Identify Patterns of Importance Risk Factors Associated with STI Testing other than HIV among Adolescents in Local School Districts and States around the United States Using YRBSS 2019 Data and Machine Learning Algorithms

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**Abstract**

**Background:** The health of American Adolescents is facing significant challenges from sexually transmitted infections (STI). Most STIs cause significant suffering in the acute phase and can produce long-term damage with severe consequences. Machine learning (ML) algorithms provide an effective tool for analyzing YRBSS datasets.

**Methods:** The study participants were collected from selected states and local school districts included in the Youth Risk Behavior Surveillance System (YRBSS) high school 2019 dataset. After training the multinomial logistic regression, random forest, support vector machines (SVM), Elastic Net regression, ridge regression, lasso regression, and classification tree methods, the best-performed and second best-performed were selected based on accuracy and applied to each State and local school district.

**Results:** Among the 12 states, there were 3797 participants included in the study, 74.27 % of participants did not have STI testing, 20.23 % had STI testing, and 5.5 % were not sure. Among the 15 local school districts, there were 2723 participants included in the study; 67.68% of participants did not have STI testing, 26.18 % had STI testing, and 6.12 % were not sure. The ridge algorithm has the highest mean value (0.7437) of accuracy for the States dataset, and the lasso algorithm has the highest mean accuracy (0.7079) value for the local school district dataset. The study successfully demonstrated that BMI, physical fights, dating sexual violence, alcohol drinking, marijuana use, heroin use, methamphetamine use, and school grade were the most important risk factors associated with STI testing other than HIV.

**Conclusion:** By using the ML algorithms, we provide a comprehensive understanding of important variables associated with STI testing other than HIV for healthcare, education, social work, and government facilities. This information can help public health workers enhance STI testing by addressing important risk factors and identifying vulnerable populations. Ultimately, our findings can serve as a valuable resource for healthcare professionals, educators, social workers, and policymakers to improve STI prevention and treatment efforts.

**Introduction**

The health of the young American population aged 15 to 24 is facing significant challenges from sexually transmitted infections (STI), which include chlamydia, gonorrhea, genital herpes, human papillomavirus (HPV), syphilis, and HIV, defined by the Centers for Diseases Control and Prevention (CDC). Young people account for at least half of all new sexually transmitted infections (STIs) contracted yearly, and a quarter of sexually active adolescent females have STIs(Shannon & Klausner, 2018). In 2021 alone, there were at least 2.5 million reported cases of chlamydia, gonorrhea, syphilis, and congenital syphilis, according to the CDC. From 2020 to 2021, syphilis cases alone have risen by 26%, and the number of syphilis cases last year was the highest since 1948(Liddon et al., 2022). Scientists believe that the number of cases is underreported, and there are untreated infections, so these numbers may be higher. Most STIs cause significant suffering in the acute phase and can produce long-term damage with severe consequences, such as miscarriage, infertility, heart and bone, and even brain damage(Nicoll & Hamers, 2002). The increase in the incidence of STDs may also bring many serious consequences, such as increased drug resistance to STDs, poor health quality of the next generation, increased social and medical costs, and increased social insecurity(WHO regional office for Europe, 2001). Considering the severe consequences and disease burden on the population and individual level of adolescent health, multiple organizations and agencies recommend some STI screening for adolescents. In addition, STIs are characterized by un-symptomatic occurrences, which can infect others unknowingly(Samkange-Zeeb et al., 2011). According to the National Academies of Sciences, health inequities have become a major challenge for the nation, resulting in health disparities between states and school districts around the United States(Weinstein et al., 2017). In addition, the communities encountered threats from inequalities in health, sociality, ethnicity, economy, employment, and education that can impede the deployment of STI testing to adolescents.

STI testing is an effective way of reducing STIs. The implementation of STI testing guided by the WHO **A**ffordable, **S**ensitive, **S**pecific, User-friendly, **R**apid and robust, **E**quipment-free, and **D**eliverable criteria become a benchmark for controlling the rapid spreading of STIs globally(Peeling, Holmes et al., 2006). The STI screening provided its value in controlling the spreading of STIs by interrupting the transmission chain between the patients and their sexually active partners(Dewart et al., 2018). Most STIs can be treated with a single dose of antibiotics. Therefore, the early and high prevalence of testing is crucial in controlling the rising STIs among adolescents in the United States(Peeling, Mabey, et al., 2006). Traditional statistical methods may have limited ability to handle such data. Machine learning (ML) mainly focuses on prediction, and epidemiology mainly needs to know causal effects (causal/etiologic inference), requires background knowledge, and is biased towards parametric/semiparametric estimation, so it is not easy to combine the two. However, in recent years an increasing number of studies on machine learning have been published in frontier epidemiological methods, with a primary focus on public health, explaining chronic diseases, risk factors for chronic diseases, and infectious, parasitic, and communicable diseases(dos Santos et al., 2019). Machine learning (ML) algorithms provide an effective tool for analyzing these datasets and can find hidden links and patterns in the data that may be difficult to spot using more traditional approaches(Mooney & Pejaver, 2018). These methods have the potential to considerably advance our knowledge of STI testing risk factors and make it possible to identify vulnerable individuals more precisely.

The low prevalence of STI testing is threatening the populational health of teenagers(St Lawrence et al., 2002). Previous studies identified barriers, such as limited access to healthcare, parental pressure, social stigma, STI-related attitudes, and limited knowledge of STIs and their consequences, that prevent adolescents from receiving STI testing(Copen et al., 2015-2016 CDC.)(Bronwen Lichtenstein, 2003)(Shepherd & Harwood, 2017). However, limited studies research the pattern of risk factors associated with STI testing and compare the difference between the pattern of risk factors in different states and local school districts. The association between risk factors and STI testing in local school districts and states has yet to be fully understood. In this study, we used machine learning methods to improve the accuracy of the model’s ability to explain the association based on the YRBSS dataset. The understanding of risk factor patterns between different states and local school districts is essential in identifying and providing appropriate aid and support precisely for vulnerable populations among adolescents. The purpose of this study is to examine the pattern of risk factors' importance associated with STI testing and compare the difference between the pattern of risk factors' importance in different states and local school districts using the data from the Youth Risk Behavior Surveillance System (YRBSS) 2019 database. We employ machine learning techniques to analyze the association between age, gender, school grade, race, unintentional injuries and violence, tobacco use, alcohol and other drug use, and risky sexual behavior with STI testing other than HIV.

