerance policies lead to increased suspension rates, in particular for minorities and students with disabilities. Initially applied to educational institutions as a reaction to several school shootings in 1994, schools quickly began instituting zero-tolerance policies for lower-level offenses, such as disruptive behavior, or non-offenses, such as carrying prescribed medication [3, 15, 16]. This uneven application of zero-tolerance policies across schools led to a similarly uneven application of these policies within schools, targeting behaviors more often associated with racial minorities [3, 15].

While restorative justice practices demonstrate potential for lowering suspension rates and increasing academic achievement, even this alternative does not reliably foster disciplinary equity, and it should be noted that schools with large numbers of racial minority students are not as likely to use restorative justice as part of their discipline process [14, 17–19]. There is no single or simple solution to equity in education, nor equity in school discipline, and it is evident that one-size-fits-all solutions like zero-tolerance policies nor customizable approaches like restorative justice provide consistent improvements.

It is pertinent to continue investigating inequality and injustice in school discipline and demonstrate that well-meaning efforts from the U.S. Department of Education, school districts, principals, and teachers have not been able to dislodge the systemic issues present in school disciplinary systems. The goal of this study is to determine which possible factors in a public-use nationally representative dataset influence discipline and contribute to the body of literature regarding discipline in K-12 public schools.

CHAPTER 2: DATA ANALYSIS

2.1 Data Description

The data for this study is from the Civil Rights Data Collection (CRDC; https://ocrdata.ed.gov/resources/downloaddatafile) and consists of educational and institutional data collected every two years by the U.S. Department of Education's Office for Civil Rights. In the public-use data file, the majority of student data are disaggregated by race, gender, and disability status; however, student-level data is available in the restricted-use data file. The public-use data consists of 30 school-level files and 3 local education agency (LEA)-level files. The data contains many relevant variables regarding, but not limited to, student enrollment, school finances, school employment records, arrest and law enforcement referral frequency, and suspension frequency.

Overall, 97,632 U.S. and Puerto Rico schools submitted their data for the 2017-18 school year and over 99% of LEAs certified their data. The data guide contains information about the certification process, which aims to ensure the data are accurate.

Despite this, we discovered a number of data quality issues, such as inconsistencies in the file detailing school expenditures, in particular for teacher salaries. A number of schools appear to have misinterpreted the questions relating to the total salary expenditures for teachers funded with federal, state, and local funds; see Appendix A. Some schools also reported having zero teachers or paying their teachers zero dollars, which is questionable, but that might be explained by the specifics and the wording in the CRDC survey questions.

Each data file contains a column "COMBOKEY" which is described in the data dictionary as providing a unique identifier for each school; however, in some files, these identifiers were not unique and were instead the same for every educational institution in the state. Additionally, the "COMBOKEY" combines the LEA ID and school ID, yet in some files, the LEA ID, school ID, or both were inconsistent with the generated combination key. This has the potential to limit researchers' ability to properly and thoroughly analyze this dataset, as connecting data points across data files can get complicated by inaccuracies in identification numbers.

For the purpose of this study and to be able to correctly use the data, we connected data points across different files using the combination key, school ID, LEA ID, and in some instances, the school's name to ensure schools with inaccurate identification numbers were not excluded from our analysis.

2.2 Data Cleaning and Selection Criteria

As was mentioned previously, the majority of student data are disaggregated in the 2017-18 public-use data file. Across all the 33 data files, there were approximately 1,898 unique variables, not including the identification features for each LEA present in each data file. Of those data files, we selected the following to use in our study: Advanced Placement, Algebra I, Calculus, Enrollment, Dual Enrollment, Gifted and Talented, Harassment and Bullying, Offenses, Referrals and Arrests, Retention, SAT and ACT Participation, School Characteristics, School Expenditures, School Support, and Suspensions, leaving us with approximately 691 variables.

In this study, racial disparities were investigated in place of gender disparities, so for most variables, male and female frequencies were combined to create totals for all students in the interest of reducing the number of variables. Additionally, data collected from schools exclusively serving pre-school age children were disregarded.

We limited our scope to elementary schools serving grades K-5, middle schools serving grades 6-8, and high schools serving grades 9-12; however, it should be noted that states and school districts differ on what they define as elementary, middle, and high school grades.

In the interest of selecting a representative set of educational institutions, all schools located in Puerto Rico were excluded due to their vastly different racial makeup compared to the majority of the U.S. Alternative schools and juvenile justice facilities were also excluded as they tend to have different disciplinary rules and actions. Table 2.1 provides a detailed breakdown of the schools excluded, resulting in 92,802 schools for consideration.

Table 2.1: Counts of schools removed due to our defined criteria.

Total Schools	97,632
Puerto Rico Schools Excluded	1,099
Alternative Schools Excluded	3,343
Juvenile Justice Facilities Excluded	602
Schools Remaining	92,802

However, student enrollment counts were restricted to between 50 and 5,000. Taking this constraint into consideration, we further reduced the number of schools for the final analysis into 41,339, where 25,538 are elementary, 10,254 are middle, and 14,030 are high schools.

2.3 Relative Rate Ratio and Overall Proportions

Since the data contained hundreds of variables, oftentimes disaggregated by race, gender, and disability status, it was desirable to find a way to summarize important variables succinctly for each educational institution. Rather than relying on raw numbers, which are potentially hazardous to interpret without context regarding the size of the school or percentage of Black enrollment for instance, we created new variables to summarize a number of interesting patterns related to enrollment, suspensions, referrals to law enforcement, and offenses.

First, we summarized the enrollment data by dividing the total number of White students enrolled at any given institution by the total number of students enrolled. This process was repeated for Black students and for non-Black students of color, referred to as "Other" throughout this thesis, leading to three ratios per school describing racial breakdown.

We took a similar approach in the suspensions data file, creating several new variables. Rather than scaling by the total count of enrollment, we obtained the total count of Black students who received one or more OOS suspension divided by the total count of Black students enrolled at the school. This ratio gives us an idea of how many Black students enrolled at an institution were exposed to suspension as a disciplinary process. This process was repeated for White and Other students. Similarly, we defined the ratios for days missed, referrals, and arrests for Black, White, and Other students.