**Methods**

**Study Population and Study Design**

The Youth Risk Behavior Surveillance System (YRBSS) includes representative samples of 9th through 12th-grade students from local school-based surveys as well as national, state, territory, tribe, and tribal government surveys. Every two years, usually during the spring semester, these surveys are carried out. The health and education departments of each state, territory, and locality undertake surveys to gather information typical of most public high school students in each jurisdiction. Based on the variables selected from the YRBSS, we were able to examine the pattern of variable importance from age, gender, school grade, race, unintentional injuries and violence, tobacco use, alcohol and other drug use, and risky sexual behavior with the outcome - STI testing other than HIV through a cross-sectional study. The study participants were collected from the Youth Risk Behavior Surveillance System (YRBSS) high school 2019 dataset. We included participants who were enrolled in high schools of selected states and local school districts aged from 12 years to 18 years or older without missing data. State, territorial, tribal government and local school district surveys with representative1 and no representative2 data are displayed. It is important to note that the YRBSS 2019 state survey does not conduct in Minnesota, Oregan, Washington, and Wyoming states. Participants were excluded from the study dataset if they had missing data from any of the survey questions.

The local high school district data were collected from 15 local high school districts provided by the YRBSS, including Broward County, FL, Chicago, IL, Eaton Consortium, MI, Fort Worth, TX, Genesee Consortium, MI, Hillsborough County, FL, Los Angeles, CA, Newark, NJ, Orange County, FL, Palm Beach County, FL, Pasco County, FL, Philadelphia, PA, Portland, OR, Shelby County, TN. **The local school district data included 2,723 participants.** The state data were collected from 12 states provided by the YRBSS state data after removing all the missing values, including Alabama, Arkansas, Illinois, Iowa, Kentucky, Michigan, Mississippi, Nebraska, Oklahoma, Pennsylvania, South Carolina, and West Virginia. **The state data included 3,797 participants.** After training the ML methods on the entire dataset, we applied the best-performed and second-best-performed ML methods to each local school district and each state to identify the pattern of variable importance. The YRBSS dataset provides de-identified data, which did not include any personal identifier and human subjects' direct contact. The Institutional Review Board (IRB) did not conduct the IRB review process. The consent process is waived.

**Measures**

All outcome and exposure variables were derived from the survey questions. The primary outcome is derived from the Youth Risk Behavior Survey question Q85:

During the past 12 months, have you been tested for a sexually transmitted disease (STD) other than HIV, such as chlamydia or gonorrhea?

A. Yes

B. No

C. Not sure

The independent variables include demographic variables, unintentional injuries and violence factors, tobacco use, alcohol and other drug use, risky sexual behavior, and cognitive and health factors. The demographic factors include age, sex, grade, and race, which were collected from YRBS questions Q1, Q2, Q3, and Q5. BMI is calculated using Height and Weight in the following formula:

*BMI = kg/m2 = Weight (in kg)/[Height (in m)2]*

The unintentional injuries and violence factors include Birth Control Use (qnothhpl), physical fights (Q17), Dating-related forced sexual activities (Q21), Bullying on school property (Q23), and Suicidal thoughts (Q26). The tobacco use is collected from the question: Tried cigarette smoking (Q30). Alcohol and other drug use factors collected from survey questions: Alcohol consumption (Q41), Marijuana use (Q47), Prescription pain medicine misuse (Q49), Cocaine use (Q50), Heroin use (Q52), and Methamphetamine use (Q53). Risky sexual behavior factors collected from survey questions: Condom use (Q63) and Sexual contact with different genders (Q65). Cognitive and health factors collected from the survey questions: HIV testing (Q84), Asthma diagnosis (Q87), and School grades (Q89). The detailed survey questions are described in the supplemental material.

**Statistical Analysis**

**Data Cleaning and Feature Selection**

The state and local school district datasets were derived from the Combined YRBS High School Datasets by selecting related risk factors based on a clinical assessment of variables that could contribute to the outcome - STD testing. The independent variables mentioned previously as treated as categorical variables in all the models except the BMI. The BMI is treated as a continuous variable in the model. All machine learning methods implemented in this study aimed to identify the unbiased pattern between STI testing and risk factors. The variables related to drug use, including cocaine use (Q50), heroin use (Q52), and methamphetamine use (Q53), were transformed into binary variables due to their skewed to one of the categories. We used complete data for all the Machine Learning methods, and no further analysis was conducted for the missing data. To address the imbalanced data, we scaled and centered the data in the analysis process. Moreover, we assess the completeness of each category for all variables and remove categories with no values to ensure the scaling of data during fitting the ML methods.

**Model Selection, tuning, and testing**

We used multinomial logistic regression, random forest, support vector machines (SVM), Elastic Net regression, ridge regression, lasso regression, and classification tree methods in the data analysis. Our study aims to explain the variable importance and association between STI testing and demographic factors, sexual factors, unintentional injuries and violence factors, alcohol and drug use, and cognitive and health factors. As a result, we did not conduct the 70/30 data separation. However, we applied 10-fold cross-validation to minimize the overfitting and select the optimized hyperparameters for each ML method applied in the analysis. Besides the primary goal of analyzing the association, the secondary goal is to assess the performance of different ML methods on the same dataset. After the data cleaning process, the ML method was applied using the “caret” package in R version 4.2.3. And the “rpart. plot” library was used to plot the decision tree plot. The “confusionMatrix” function was used in this study to obtain the accuracy and its 95% CI for each ML method. Accuracy is the measure used to select the ML method with the best performance on the data. The comparison of accuracy across ML methods used in this study was made by the “resamples” function from the “caret” package. The “resamples” function provides the minimum, 1st quartile, median, mean, 3rd quartile, and maximum value of accuracy for each ML algorithm. The ML algorithms were trained on the whole dataset of State and local school districts. And then, we applied the best-performed ML algorithm and second best-performed to each State and each local school district dataset to explore the pattern of important variables associated with the outcome – STI testing (Q85) to ensure model accuracy and validation.