Table 2.2 presents an overview of these ratios, converted to percentages for ease of comparison. For example, note that Black students are subjected to OOS suspensions at a rate more than double that of their White counterparts at all levels of schooling.

Table 2.2: Relative Rates for Variables of Interest

	Grade Level								
	Elementary			Middle			High		
Relative Rates	BL	WH	O	BL	WH	O	BL	WH	O
OOS	4.34	2.11	1.76	14.4	6.56	7.01	11.91	5.58	6.01
Days missed	13.7	6.42	5.32	75.5	30.7	34.4	65.2	28.0	31.1
Referrals	0.17	0.09	0.07	1.32	0.58	0.60	1.58	0.69	0.77
Arrests	0.02	0.03	0.01	0.12	0.31	0.13	0.16	0.46	0.17

2.4 Descriptive Statistics

To better understand the spread of enrollment in our selected schools, we calculated the proportion of enrollment for each race and each grade level, averaged across the various schools; see Figure 2.1. Note that, White students comprise the majority at all schooling levels, while Black students account for the smallest proportion. It appears that enrollment is relatively similar across grade level.

Since existing literature suggests that students of color, and particularly Black students, experience higher rates of OOS suspensions, we decided to further investigate

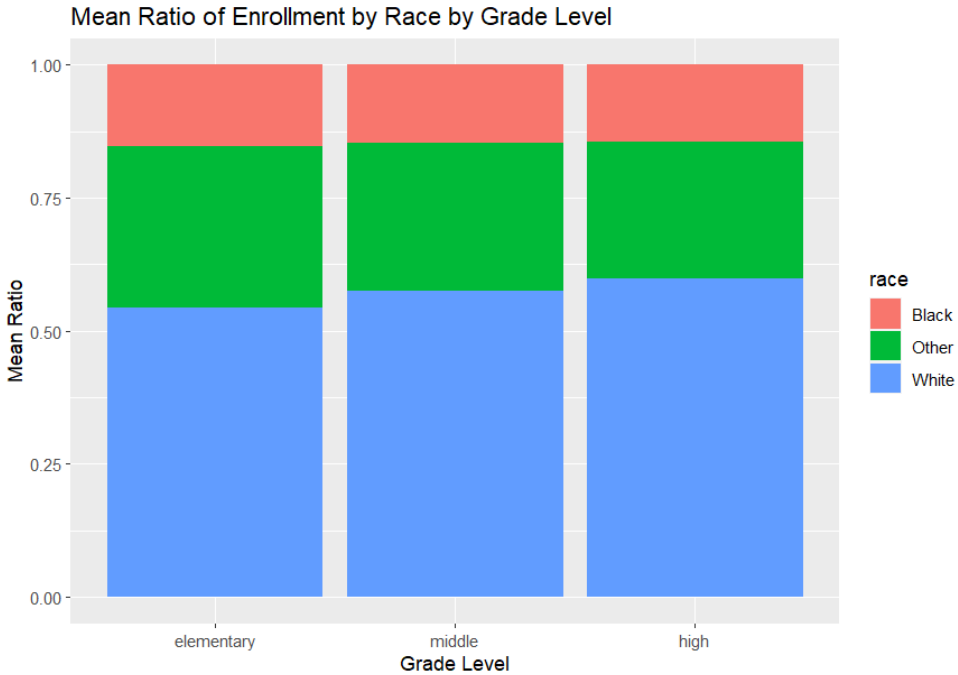

Figure 2.1: The average proportion of enrollment per race across elementary, middle, and high schools.

this to see if the claim could be corroborated or further explained using our sample. Figure 2.2 shows the proportion of OOS suspensions per race across elementary, middle, and high school levels, where the proportions are averaged for the various schools. We observe that, although White students comprise the majority of enrollment, Black students account for a higher proportion of OOS suspensions at all grade levels.

To further investigate the proportions of enrollment and OOS suspensions per race, we decided to categorize schools into four regions: midwest, northeast, south, and west. Figure 2.3 demonstrates the average proportions of enrollment and OOS suspensions per race across the four regions for the elementary, middle, and high school levels. We observe that there is no obvious discrepancy between the proportions per race across the different regions, implying that the region does not appear to influence enrollment or OOS suspension.

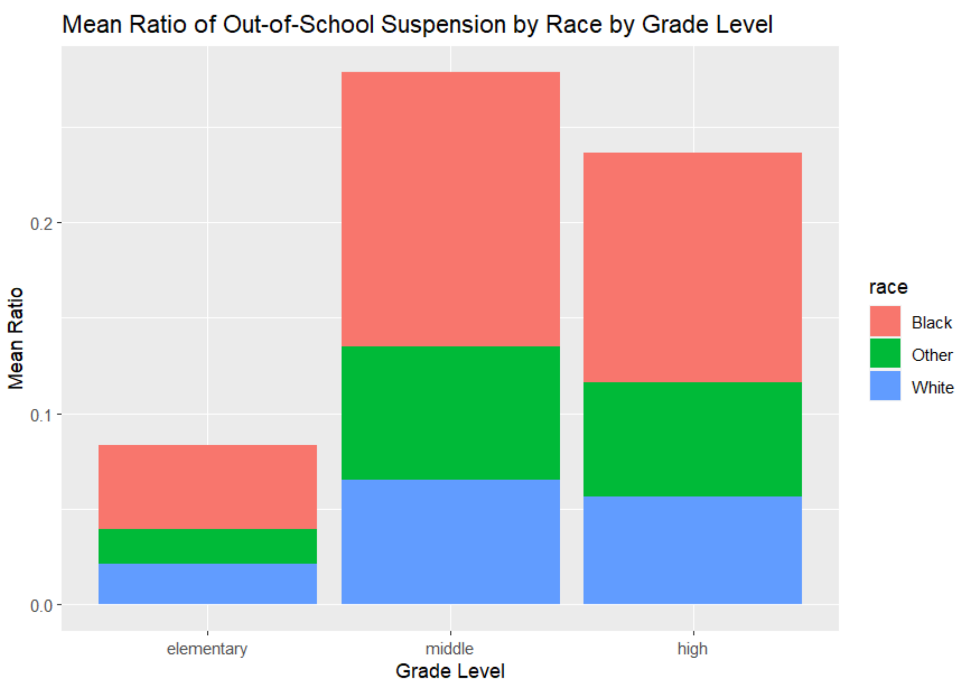

Figure 2.2: The average proportion of OOS suspension per race across elementary, middle, and high schools.

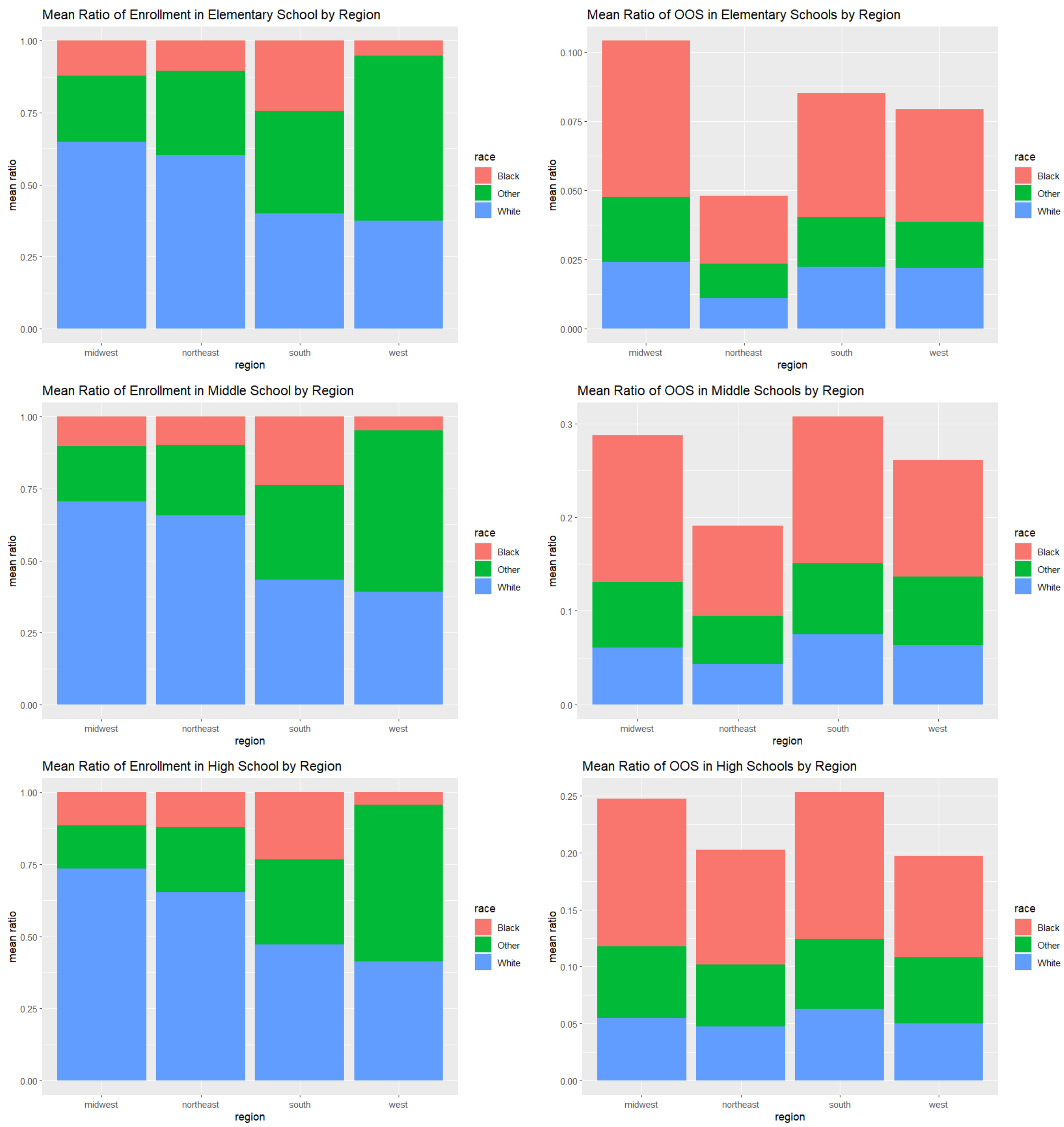

Figure 2.3: The average proportions of enrollment and OOS suspension per race across different regions for elementary, middle, and high schools.

CHAPTER 3: METHODOLOGY

3.1 Previous Considerations

Previous literature focuses on investigating which factors strongly influence suspension rates and uncovering race-, gender-, and sexual orientation-based biases. Common approaches include regression, such as multiple linear regression and mixed effects multiple linear regression [20, 21]. Although linear regression has been set to be a standard and powerful tool, other techniques can be more efficient. Logistic regression has also made its appearance in education equity research, where its main purpose is to predict the possibility of a student being suspended and determine important factors that mostly affect this probability [9, 22–27]. While these statistical methods have been sufficient for making policy recommendations and analyzing data, outliers and multicollinearity are problems we observed in the CRDC dataset and can pose challenges. For that reason, we decided to search for an alternative approach to alleviate the struggle of ensuring data meets linear or logistic regression assumptions.

Although the social sciences and in particular, educational research, do not often implement machine learning techniques, we decided to use the random forest approach as it can be very efficient when trying to classify the response and determine the prediction strength of the various predictor variables. However, for comparison purposes, we also run the logistic regression model and consider the prediction accuracy between the two methods.

3.2 The Current Study

To ensure easy reading of the remaining sections, we now introduce the variables that will be considered for the logistic regression and random forest models.

Previous studies mentioned in the literature did not consider the severity of offenses at a school when trying to understand increased or decreased suspension rates. One may argue that the increased instances of OOS suspensions for Black students occur in high risk, high crime schools. To investigate this, we use the "Offenses" data file which contains information on offenses such as robberies or physical attacks at each school. We separate the variables into categories of either "severe" or "non-severe", where any incident including a weapon falls into the "severe" category alongside rape and sexual assault. We then create a severity ratio for each school, calculated as the number of severe offenses divided by the total number of offenses at the school to provide an imperfect snapshot of how many serious offenses occurred.

We also consider a number of other ratios, including the student-teacher ratio, calculated by summing the total student enrollment at a school and dividing by the number of full-time equivalent teachers; the proportion of certified teachers, calculated by summing the total number of certified teachers at the school and dividing by the number of full-time equivalent teachers; and the expenditures per student, calculated by using the total salaries for all personnel divided by the total number of students enrolled. In addition to these ratios, several relative rate ratios were included in the analysis at the middle and high school level, which are based on the variables calculated in Section 2.3; more details below.