The default hyperparameter can be a good starting point for gaining a basic understanding of the ML method. However, the default parameters might not always be the best for the data, resulting in subpar performance and incorrect forecasts. Hyperparameter tuning is an important process to optimize the performance of the ML method. The type of hyperparameters is unique for different ML methods. The tuning is conducted by providing a range of values in the parameter setting “tuneGrid” of the “train” function, which can provide the best-tuned hyperparameter in the “besTune” column of the training results. Besides the accuracy and best hyperparameters, we also plot the variable importance table by “varImp” function. The more significant the variable, the more crucial it is to the model's effectiveness. The dataset used in the ML methods training and R code can be found in the GitHub repository: <https://github.com/yh3430/CU_2023_thesis>

**Results**

Table. 1 shows the number of participants distribution of all variables, including demographic and all questionnaire variables for 12 states (table. 1 is listed in the appendix). Among the 12 states, there were 3797 participants included in the study, 74.27 % of participants did not have STI testing, 20.23 % had STI testing, and 5.5 % were not sure. Michigan (MI) has the highest percentage of participants who had STI testing. 53.28 % of participants from 12 states were female, and 45.72 % were male. The mean BMI of participants from 12 states was 24.20. 63 % of participants from 12 states were White, 14.35% were Black or African American, 14.49 % were Hispanic/Latino, and 8.16 % were all other races. Table. 2 shows the number of participants distribution of all variables, including demographic and all questionnaire variables (table. 2 listed in the appendix). Among the 15 local school districts, there were 2723 participants included in the study; 67.68% of participants did not have STI testing, 26.18 % had STI testing, and 6.12 % were not sure. Philadelphia, PA (PH) has the highest percentage of participants who had STI testing. 54.39 % of participants from 15 local school districts were female, and 45.61 % were male. The mean BMI of participants from 15 local school districts was 23.64. 29.97 % of participants from 15 local school districts were White, 21.26 % were Black or African American, 37.94 % were Hispanic/Latino, and 10.83 % were all other races.

After training the State and local school district datasets separately with multiple ML algorithms, Table. 3 and Table. 4 show the accuracy of all the trained ML algorithms for states and local school districts. Based on the table. 3, the ridge algorithm has the highest mean value of accuracy for the states dataset, which is also shown in the Figure. 1 (a). In addition, random forest, lasso, and ridge algorithms present similar accuracies based on the state datasets. For ML methods trained on local school district data, table. 4 shows that the lasso algorithm has the highest mean accuracy value for the local school district dataset, as shown in Figure. 2 (b). In addition, lasso and ridge algorithms present similar accuracies based on the local school district datasets.

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| --- | --- | --- | --- | --- | --- | --- |
|  | **Min** | **1st Qu** | **Median** | **Mean** | **3rd Qu** | **Max** |
| multinominal | 0.4357 | 0.4504 | 0.4671 | 0.4690 | 0.4872 | 0.5132 |
| random forest | 0.6974 | 0.7164 | 0.7280 | 0.7219 | 0.7289 | 0.7375 |
| SVM | 0.4042 | 0.4471 | 0.4586 | 0.4595 | 0.4789 | 0.5079 |
| lasso | 0.7297 | 0.7370 | 0.7447 | 0.7437 | 0.7495 | 0.7579 |
| ridge | 0.7297 | 0.7380 | 0.7464 | 0.7447 | 0.7495 | 0.7605 |
| elastic net | 0.4331 | 0.4517 | 0.4658 | 0.4674 | 0.4826 | 0.5132 |
| classification tree | 0.4514 | 0.4721 | 0.4816 | 0.4800 | 0.4852 | 0.5039 |

*Table. 3, resampled accuracy for ML algorithms trained by State data*

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| --- | --- | --- | --- | --- | --- | --- |
|  | **Min** | **1st Qu** | **Median** | **Mean** | **3rd Qu** | **Max** |
| multinominal | 0.4485 | 0.4639 | 0.5119 | 0.4985 | 0.5233 | 0.5401 |
| random forest | 0.6496 | 0.6667 | 0.6782 | 0.6768 | 0.6866 | 0.7044 |
| SVM | 0.4359 | 0.4656 | 0.4890 | 0.4864 | 0.5120 | 0.5328 |
| lasso | 0.6788 | 0.7014 | 0.7099 | 0.7079 | 0.7163 | 0.7436 |
| ridge | 0.6765 | 0.6932 | 0.7062 | 0.7054 | 0.7153 | 0.7473 |
| elastic net | 0.5803 | 0.6432 | 0.6545 | 0.6604 | 0.6933 | 0.7143 |
| classification tree | 0.1912 | 0.6273 | 0.6319 | 0.5880 | 0.6447 | 0.6520 |

*Table. 4, resampled accuracy for ML algorithms trained by local school district data.*

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*Figure. 1 (a and b), resampled accuracy for ML algorithms trained by State data (figure 1 (a) on the left) and local school district data (figure 1 (b) on the right).*

In analyzing state and local school district data, we compared the variable importance using the best-performed ML algorithm selected from Table 3 and Table 4. Table 5 listed the variable for each State with variable importance > 50. Each State shows a different pattern of variable importance. However, variables q17 about physical fights, q21 about dating forcing sex, q41 about alcohol drinking, q52 about heroin use, q53 methamphetamine use, and q89 school grade were observed in most of the States. Datasets of Iowa (IA), Nebraska (NE), and South Carolina (SC) have few than 8 observations for “Not sure” of outcome variable – Q85, which can lead to some bias in our model. Table 6 listed the variable for each State with variable importance > 10. Each local school district demonstrates a distinct pattern of variable importance. However, variables q17 about physical fights, q21 about dating forcing sex, q41 about alcohol drinking, q47 about marijuana, q52 about heroin use, q53 about methamphetamine use, and q89 school grade were observed in most of the local school districts. Datasets of Broward County, FL (FT), Genesee Consortium, MI (GE), and Los Angeles, CA (LO) have few than 8 observations for “Not sure” of outcome variable – Q85, which can lead to some bias in our model. In addition, datasets of Eaton Consortium, MI (EA), Newark, NJ (NW), and Shelby County, TN (ST) did not converge. Datasets of Broward County, FL (FT), Eaton Consortium, MI (EA), Fort Worth, TX (FW), Hillsborough County, FL (HL), Los Angeles, CA (LO), and Philadelphia, PA (PH) did not show any variables that have importance > 10.

To address the statistical issues that we encountered in applying the lasso and ridge regression algorithms to each State and local school district, we used the random forest method (3rd in accuracy, see Figure. 1 (a) and (b)) to analyze the variable importance for each State and local school district. Table. 7 show the top 3 important variables for each local school district. For the local school district data, BMI is the most important variable for all local school districts except Shelby County (S). Variables q41, q47, and q89 were about alcohol drinking, marijuana use, and school grade, which were the variables that appeared most often in the Table. 7. Based on Table. 8, the top 3 important variables for the State data include BMI, q41, q47, and q89, which were about alcohol drinking, marijuana use, and school grade. BMI is the most important variable associated with STI testing other than HIV for all States.

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| Table. 7, Top 3 important variables for each local school district using the Random Forest method. | | | | | | |
|  | **1st variable** | **variable importance** | **2nd variable** | **variable importance** | **3rd variable** | **variable importance** |
| Broward County, FL (FT) | bmi | 11.96 | q47 | 6.87 | q41 | 6.24 |
| Chicago, IL (CH) | bmi | 12.79 | q47 | 6.56 | q41 | 5.65 |
| Eaton Consortium, MI (EA) | bmi | 8 | q89 | 4.02 | race4 | 3.77 |
| Fort Worth, TX (FW) | bmi | 13.9 | q47 | 7.99 | q89 | 7.79 |
| Genesee Consortium, MI (GE) | bmi | 9,79 | q89 | 5.31 | age | 4.68 |
| Hillsborough County, FL (HL) | bmi | 10.93 | q47 | 9.95 | q17 | 6.99 |
| Los Angeles, CA (LO) | bmi | 7.72 | age | 3.02 | q41 | 2.8 |
| Newark, NJ (NW) | bmi | 10.14 | q47 | 7.64 | q89 | 5.24 |
| Orange County, FL (OL) | bmi | 7.52 | q89 | 4.05 | q47 | 3.61 |
| Palm Beach County, FL (PB) | bmi | 17.2 | q47 | 10.46 | q41 | 9.45 |
| Pasco County, FL (PS) | bmi | 12.13 | q47 | 6.41 | q17 | 5.58 |
| Philadelphia, PA (PH) | bmi | 11.15 | q89 | 8.22 | race4 | 7.61 |
| Portland, OR (PO) | bmi | 15.13 | age | 7.98 | q47 | 7.95 |
| San Francisco, CA (SF) | bmi | 15.11 | q89 | 9.05 | q47 | 7.83 |
| Shelby County, TN (ST) | q47 | 10.46 | bmi | 9.85 | q17 | 6.55 |

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| Table. 8, Top 3 important variables for each State using Random Forest method. | | | | | |  |
|  | **1st variable** | **variable importance** | **2nd variable** | **variable importance** | **3rd variable** | **variable importance** |
| Alabama (AL) | bmi | 16.94 | q89 | 9.14 | age | 8.66 |
| Arkansas (AR) | bmi | 16.24 | q47 | 8.06 | q41 | 7.34 |
| Iowa (IA) | bmi | 12.16 | q89 | 6.24 | q41 | 5.98 |
| Illionois (IL) | bmi | 26.05 | q47 | 12.65 | q89 | 12.06 |
| Kentucky (KY) | bmi | 19.83 | q89 | 10.32 | age | 8.68 |
| Michigan (MI) | bmi | 40.92 | q89 | 19.93 | q47 | 18.86 |
| Mississippi (MS) | bmi | 12.27 | q47 | 9.63 | q41 | 7.06 |
| Nebraska (NE) | bmi | 9.53 | q89 | 4.77 | q41 | 4.42 |
| Oklahoma (OK) | bmi | 19.05 | q41 | 10.67 | q89 | 9.43 |
| Pennsylvania (PA) | bmi | 24.66 | q89 | 13.9 | q41 | 13.29 |
| South Carolina (SC) | bmi | 6.8 | q47 | 4.91 | q89 | 4.41 |
| West Virginia (WV) | bmi | 18.95 | q89 | 11.28 | age | 8.48 |

**Discussion**

In this study, we examined the pattern of variable importance for each State and each local school district with the outcome - STI testing other than HIV using the best-performed ML method trained on the whole dataset of State and local school districts. We compare the performance of multinomial logistic regression, random forest, support vector machines (SVM), Elastic Net regression, ridge regression, lasso regression, and classification tree methods on the State and local school districts dataset. Based on the results and plot of “resamples,” we were able to know that the best-performed algorithm for State data is ridge regression (mean accuracy = 0.7447), and the best-performed algorithm for local school district data is lasso regression (mean accuracy = 0.7079). Considering the nature of the training data, the lasso and ridge algorithms have the best performance due to their ability to handle multicollinearity, feature scaling, and interpretability. Based on the ridge regression trained on the whole State data, we were able to reveal the pattern of variable importance for each State, which was different. The lasso regression trained on the whole local school data also demonstrated the distinct pattern of variable importance for each local school district. However, most of the States and local school districts share variables q17 about physical fights, q21 about dating forcing sex, q41 about alcohol drinking, q47 about marijuana, q52 about heroin use, q53 about methamphetamine use, and q89 school grade in common. It is not surprising for us to see the distinct patterns of variable importance because we have observed inequities across the United States in multiple fields, such as healthcare quality, social economics, health status, disease prevalence, and healthcare accessibility(Holowatyj et al., 2020; Merkt et al., 2021; Rowley, 2022; Wang et al., 2021). To address the statistical issues that we encountered in applying the lasso and ridge regression algorithms to each State and local school district, we used the random forest method (3rd in accuracy, see Figure. 1 (a) and (b)) to analyze the variable importance for each State and local school district. The random forest algorithm demonstrated different results from the lasso and ridge regression. The top 3 important variables for the State and local school district data include BMI, q41, q47, and q89, which were about alcohol drinking, marijuana use, and school grade. BMI is the most important variable for all States and all local school districts except Shelby County (SC). Although the random forest algorithm had slightly lower accuracy when compared with lasso and ridge regression trained on the whole dataset, the random forest provided more meaningful results.

Machine learning algorithms are widely used in explaining, predicting, or creating risk scores for many diseases or events, such as cardiovascular disease risk prediction, HIV/STI testing clinic attendance, Covid-19 severity, and diabetic kidney diseases(Alaa et al., 2019; Chan et al., n.d.; Chen et al., 2021; Xu et al., 2022). Previous studies only compared the performance of a few ML algorithms and risk factors on data collected at national levels. And limited studies accessed the importance of risk factors associated with STI testing. Our study has the advantage of comparing the performance of multiple ML algorithms on States and local school district data and applying the two different ML algorithms to each State and local school district to ensure accurate results. In addition, we assessed the performance of ML methods using accuracy and trained the ML algorithms on two datasets to enhance the model selection, validation, and generalizability. These approaches were particularly beneficial when analyzing imbalanced datasets with limited sample sizes and complex feature types, which may be less accurate when analyzed using traditional statistical methods. By using the ML algorithms, we provide a comprehensive understanding of important variables associated with the outcome – Q85 STI testing other than HIV for healthcare, education, social work, and government facilities. This information can help public health workers enhance STI testing by addressing important risk factors and identifying vulnerable populations. Ultimately, our findings can serve as a valuable resource for healthcare professionals, educators, social workers, and policymakers to improve STI prevention and treatment efforts.