Furthermore, we consider the total number of security guards, the total number of sworn law enforcement officers, the total number of harassment and bullying allegations for sex, race, sexual orientation, and religion, the ratio of certified teachers, and the number of first year teachers. Our motivation for the latter two is mostly related to teacher experiences and teacher training, or lack thereof, as this could potentially lead to increased discipline to avoid unfamiliar behavioral issues. We will also consider the number of students retained at each grade level (TOT_RET) to determine if being "held back" has the potential to increase the odds of Black students being suspended.

There are also variables to consider for middle and high schools that are understandably nonexistent in elementary schools. The number of advanced mathematics courses, the number of students enrolled in Algebra I, the number of students enrolled in Calculus, the number of AP courses, the number of students dual enrolled, and the number of students participating in college entrance test preparation are of interest, as they represent higher achievement pathways.

Here is a breakdown of the variables used for the different school levels:

- For all school levels, we consider the sum of the number of counselors, social workers, and psychologists (TOT_COUNS), the student-teacher ratio (RAT_STU_TCH), the severity ratio (RAT_SEV), the ratio of expenditures per student (RAT_EXP_PER), the total number of law enforcement officers (TOT_LEO), the total number of security guards (TOT_SG), the total number of first year teachers (TOT_FYT), the proportion of certified teachers (RAT_CERT), the total number of students enrolled in gifted and talented programs (TOT_GTENR), the total number of students retained (TOT_RET), and the total number of bullying or harassment allegations (TOT_HAR).

- For middle school levels, we additionally consider the total number of Algebra I classes offered in grade 7 or grade 8 (TOT_ALG1) and the ratio of Black students to White students enrolled in Algebra I classes in grade 8 only (RAT_ALG1_BLWH), as data was not available for grade 7 enrollment. However, TOT_RET is excluded from the analysis, as it has more than 50% missing values.

- For high school levels, we additionally consider the total number of calculus classes offered (TOT_CAL), the ratio of Black students to White students enrolled in a calculus class (RAT_CAL_BLWH), the total number of AP courses offered (TOT_AP), the total number of students participating in the SAT or ACT (TOT_SAT), the ratio of Black students to White students participating in the SAT or ACT (RAT_SAT_BLWH), and the ratio of Black students to White students dual enrolled (RAT_DE_BLWH). As there are more higher education and higher achievement options available to high school students, these variables are understandably not feasible for middle school and elementary school levels.

Below is a summary table of the variables under consideration.

Table 3.1: Variables of interest for the analysis for the different grade levels.

Elementary School	Middle School	High School
TOT_COUNS	TOT_COUNS	TOT_COUNS
RAT_STU_TCH	RAT_STU_TCH	RAT_STU_TCH
TOT_OFF	TOT_OFF	TOT_OFF
RAT_SEV	RAT_SEV	RAT_SEV
RAT_EXP_PER	RAT_EXP_PER	RAT_EXP_PER
TOT_LEO	TOT_LEO	TOT_LEO
TOT_FYT	TOT_FYT	TOT_FYT
RAT_CERT	RAT_CERT	RAT_CERT
TOT_GTENR	TOT_GTENR	TOT_GTENR
TOT_RET		TOT_RET
TOT_HAR	TOT_HAR	TOT_HAR
	TOT_ALG1	TOT_CAL
	RAT_ALG1_BLWH	RAT_CAL_BLWH
		TOT_AP
		TOT_SAT
		RAT_SAT_BLWH
		TOT_DEENR
		RAT_DE_BLWH

3.3 Logistic Regression

We now present a brief overview of the logistic regression method. Let Y denote a binary response and $\mathbf{X}$ denote a p-dimensional set of predictor variables. Logistic regression models the probability of an event through a linear relationship between the predictor variables. Formally, we assume that $Y = \boldsymbol{\beta}^\top \mathbf{X} + \varepsilon$, where $\boldsymbol{\beta}$ is a

p-dimensional set of unknown coefficients and ε denotes the error term. Logistic regression assumes that Y follows a Bernoulli distribution with probability of success π. Therefore, instead of modeling Y, we instead model the probability π using

$$\pi = \frac{e^{\boldsymbol{\beta}^\top \mathbf{X}}}{1 + e^{\boldsymbol{\beta}^\top \mathbf{X}}} = \frac{1}{1 + e^{-\boldsymbol{\beta}^\top \mathbf{X}}}.$$

The coefficients in logistic regression represent the change in the log odds of the response variable after a one-unit increase in the given predictor variable with all others held constant. For interpretation purposes, the raw coefficients are exponentiated to produce the odds ratio. If an odds ratio is greater than 1, then the outcome event is more likely to occur, and if it is less than one, that event is less likely to occur.

For this analysis, the event of interest is the fraction of the ratio of Black students exposed to OOS suspension and the ratio of White students exposed to OOS suspension. A value greater than 1 indicates that Black students are at higher risk for OOS suspension than White students. To create the binary response variable, we set Y to be 1 if the ratio is greater than 1 and 0 if the ratio is less than 1. The set of variables $\mathbf{X}$ is listed in Table 3.1 for each school grade level.

Remark. In some cases, zeros in the denominator of our ratio variables resulted in NAs. To avoid this problem, we replaced zeros with a small number, 0.0001, before creating ratio variables to preserve the relationship between the numerator and denominator without introducing NAs. Specific variables where we took this approach include the response variable, i.e., the ratio of Black students to White students exposed to OOS suspension, and other various risk ratios including RAT_ALG1_BLWH, RAT_CAL_BLWH, RAT_SAT_BLWH, and RAT_DE_BLWH.

While there are many ways to assess variable importance in logistic regression, in this study we calculate and rank the absolute value of the test statistic as it is one of the most easily implementable methods in `R`. Using other, more sophisticated methods to calculate variable importance would likely produce different results.