The study has a few limitations. First, the ML algorithms were trained on the entire dataset and then applied to a subset of the data. This approach can lead to bias in the results, as the selected ML algorithm might not perform optimally on the specific subset. To address this problem, two ML methods were applied to different subsets of the data. One reason for using this approach is that we have limited computer performance. By training and applying multiple algorithms on smaller subsets, we can reduce the computational resources required while also mitigating the potential for bias by using more tailored models for each subset. Second, training time can depend on sample size, algorithms, computer performance, and the complexity of the feature. Limited training time can restrict model selection and tuning options, potentially affecting the overall performance of the chosen models. Third, the cross-sectional study design lacks the ability to establish a causal relationship between the outcome – STI testing other than HIV and risk factors. The future study can include longitudinal studies to enhance the understanding of causality better. Fourth, the measurement of ML algorithms’ performance is based on a single performance metric – accuracy, which may affect the viability of the ML method in a given situation. Additional performance metrics, such as precision, recall, kappa, and F1 score, could provide a more comprehensive evaluation. Fifth, the accuracies for the selected ML algorithms were all around 0.7, which indicated a strong performance. However, there is still significant room for improvement before these models can be deemed appropriate for public health use. Enhancing the performance of these models is crucial for practical applications. Sixty, even though the selected ML model provided meaningful insight into the pattern of important risk factors associated with STI testing across States and local school districts around the United States, there is potential for further improvement by incorporating additional data features. By refining the ML models and including more relevant information, we can achieve better performance and a more comprehensive understanding of the factors affecting STI testing.

Above all, the study successfully demonstrated that BMI, physical fights, dating sexual violence, alcohol drinking, marijuana use, heroin use, methamphetamine use, and school grade were the most important risk factors associated with STI testing other than HIV. Public health professionals can improve STI testing by addressing key risk factors and identifying susceptible populations with the use of this knowledge. Finally, our findings can help to improve STI prevention and treatment efforts by healthcare professionals, educators, social workers, and politicians. Furthermore, we compared the performance of the multiple ML algorithms on two datasets and showed the advantage of ML algorithms in solving complex public health challenges. Future research can benefit from using longitudinal data and cohort study designs. As we move into the post-Covid-19 pandemic stage, public health faces increasing threats and challenges from various aspects. As a powerful tool, the ML approach can aid in addressing these threats and challenges, ultimately improving public health outcomes, and promoting overall well-being.

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**Appendix**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Table. 1 Population characteristics of study population for States (n = 3,797)** | | | | | |
| **Participants’ characteristics** | **STI testing - Yes** | **STI testing - No** | **STI testing - Not sure** | **No. of participants** | **%** |
| **n (%)** | **n (%)** | **n (%)** |
| **Participants** | 768 (20.23) | 2820 (74.27) | 209 (5.5) | **3797** |  |
| **(Total = 3797)** |
| **sitename** (n=3797 participants) | |  |  |  |  |
| Alabama (AL) | 57 | 234 | 17 | 308 | 8.11% |
| Arkansas (AR) | 52 | 234 | 17 | 303 | 7.98% |
| Illinois (IL) | 94 | 286 | 18 | 398 | 10.48% |
| Iowa (IA) | 41 | 187 | 6 | 234 | 6.16% |
| Kentucky (KY) | 60 | 231 | 22 | 313 | 8.24% |
| Michigan (MI) | 152 | 395 | 34 | 581 | 15.30% |
| Mississippi (MS) | 42 | 207 | 14 | 263 | 6.93% |
| Nebraska (NE) | 30 | 163 | 8 | 201 | 5.29% |
| Oklahoma (OK) | 65 | 263 | 19 | 347 | 9.14% |
| Pennsylvania (PA) | 83 | 326 | 31 | 440 | 11.59% |
| South Carolina (SC) | 25 | 95 | 5 | 125 | 3.29% |
| West Virginia (WV) | 67 | 199 | 18 | 284 | 7.48% |
| **Sex** (n=3,797 participants) |  |  |  |  |  |
| Female | 502 (24.81) | 1431 (70.74) | 90 (4.45) | 2023 | 53.28% |
| Male | 266 (14.99) | 1389 (78.30) | 119 (6.71) | 1774 | 46.72% |
| **Age** (n=3,797 participants) | | | | | |
| 13 years old | NA | 5 | NA | 5 | 0.13% |
| 14 years old | 22 | 102 | 6 | 130 | 3.42% |
| 15 years old | 102 | 466 | 46 | 614 | 16.17% |
| 16 years old | 174 | 777 | 60 | 1011 | 26.63% |
| 17 years old | 289 | 898 | 64 | 1251 | 32.95% |
| ≥ 18 years | 181 | 572 | 33 | 786 | 20.70% |
| **Grade** (n=3797 participants) | | | | | |
| 9th grade | 87 (17.40) | 374 (74.80) | 39 (7.80) | 500 | 13.17% |
| 10th grade | 144 (17.04) | 656 (77.63) | 45 (5.33) | 845 | 22.25% |
| 11th grade | 253 (20.74) | 887 (72.70) | 80 (6.56) | 1220 | 32.13% |
| 12th grade | 284 (23.05) | 903 (73.30) | 45 (3.65) | 1232 | 32.45% |
| **Race** (n=3797 participants) |  |  |  |  |  |
| White | 433 (18.1) | 1827 (76.38) | 132 (5.52) | 2392 | 63.00% |
| Black or African American | 147 (26.97) | 366 (67.16) | 32 (5.87) | 545 | 14.35% |
| Hispanic/Latino | 119 (21.64) | 399 (72.55) | 32 (5.82) | 550 | 14.49% |
| All Other Races | 69 (22.26) | 228 (73.55) | 13 (4.19) | 310 | 8.16% |
| **Body mass index, BMI** (n=3797 participants)**,** | | | | | |
| Min 13.25 | 1st Quartile 20.62 | Median 22.89 | Mean 24.20 | 3rd Quartile 26.51 | Max 54.40 |
| **qnothhpl** (n=3797 participants) | |  |  |  |  |
| Yes | 384 (28.28) | 912 (67.16) | 62 (4.56) | 1358 | 35.77% |
| No | 384 (15.74) | 1908 (78.23) | 147 (6.03) | 2439 | 64.23% |
| **Q17** (n=3797patients) | |  |  |  |  |
| 0 times | 505 | 2033 | 143 | 2681 | 70.61% |
| 1 times | 106 | 371 | 25 | 502 | 13.22% |
| 2 or 3 times | 96 | 272 | 23 | 391 | 10.30% |
| 4 or 5 times | 23 | 65 | 8 | 96 | 2.53% |
| 6 or 7 times | 10 | 25 | 3 | 38 | 1.00% |
| 8 or 9 times | 6 | 14 | 1 | 21 | 0.55% |
| 10 or 11 times | 4 | 4 | NA | 8 | 0.21% |
| 12 or more times | 18 | 36 | 6 | 60 | 1.58% |
| **Q21** (n=3797 participants) | |  |  |  |  |
| No date or go out with anyonw during the past 12 months | 63 | 222 | 18 | 303 | 7.98% |
| 0 times | 641 | 2412 | 178 | 3231 | 85.09% |
| 1 times | 27 | 81 | 4 | 112 | 2.95% |
| 2 or 3 times | 22 | 61 | 7 | 90 | 2.37% |
| 4 or 5 times | 4 | 25 | NA | 29 | 0.76% |
| 6 or more times | 11 | 19 | 2 | 32 | 0.84% |
| **Participant’s characteristics** | **Pneumonia** | **Pneumonia** | **Non- pneumonia** | **No. of patients** | **%** |
| **n (%)** | **n (%)** | **n (%)** |
| **Q23** (n=3797patients) | |  |  |  |  |
| Yes | 205 | 580 | 56 | 841 | 22.15% |
| No | 563 | 2240 | 153 | 2956 | 77.85% |
| **Q26** (n=3797 participants) | |  |  |  |  |
| Yes | 242 | 659 | 45 | 946 | 24.91% |
| No | 526 | 2161 | 164 | 2851 | 75.09% |
| **Q30** (n=3797patients) | |  |  |  |  |
| Yes | 397 | 1127 | 106 | 1630 | 42.93% |
| No | 371 | 1693 | 103 | 2167 | 57.07% |
| **Q41** (n=3797 participants) | |  |  |  |  |
| 0 days | 387 | 1532 | 110 | 2029 | 53.44% |
| 1 or 2 days | 169 | 654 | 50 | 873 | 22.99% |
| 3 to 5 days | 106 | 311 | 26 | 443 | 11.67% |
| 6 to 9 days | 54 | 185 | 8 | 247 | 6.51% |
| 10 to 19 days | 34 | 103 | 11 | 148 | 3.90% |
| 20 to 29 days | 7 | 21 | 2 | 30 | 0.79% |
| All 30 days | 11 | 14 | 2 | 27 | 0.71% |
| **Q47** (n=3797patients) | |  |  |  |  |
| 0 times | 419 | 1912 | 138 | 2469 | 65.03% |
| 1 or 2 times | 96 | 310 | 20 | 426 | 11.22% |
| 3 or 9 times | 76 | 221 | 15 | 312 | 8.22% |
| 10 to 19 times | 49 | 131 | 13 | 193 | 5.08% |
| 20 to 39 times | 44 | 93 | 8 | 145 | 3.82% |
| 40 or more times | 84 | 153 | 15 | 252 | 6.64% |
| **Q49** (n=3797 participants) | |  |  |  |  |
| 0 times | 559 | 2316 | 157 | 3032 | 79.85% |
| 1 or 2 times | 75 | 235 | 13 | 323 | 8.51% |
| 3 to 9 times | 49 | 126 | 20 | 195 | 5.14% |
| 10 to 19 times | 36 | 59 | 2 | 97 | 2.55% |
| 20 to 39 times | 18 | 43 | 8 | 69 | 1.82% |
| 40 or more times | 31 | 41 | 9 | 81 | 2.13% |
| **Q50** (n=3797patients) | |  |  |  |  |
| 0 times | 693 | 2713 | 195 | 3601 | 94.84% |
| 1 or 2 times | 32 | 66 | 3 | 101 | 2.66% |
| 3 or 9 times | 20 | 18 | 6 | 44 | 1.16% |
| 10 to 19 times | 11 | 10 | 3 | 24 | 0.63% |
| 20 to 39 times | 2 | 3 | 1 | 6 | 0.16% |
| 40 or more times | 10 | 10 | 1 | 21 | 0.55% |
| **Q52** (n=3797 participants) | |  |  |  |  |
| 0 times | 750 | 2797 | 206 | 3753 | 98.84% |
| 1 or 2 times | 9 | 11 | 2 | 22 | 0.58% |
| 3 to 9 times | 1 | 2 | NA | 3 | 0.08% |
| 10 to 19 times | 1 | 1 | NA | 2 | 0.05% |
| 20 to 39 times | NA | 2 | NA | 2 | 0.05% |
| 40 or more times | 7 | 7 | 1 | 15 | 0.40% |
| **Q53** (n=3797patients) | |  |  |  |  |
| 0 times | 738 | 2788 | 204 | 3730 | 98.24% |
| 1 or 2 times | 11 | 15 | 1 | 27 | 0.71% |
| 3 or 9 times | 3 | 4 | 3 | 10 | 0.26% |
| 10 to 19 times | 4 | 3 | NA | 7 | 0.18% |
| 20 to 39 times | 2 | 1 | NA | 3 | 0.08% |
| 40 or more times | 10 | 9 | 1 | 20 | 0.53% |
| **Q63** (n=3797 participants) | |  |  |  |  |
| Yes | 321 | 1558 | 120 | 1999 | 52.65% |
| No | 447 | 1262 | 89 | 1798 | 47.35% |
| **Q65** (n=3797patients) | |  |  |  |  |
| Female | 255 | 1369 | 117 | 1741 | 45.85% |
| Males | 418 | 1269 | 74 | 1761 | 46.38% |
| Female and males | 95 | 182 | 18 | 295 | 7.77% |
| **Q84** (n=3797 participants) | |  |  |  |  |
| Yes | 532 | 182 | 25 | 739 | 19.46% |
| No | 172 | 2477 | 27 | 2676 | 70.48% |
| Not sure | 64 | 161 | 157 | 382 | 10.06% |
| **Q87** (n=3797patients) | |  |  |  |  |
| Yes | 233 | 659 | 53 | 945 | 24.89% |
| No | 497 | 2085 | 136 | 2718 | 71.66% |
| Not sure | 38 | 76 | 20 | 134 | 3.53% |
| **Q89** (n=3797 participants) | |  |  |  |  |
| Mostly A's | 245 | 1118 | 63 | 1426 | 37.56% |
| Mostly B's | 274 | 1036 | 85 | 1395 | 36.74% |
| Mostly C's | 162 | 465 | 40 | 667 | 17.57% |
| Mostly D's | 42 | 94 | 11 | 147 | 3.87% |
| Mostly F's | 13 | 35 | 2 | 50 | 1.32% |
| None of these grades | 2 | 9 | NA | 11 | 0.29% |
| Not sure | 30 | 63 | 8 | 101 | 2.66% |