3.4 Random Forest

Random forest is often described as an ensemble decision tree-based machine learning algorithm that takes the average of hundreds of decision trees [28–30]. Although used infrequently in social science research, random forest is robust against outliers and multicollinearity, two features that are often encountered in educational data and violate primary assumptions of logistic regression. This method is an alternative to logistic regression for classification and would allow researchers to use imperfect data to reach conclusions about the importance of variables in predicting the response while lightening the amount of work required in the data cleaning and assumption checking steps of analysis. Furthermore, as big data becomes more and more prevalent, the random forest algorithm performs well with large datasets and hundreds or thousands of variables.

Below we present a summary of the algorithm for random forest. For more details, see [28].

Algorithm 1 Random Forest for Classification

1. For $b = 1$ to B, where B denotes the number of trees:
   (a) Draw a bootstrap sample $\mathbf{X}^*$ of size N from the training data.
   (b) Grow a random forest tree T_b to the bootstrapped data, by recursively repeating the following steps for each terminal node of the tree, until the minimum node size n_{min} is reached.
      i. Select m variables at random from the p variables.
      ii. Pick the best variable/split-point among the m.
      iii. Split the node into two daughter nodes.
2. Output the ensemble of trees $\{T_b\}_1^B$.

To make a prediction at a new point $\mathbf{x}$: Let $\hat{C}_b(\mathbf{x})$ be the class prediction of the bth random forest tree. Then $\hat{C}_{rf}^B(\mathbf{x}) = \text{majority vote } \{\hat{C}_b(\mathbf{x})\}_1^B$.

The number of trees in our study, for all grade levels, was $B = 500$. For elementary and middle schools, $m = 3$ variables were selected at random from $p = 11$ and $p = 12$ total variables, respectively. For high school, $m = 4$ variables were selected at random from $p = 18$ total variables. These choices for m were chosen by default from the `randomForest` package and were not tuned.

The response in this method is the same as defined for logistic regression in the previous section, i.e., the fraction of the ratio of Black students and the ratio of White students exposed to OOS suspension, and the set of predictor variables is given in Table 3.1 for all grade levels.

The goal of this study is to discuss and interpret the variable importance that allow us to determine which variables have the most prediction strength. That is, we are interested in discovering which variables have a strong relationship with the OOS suspension risk ratio. It should be noted, however, that variable importance does not suggest a specific relationship between the response and the predictors, only the strength of the relationship.

The `randomForest` package reports the variable importance using the prediction strength of a given variable via the mean decrease in Gini index, which is demonstrated to be biased [30, 31]. The package can additionally measure the prediction strength via the mean decrease in accuracy (MDA), which is understood to be the most efficient variable importance measure for random forests [32]. Despite the wide use of MDA, Bénard, Da Viega, and Scornet proposed an alternative variable importance measure which also details the properties, inconsistencies, and issues with using MDA [32].

Although both measures have limitations, we decided to proceed using the MDA as it is more easily interpreted and mathematically understandable than the mean decrease in Gini index. The MDA refers to the decrease in classification accuracy when a variable is removed from the analysis; for example, a MDA of 15 would indicate than when that variable is removed from the model, the accuracy of classification is 15% lower.

CHAPTER 4: RESULTS

4.1 Computational Remarks

For this work, we utilized the `R` packages `glm` for logistic regression and `randomForest` for random forest.

Training and test sets were created for each grade level for use in both logistic regression and random forest. 80% of the data was reserved for training and 20% was reserved for testing. The test and training sets were split using random sampling without replacement. Both methods utilized identical training and test datasets; however, it should be noted that logistic regression deletes observations that contain NAs. Therefore, logistic regression uses only complete data points, resulting in data loss without additional analysis steps, like imputation or variable selection, taken. Conversely, the default setting for the `randomForest` package in `R` causes the algorithm to fail if there are any missing values. For that reason, we set the option to simply drop cases with NAs, similar to the approach of the `glm` package's logistic regression. While we opted not to because we did not see a dramatic increase in accuracy, the `randomForest` package also has a setting that can seamlessly replace missing values with the median and mode, a simple imputation method.

4.2 Comparing the Performance of Random Forest with Logistic Regression

The question of why Black students are over-represented in suspensions and which factors specifically contribute to increased risk for Black students, is not a simple investigation. The exploratory analysis demonstrates that neither grade level nor region can account for the differences, and we suspect that many other factors influence the disproportionate rates of suspension for Black students. We also acknowledge that the factors affecting elementary schools and how they implement discipline may not be the same as the factors affecting middle or high schools.

With that in mind, we run both logistic regression and random forest for each grade level to isolate important factors. The variables included in each model are defined in Section 3.2. We used the test data to measure the accuracy of each model. Specifically, for logistic regression, the predicted response variable was set to 1 if the estimated probability was greater than 0.5, and was set to 0 otherwise. For random forest, the prediction is achieved according to the algorithm described in Section 3.4. Finally, a confusion matrix with correct and wrong predictions was given for each method. The results are summarized in Table 4.1. We observe that at all grade levels, random forest outperforms logistic regression by several percentage points and is more successful at classifying the test data.

Table 4.1: Accuracy results for classification

Grade Level	RF Accuracy	LR Accuracy	# Variables
Elementary	63%	57%	11
Middle	77%	71%	12
High	81%	78%	18

As far as the importance of variables, which is measured by the absolute value of the test statistic for the logistic regression and the MDA for the random forest, we decided to report the five top variables for each method and each grade level; see Table 4.2. We observe that some variables consistently appear as having a high importance for both methods (denoted with an asterisk in the table).