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Table. 2 Population characteristics of study population for local school district(n = 2723)** | | | | | |
| **Participants’ characteristics** | **STI testing - Yes** | **STI testing - No** | **STI testing - Not sure** | **No. of participants** | **%** |
| **n (%)** | **n (%)** | **n (%)** |
| **Participants** | 713(26.18) | 1843(67.68) | 167(6.13) | **2723** |  |
| **(Total = 3797)** |
| **sitename** (n=3797 participants) | |  |  |  |  |
| Broward County, FL (FT) | 48 | 113 | 6 | 167 | 6.13% |
| Chicago, IL (CH) | 48 | 98 | 11 | 157 | 5.77% |
| Eaton Consortium, MI (EA) | 21 | 99 | 9 | 129 | 4.74% |
| Fort Worth, TX (FW) | 45 | 174 | 18 | 237 | 8.70% |
| Genesee Consortium, MI (GE) | 38 | 120 | 8 | 166 | 6.10% |
| Hillsborough County, FL (HL) | 37 | 196 | 14 | 247 | 9.07% |
| Los Angeles, CA (LO) | 26 | 79 | 4 | 109 | 4.00% |
| Newark, NJ (NW) | 40 | 87 | 13 | 140 | 5.14% |
| Orange County, FL (OL) | 22 | 92 | 9 | 123 | 4.52% |
| Palm Beach County, FL (PB) | 58 | 224 | 23 | 305 | 11.20% |
| Pasco County, FL (PS) | 37 | 151 | 9 | 197 | 7.23% |
| Philadelphia, PA (PH) | 102 | 59 | 10 | 171 | 6.28% |
| Portland, OR (PO) | 76 | 128 | 9 | 213 | 7.82% |
| San Francisco, CA (SF) | 73 | 116 | 14 | 203 | 7.46% |
| Shelby County, TN (ST) | 42 | 107 | 10 | 159 | 5.84% |
| **Sex** (n=3797 participants) | | | | | |
| Female | 463 | 940 | 78 | 1481 | 54.39% |
| Male | 250 | 903 | 89 | 1242 | 45.61% |
| **Age** (n=3,797 participants) | | | | | |
| 14 years old | 19 | 81 | 11 | 111 | 4.08% |
| 15 years old | 82 | 313 | 25 | 420 | 15.42% |
| 16 years old | 180 | 496 | 52 | 728 | 26.74% |
| 17 years old | 281 | 612 | 50 | 943 | 34.63% |
| ≥ 18 years | 151 | 341 | 29 | 521 | 19.13% |
| **Grade** (n=3797 participants) | | | | | |
| 9th grade | 51 | 197 | 27 | 275 | 10.10% |
| 10th grade | 129 | 441 | 39 | 609 | 22.37% |
| 11th grade | 238 | 534 | 50 | 822 | 30.19% |
| 12th grade | 295 | 671 | 51 | 1017 | 37.35% |
| **Race** (n=3797 participants) |  |  |  |  |  |
| White | 166 | 606 | 44 | 816 | 29.97% |
| Black or African American | 194 | 353 | 32 | 579 | 21.26% |
| Hispanic/Latino | 271 | 686 | 76 | 1033 | 37.94% |
| All Other Races | 82 | 198 | 15 | 295 | 10.83% |
| **Body mass index, BMI** (n=3797 participants)**,** | | | | | |
| Min 13.58 | 1st Quartile 20.38 | Median 22.49 | Mean 23.64 | 3rd Quartile 25.72 | Max 58.89 |
| **qnothhpl** (n=3797 participants) | |  |  |  |  |
| Yes | 285 | 405 | 42 | 732 | 26.88% |
| No | 428 | 1438 | 125 | 1991 | 73.12% |
| **Q17** (n=3797patients) | |  |  |  |  |
| 0 times | 467 | 1334 | 143 | 1905 | 69.96% |
| 1 times | 86 | 231 | 25 | 344 | 12.63% |
| 2 or 3 times | 92 | 179 | 23 | 296 | 10.87% |
| 4 or 5 times | 29 | 55 | 8 | 89 | 3.27% |
| 6 or 7 times | 10 | 17 | 3 | 28 | 1.03% |
| 8 or 9 times | 4 | 8 | 1 | 13 | 0.48% |
| 10 or 11 times | 7 | 3 | NA | 10 | 0.37% |
| 12 or more times | 18 | 16 | 4 | 38 | 1.40% |
| **Q21** (n=3797 participants) | |  |  |  |  |
| No date or go out with anyonw during the past 12 months | 55 | 171 | 13 | 239 | 8.78% |
| 0 times | 588 | 1559 | 145 | 2292 | 84.17% |
| 1 times | 33 | 54 | 4 | 91 | 3.34% |
| 2 or 3 times | 24 | 2713 | 4 | 55 | 2.02% |
| 4 or 5 times | 4 | 13 | NA | 17 | 0.62% |
| 6 or more times | 9 | 19 | 1 | 29 | 1.07% |
|  |  |  |  |  |  |
| **Table. 2 Population characteristics of study population from states (n = 3,797)** | | | | | |
| **Participant’s characteristics** | **Pneumonia** | **Pneumonia** | **Non- pneumonia** | **No. of patients** | **%** |
| **n (%)** | **n (%)** | **n (%)** |
| **Q23** (n=3797patients) | |  |  |  |  |
| Yes | 122 | 266 | 22 | 410 | 15.06% |
| No | 591 | 1577 | 145 | 2313 | 84.94% |
| **Q26** (n=3797 participants) | |  |  |  |  |
| Yes | 192 | 412 | 43 | 647 | 23.76% |
| No | 521 | 1431 | 124 | 2076 | 76.24% |
| **Q30** (n=3797patients) | |  |  |  |  |
| Yes | 223 | 492 | 59 | 774 | 28.42% |
| No | 490 | 1351 | 108 | 1949 | 71.58% |
| **Q41** (n=3797 participants) | |  |  |  |  |
| 0 days | 375 | 1055 | 101 | 1531 | 56.22% |
| 1 or 2 days | 152 | 405 | 32 | 589 | 21.63% |
| 3 to 5 days | 101 | 222 | 17 | 340 | 12.49% |
| 6 to 9 days | 50 | 94 | 10 | 154 | 5.66% |
| 10 to 19 days | 26 | 51 | 6 | 83 | 3.05% |
| 20 to 29 days | 5 | 10 | NA | 15 | 0.55% |