Some of the important variables are unsurprising. The literature mentions counselors (TOT_COUNS), expenditures per student (RAT_EXP), teacher experience and certification (TOT_FYT, RAT_CERT), and academic opportunities (TOT_GTENR, TOT_AP, RAT_ALG1_BLWH, RAT_SAT_BLWH, RAT_DE_BLWH, and RAT_CAL_BLWH) as factors affecting suspension odds. We did not encounter literature discussing how retention rates (TOT_RET) affect suspension odds, nor did we

Table 4.2: Variable importance results for random forest and logistic regression; *commonalities

Grade Level	Random Forest	Logistic Regression
Elementary	(1) TOT_COUNS*	(1) TOT_RET*
	(2) TOT_RET*	(2) RAT_CERT*
	(3) RAT_SEV	(3) TOT_COUNS*
	(4) RAT_CERT*	(4) RAT_STU_TCH*
	(5) RAT_STU_TCH*	(5) TOT_FYT
Middle	(1) RAT_ALG1_BLWH	(1) TOT_COUNS*
	(2) TOT_COUNS*	(2) TOT_FYT
	(3) RAT_STU_TCH	(3) TOT_HAR
	(4) TOT_GTENR*	(4) TOT_GTENR*
	(5) RAT_CERT*	(5) RAT_CERT*
High	(1) RAT_SATACT_BLWH	(1) TOT_COUNS*
	(2) RAT_DE_BLWH	(2) RAT_EXP
	(3) RAT_CAL_BLWH	(3) RAT_STU_TCH
	(4) TOT_COUNS*	(4) TOT_RET*
	(5) TOT_RET*	(5) TOT_AP

encounter literature discussing how suspensions interact with harassment and bullying allegations (TOT_HAR). Although the variable importance results do not indicate a specific relationship between the response and the predictor variables, we were able to identify key factors for further investigation. We were also able to demonstrate that, similar to logistic regression, random forest can produce variable importance results that are simple to understand.

Through logistic regression, we were able to calculate the coefficients for each variable at each grade level. We exponentiate each coefficient to calculate the odds ratio and we report the values in Table 4.3. An odds ratio greater than 1 indicates that Black students, relative to their enrollment, are more likely to be suspended than White students, relative to their enrollment. An odds ratio lower than 1 is associated with lower odds of that same outcome.

We can broadly categorize RAT_STU_TCH, RAT_CERT, TOT_COUNS, TOT_LEO, TOT_SG, RAT_EXP, and TOT_FYT as variables representing school support, RAT_SEV, TOT_RET, and TOT_HAR as variables representing social

Table 4.3: Logistic regression coefficients, exponentiated to the odds ratio (OR). An asterisk (*) indicates a p-value less than 0.05.

	Grade Level					
	Elementary		Middle		High	
Variable	OR	p-value	OR	p-value	OR	p-value
TOT_COUNS	1.384	$<$ 2e-16*	1.306	2.64e-16*	1.155	6.92e-09*
RAT_STU_TCH	0.954	$<$ 2.77e-12*	0.984	0.09921	0.936	5.64e-06*
RAT_SEV	2.239	6.98e-07*	0.706	0.08772	0.468	0.021020*
RAT_EXP	0.999	0.081759	0.999	3.87e-07*	0.999	0.000234*
TOT_LEO	1.004	0.837234	0.153	0.02249*	0.998	0.970510
TOT_FYT	1.053	5.99e-11*	1.086	2.09e-11*	1.020	0.098393
RAT_CERT	0.023	$<$ 2e-16*	0.036	1.39e-05*	0.111	0.032177*
TOT_GTENR	0.999	0.173414	1.002	2.57e-06*	1.001	0.033027*
TOT_SG	0.958	0.271897	1.111	0.03136*	1.000	0.937871
TOT_RET	1.023	$<$ 2e-16*			1.004	0.001377*
TOT_HAR	1.055	0.000253*	1.036	1.33e-06*	1.052	0.002128*
TOT_ALG1			0.992	0.24977		
RAT_ALG1_BLWH			0.999	0.00196*		
TOT_CAL					0.975	0.068044
RAT_CAL_BLWH					1.000	0.987119
TOT_AP					1.030	0.000801*
TOT_DEENR					0.999	0.012794*
RAT_DE_BLWH					0.999	0.003971*
TOT_SAT					1.000	0.028861*
RAT_SAT_BLWH					1.000	0.336535

and environmental factors at the school, and the remaining variables, i.e., the latter nine in Table 4.3 and TOT_GTENR, representing the college trajectory as they are pathways to higher education.

Variables with significant OR across all grade levels ($p < 0.05$) include TOT_COUNS, RAT_CERT, TOT_RET (middle school excluded due to missingness), and TOT_HAR. Additionally, RAT_STU_TCH, RAT_SEV, RAT_EXP, TOT_FYT, and TOT_GTENR had a significant OR in two grade levels. Counselors, student-teacher ratio, and expenditures per student were each mentioned to be significant factors affecting discipline and academic outcomes in previous literature; however, we encountered an unusual finding. As the total number of counselors increases, our model expects the risk ratio for Black students in OOS suspension to increase. This result was surprising and counter-intuitive as the literature suggests counseling and psychological staff are effective at resolving student issues without escalating to punishments like OOS suspension. To investigate further, we ran the logistic regression once more after removing the number of social workers from the sum TOT_COUNS. Even with this adjustment, the OR remained greater than one. We also removed psychologists from the sum and only considered the number of school counselors but did not see a significant change. This unusual result could be due to us opting to take this variable as a total, and not a scaled value (i.e. student-to-counselor ratio). It is just as likely, however, that the positive effects of counselors are not shown in the data because the role of counselors in schools is not standardized across the U.S., and the findings mentioned in the literature review are the result of small-scale studies.

Another finding that might be considered incongruent with the literature is that as the number of students per teacher increases, we expect the risk ratio to decrease. One explanation, also mentioned above, could be that the majority of studies mentioning this effect are small-scale studies. Another possible explanation for this could be that the effect is masked by an overall quite small student-teacher ratio in our sample. In our high school sample, for instance, the mean student-teacher ratio was approximately 16.6, and mean ratios were even lower for middle (15.8) and elementary (15.4) schools.

We found that TOT_RET and TOT_HAR ranked high in predictive power. We did not encounter corroborating evidence for these in the literature review in small-scale studies, much less in any nationally representative one. This suggests there should be more of a focus on minimizing retention as this increases the risk of disproportionate suspension at the elementary (OR 1.023) and high (OR 1.004) school level.

Teacher preparation also appears to affect suspension odds, based on our findings for RAT_CERT and TOT_FYT, and the literature corroborates this [3, 7, 11, 25, 33]. Our results indicate that higher proportions of certified teachers lower the odds of disproportionate suspension, and higher numbers of first-year teachers increase the odds significantly at the elementary (OR 1.053) and middle (OR 1.086) school level.

Several of our college trajectory variables were only included in the model at a single grade level but were determined to be significant. Specifically RAT_ALG1_BLWH (OR 0.999) and RAT_DE_BLWH (OR 0.999) provide us with insight, as these demonstrate that increasing the proportion of Black students participating in higher achievement options lowers the odds of Black students facing disproportionate discipline. We can also note that the results for TOT_AP (OR 1.030), TOT_DEENR (OR 0.999), and TOT_SAT (OR 1.000) are significant at the high school level. Dual enrollment appears to reduce the odds of Black students being suspended unfairly, while having more numerous AP courses or more students participating in college placement tests appears to marginally increase the odds. The variable TOT_GTENR was included at all models and found to have a significant influence on the odds of suspension at the middle (OR 1.002) and high (OR 1.001) school level. One interpretation of this, similar to our conclusion for TOT_COUNS, is that providing services and activities outside the typical scope of the school is expensive, and therefore less likely in highly diverse or low-income schools.

Lastly, we would like to mention one variable that we expected to be significant but in our study was not. TOT_LEO was only found to significantly reduce the odds of disproportionate suspension at the middle school level, a finding which is at odds with the current body of research [5, 7]. The literature indicates that police presence on school campuses puts Black students at particular risk for suspension and harsher punishments. At the elementary and high school level, however, this variable was not found to be significant in predicting the odds of suspension.

4.3 Implications of these results (better title later)

In this work, we observed that random forest outperforms logistic regression for each grade level. Additionally, while not identical, it produced similar variable importance results to that of logistic regression. It should be noted that our data inherently contains outliers, however, violating an assumption of logistic regression which could affect the veracity of the coefficients. As mentioned previously, this is one benefit of using random forest to determine variable importance and prediction strength; in comparison to logistic regression, it is robust against outliers. This analysis introduces random forest as a viable method in education research and a powerful tool worth knowing. The high school model contains 18 predictor variables and, notably, these variable importance results aligned the least, although random forest and logistic regression agree that TOT_COUNS and TOT_RET have prediction strength. The elementary school importance results are almost identical, suggesting that smaller models may perform similarly between the two methods. Although the variable importance results do not align perfectly, the results for random forest raise new potential research questions to understand why this algorithm determined the risk ratios of Black students versus White students to have high predictive strength.

At all levels, however, each method agreed that the total number of counselors was a potent variable with great prediction strength. Random forest does not indicate what the relationship may be between this predictor and the response, while the coefficients of logistic regression can be interpreted in that manner. Still, understanding what variables strongly influence a response even if we are not sure of the precise relationship is a worthy endeavor and one that education researchers and social scientists may often find themselves interested in. In our case, we narrowed an even larger dataset down to several hundred variables. Creating a random forest and reviewing the variable importance results could inform research directions or variables of interest for inclusion in a model. While variable selection based on background knowledge or significance tests is perfectly adequate, random forest provides an alternative starting point in model building for large datasets in particular.

While we primarily used logistic regression to compare its performance to that of random forest, we also obtained the odds ratios by exponentiating the coefficients. While some of our results did not align with the literature, we discovered variables that have a significant effect across the nation, providing new pathways for school discipline research.

CHAPTER 5: DISCUSSION AND CONCLUSION

This work considers the use of two techniques, that of logistic regression and random forest, in order to determine which factors raise the risk of disciplinary action such as OOS. The results suggest that random forest outperforms logistic regression in terms of prediction accuracy. Although random forest is not a commonly used method in educational research, this work hopes to bring awareness and suggest an alternative method for researchers. Classification is, and will continue to be, a problem of interest for education researchers and social scientists. As the amount of available data increases and the data collection process becomes more robust, it is important to explore the use and power of different tools such as random forest versus more traditional methods like logistic regression.

Logistic regression does, however, have the benefit of being able to produce coefficients that allow us to interpret the relationship between the response and the predictors. Using this nationally representative dataset of more than 40,000 schools, we were unable to replicate some of the results found in smaller scale studies such as more counselors reducing the odds of suspension and more law enforcement officers raising the odds of suspension. We did, however, discover that the total number of students retained as well as the number of harassment and bullying allegations increase the odds of disproportionate suspension for Black students. Additionally, our analysis found that increasing the ratio of Black to White students participating in Algebra I in grade 8 or dual enrollment in high school decreases the odds of disproportionate suspension for Black students. Therefore, as previous literature suggests, should continue to provide opportunities for academic growth and pathways to higher education especially in high-poverty, rural, diverse schools. Schools should also continue to recruit certified teachers in particular, as the odds ratio indicates that keeping the proportion of certified teachers high greatly reduces the risk of disproportionate suspension for Black students.

There is a need for more data surrounding counselors, the roles they play at schools, and how they interact with students to provide more context to our findings for the 2017-2018 school year. Lack of funding and lack of access to qualified counselors is just one explanation for why the total number of counselors would heighten the odds of suspension for Black students versus their White peers, when the opposite has been found in studies with a smaller scope. As the role of a school counselor is different from district to district and school to school, unfortunately simply having the total number of full-time counselors is not very informative. The literature review mentions the promise of restorative practices, which many counselors likely implement in their work, but as the job description is not standardized, we are unable to fully evaluate the effect of counselors in this way. Expanding surveys like the CRDC to collect data related to social and environmental factors at the school would support comprehensive research like this, without requiring the additional costs, time, and effort associated with small-scale studies. For example, collecting data on how many incidents the counselor took part in resolving, or whether or not the school implements restorative practices or social-emotional learning.

Our closer look into the severity of offenses at the schools included in our study is a practice we would recommend continuing, as we believe it is crucial context in the discussion of school discipline. We found that, at the elementary school level, Black students were more than twice as likely to be suspended at schools with higher severity ratios; however, at the high school level, Black students were less likely to be suspended at schools with higher severity ratios. Further research and analysis should be conducted to understand this relationship between severe offenses and suspensions. Ensuring there is publicly available data on not only the number of suspensions and the number of offenses, but the number of suspensions, referrals, arrests, or expulsions resulting from specific kinds of offenses would be invaluable insight to address this issue.

We would also like to address some limitations of this study. One such limitation is the criteria used in defining elementary, middle, and high schools. Many school districts have different standards for what grades are served at each grade level, so some schools were naturally excluded and their data was not used in this study. Future analysis might include a more broad definition of school grade levels as well as a broader range for enrollment, as we limited ours to between 50 and 5,000 students.

Also seen as an advantage, the large-scale nature of this dataset could be considered a limitation. As we are dealing with data from across all 50 states plus the District of Columbia, and all the counties and school districts within, our analysis may not capture subtleties in the data that are more apparent in small-scale studies limited to particular schools, districts, or states. Context is crucial when trying to understand school discipline, and the political, racial, socioeconomical landscape of the U.S. is highly varied and oftentimes segregated. While there is a need for more large-scale data analysis for education, which was one goal of this thesis, there also continues to be a need for small-scale experiments and analyses than can deepen our insight of how factors interact at a school-, city-, district-, or state-level even if we may not see those trends emerge overall for the U.S.

As suggested in many of the studies cited in our literature review, to fully evaluate how race and student discipline interact, there is a need for more robust and comprehensive data related to school climate, school support staff demographics and background, teacher demographics and background, and school policy implementation practices which is not available through the CRDC. We acknowledge the difficulties in obtaining such data; however, it would be crucial to advance nationally representative research on discipline inequities and continue informing wide-reaching policies.

Future research could utilize more control variables. This could aid in isolating important factors and discovering significant results under specific conditions, rather than looking at the factors overall as we did in this study. While this thesis contains some initial steps that can be taken to approach this dataset, next steps could include implementing imputation on incomplete observations or variable selection for model optimization and comparison.

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EXPD: School Expenditures (Personnel and Non-Personnel)

Module Instructions

DATES

Report data based on the 12-month fiscal school year, as defined by the LEA.

NOT APPLICABLE (NA) and ZERO (0) FILLS IN TABLES

The online tool remembers information that has been entered in other tables and modules and uses that information to fill related tables with either a Not Applicable (NA) code or zero (0) where appropriate. For example, if it is reported that a school does not have any females who are EL, other tables that ask for counts of females who are EL will be automatically filled with a zero.

SPECIAL INSTRUCTIONS

When determining expenditures for teachers and personnel funded with federal, state, and local funds, refer to the list of school-level expenditures to determine what should be included and excluded.

The number of teachers and personnel should be reported in full-time equivalency of assignment (FTE).

FTE and expenditure values should be entered as a decimal number to the hundredths place (i.e., two decimal places; e.g., 4.00, 4.75).

KEY DEFINITIONS

Full-time equivalent (FTE) is a unit that indicates the workload of an employed person in a way that makes workloads comparable across various contexts. FTE is used to measure a worker's service in a place (e.g., school). FTE is the number of total hours the person is expected to work divided by the maximum number of compensable hours in a full-time schedule. An FTE of 1.00 means that the person is equivalent to a full-time worker, while an FTE of 0.50 signals that the worker is only half-time.

Instructional aides – Includes aides or assistants of any type who assist in the instructional process.

Support services staff for pupils and support services staff for instructional staff – Includes guidance counselors, nurses, attendance officers, speech pathologists, other staff who provide support services for students, staff involved in curriculum development, staff training, operating the library, media and computer centers.

School administration staff – Includes principals and other staff involved in school administration.

Instructional aide expenditures are associated with activities dealing directly with the interaction between teachers and students.

Total personnel – regular instructional and support personnel is defined as follows:

- Instructional staff – Includes teachers and instructional aides.
- Support services staff for pupils – Includes guidance counselors, nurses, attendance officers, speech pathologists, and other staff who provide support services to students.
- Support services staff for instructional staff – Includes staff involved in curriculum development, staff training, operating the library, media and computer centers.
- School administration staff – Includes principals and other staff involved in school administration.

Total personnel salaries include expenditures for regular instructional and support staff that are associated with the following types of activities:

- Instructional functions – Activities dealing directly with the interaction between teachers and students.
- Support services for pupils – Activities designed to assess and improve the well-being of students and to supplement the teaching process.
- Support services for instructional staff – Activities associated with assisting the instructional staff with the content and process of providing learning experiences for students.
- School administration – Activities related to overall administration for a school.

Items noted with an asterisk "" reflect guiding questions. Answers to these questions determine whether a school is presented with subsequent items.*

Non-personnel expenditures may include (but is not limited to) the following types of expenditures: Professional development for teachers and other staff; instructional materials and supplies; computers, software, and other technology; contracted services such as distance learning services; and library books and media center learning materials.

Support services staff expenditures are associated with activities designed to: assess and improve the well-being of students and to supplement the teaching process; and assist the instructional staff with the content and process of providing learning experiences for students.

School administration staff expenditures are associated with activities related to overall administration for a school.

INCLUSIONS AND EXCLUSIONS

Expenditures	**For expenditures for personnel/ non-personnel funded with state and local funds, include and exclude the following:**	**For expenditures for personnel/ non-personnel funded with federal, state, and local funds, include and exclude the following:**
ALL Expenditures (Personnel and Non-Personnel)		
Expenditures paid from federal funds other than Impact Aid and State Fiscal Stabilization Fund if used under the Impact Aid authority	Exclude	Include
Expenditures paid from federal Impact Aid funds and State Fiscal Stabilization Fund if used under the Impact Aid authority	Include	Include
Expenditures for preschool programs	Exclude	Include
Expenditures for school nutrition programs	Exclude	Exclude
Expenditures for adult education	Exclude	Exclude
Expenditures for special education	Exclude	Include
Expenditures for programs that serve students from more than one school attendance area at a single school site (e.g., summer school programs that are housed in a subset of the district's schools but serve students from throughout the school district)	Exclude	Include
Expenditures made by regional educational agencies on behalf of schools	Exclude	Include
Additional Inclusions and Exclusions for Salary Expenditures for School Personnel		
Base salary, incentive pay, and bonuses	Include	Include
Supplemental pay for additional roles	Include	Include
Expenditures for employee benefits	Exclude	Exclude
Additional Inclusions and Exclusions for Non-Personnel Expenditures		
Expenditures for professional development for teachers and other staff	Include	Include
Expenditures for instructional materials and supplies	Include	Include
Expenditures for computers, software, and other technology	Include	Include
Expenditures for contracted services such as distance learning services	Include	Include
Expenditures for library books and media center learning materials	Include	Include
Other non-personnel expenditures (associated with regular instruction, pupil support, instructional support, and school administration)	Include	Include