| All 30 days | 4 | 6 | 1 | 11 | 0.40% |
| **Q47** (n=3797patients) | |  |  |  |  |
| 0 times | 371 | 1109 | 93 | 1573 | 57.77% |
| 1 or 2 times | 108 | 239 | 25 | 372 | 13.66% |
| 3 or 9 times | 75 | 201 | 16 | 292 | 10.72% |
| 10 to 19 times | 51 | 100 | 11 | 162 | 5.95% |
| 20 to 39 times | 49 | 83 | 12 | 144 | 5.29% |
| 40 or more times | 59 | 111 | 10 | 180 | 6.61% |
| **Q49** (n=3797 participants) | |  |  |  |  |
| 0 times | 570 | 1490 | 130 | 2190 | 80.43% |
| 1 or 2 times | 48 | 165 | 17 | 230 | 8.45% |
| 3 to 9 times | 39 | 91 | 6 | 136 | 4.99% |
| 10 to 19 times | 27 | 44 | 6 | 77 | 2.83% |
| 20 to 39 times | 10 | 19 | 1 | 30 | 1.10% |
| 40 or more times | 19 | 34 | 7 | 60 | 2.20% |
| **Q50** (n=3797patients) | |  |  |  |  |
| 0 times | 654 | 1756 | 161 | 2571 | 94.42% |
| 1 or 2 times | 23 | 55 | 3 | 81 | 2.97% |
| 3 or 9 times | 22 | 24 | 2 | 48 | 1.76% |
| 10 to 19 times | 4 | 3 | 1 | 8 | 0.29% |
| 20 to 39 times | 5 | 1 | NA | 6 | 0.22% |
| 40 or more times | 5 | 4 | NA | 9 | 0.33% |
| **Q52** (n=3797 participants) | |  |  |  |  |
| 0 times | 702 | 1826 | 167 | 2695 | 98.97% |
| 1 or 2 times | 2 | 10 | NA | 12 | 0.44% |
| 3 to 9 times | 2 | 1 | NA | 3 | 0.11% |
| 10 to 19 times | 3 | 3 | NA | 6 | 0.22% |
| 20 to 39 times | 1 | NA | NA | 1 | 0.04% |
| 40 or more times | 3 | 3 | NA | 6 | 0.22% |
| **Q53** (n=3797patients) | |  |  |  |  |
| 0 times | 694 | 1824 | 164 | 2682 | 98.49% |
| 1 or 2 times | 6 | 11 | 3 | 20 | 0.73% |
| 3 or 9 times | 4 | 1 | NA | 5 | 0.18% |
| 10 to 19 times | NA | 1 | NA | 1 | 0.04% |
| 20 to 39 times | 6 | 1 | NA | 7 | 0.26% |
| 40 or more times | 3 | 5 | NA | 8 | 0.29% |
| **Q63** (n=3797 participants) | |  |  |  |  |
| Yes | 323 | 1093 | 92 | 1508 | 55.38% |
| No | 390 | 750 | 75 | 1215 | 44.62% |
| **Q65** (n=3797patients) | |  |  |  |  |
| Female | 234 | 909 | 90 | 1233 | 45.28% |
| Males | 387 | 767 | 69 | 1223 | 44.91% |
| Female and males | 92 | 167 | 8 | 267 | 9.81% |
| **Q84** (n=3797 participants) | |  |  |  |  |
| Yes | 512 | 162 | 31 | 705 | 25.89% |
| No | 151 | 1559 | 28 | 1738 | 63.83% |
| Not sure | 50 | 122 | 108 | 280 | 10.28% |
| **Q87** (n=3797patients) | |  |  |  |  |
| Yes | 210 | 437 | 36 | 683 | 25.08% |
| No | 471 | 1343 | 120 | 1934 | 71.02% |
| Not sure | 32 | 63 | 11 | 106 | 3.89% |
| **Q89** (n=3797 participants) | |  |  |  |  |
| Mostly A's | 235 | 593 | 43 | 871 | 31.99% |
| Mostly B's | 259 | 743 | 60 | 1062 | 39.00% |
| Mostly C's | 132 | 344 | 42 | 518 | 19.02% |
| Mostly D's | 35 | 61 | 8 | 104 | 3.82% |
| Mostly F's | 22 | 23 | 5 | 50 | 1.84% |
| None of these grades | 4 | 9 | 1 | 14 | 0.51% |
| Not sure | 26 | 70 | 8 | 104 | 3.82% |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Table. 5 variable importance table for each State, variable importance > 50** | | | |  |  |  |
|  | **Class 1** | **Importance value for class 1** | **Class 2** | **Importance value for class 2** | **Class 3** | **Importance value for class 3** |
| Alabama (AL) | Q53-2 | 100 | Q53-2 | 88.54 | Q17-6 | 92.06 |
|  | Q89-6 | 65.18 | Q49-6 | 76.45 |  |  |
|  | Q41-7 | 65.18 | Q50-2 | 56.33 |  |  |
|  | Q52-2 | 65.18 | Q87-3 | 54.83 |  |  |
|  | Q89-7 | 54.94 | Q89-6 | 53.76 |  |  |
|  | Q49-4 | 54.94 | Q41-7 | 53.76 |  |  |
|  |  |  | Q52-2 | 53.76 |  |  |
|  |  |  | Q41-6 | 50.05 |  |  |
|  |  |  | Q21-4 | 50.05 |  |  |
| Arkansas (AR) | Q49-4 | 77.58 | Q21-5 | 66.16 | Q17-4 | 100 |
|  | Age-3 | 75.46 | Q47-6 | 64.62 | Q87-3 | 65.01 |
|  | Q89-4 | 73.72 | Q89-6 | 63.5 | Q17-5 | 54.31 |
|  | Q52-2 | 56.12 | Q41-7 | 63.41 | Q21-4 | 53.98 |
|  | Q17-4 | 54.61 | Q89-5 | 62.92 |  |  |
|  | Q89-6 | 53.23 | Q17-5 | 62.73 |  |  |
|  | Q41-7 | 53.12 |  |  |  |  |
|  | Q21-5 | 51.72 |  |  |  |  |
|  | Q50-2 | 50.71 |  |  |  |  |
| Illinois (IL) | Q17-7 | 100 | Q17-7 | 90.57 |  |  |
|  | Q41-6 | 64.66 | Q41-6 | 57.7 |  |  |
|  | Q49-4 | 54.71 | Q41-7 | 56.11 |  |  |
| Iowa (IA) | Q52-2 | 100 | Q52-2 | 96.89 |  |  |
|  | Q17-8 | 100 | Q17-8 | 96.89 |  |  |
|  | Q17-6 | 100 | Q17-6 | 96.89 |  |  |
|  | Q53-2 | 100 | Q53-2 | 96.89 |  |  |
|  | Q41-7 | 70.46 | Q41-7 | 67.31 |  |  |
|  | Q65-4 | 51.7 | Q65-4 |  |  |  |
| Kentucky (KY) | Q53-2 | 64.57 | Q41-6 | 100 | Q41-6 | 58.23 |
|  |  |  | Q53-2 | 55.01 |  |  |
| Michigan (MI) | Q41-7 | 94.99 | Q17-7 | 87.18 | Q89-6 | 100 |
|  | Q89-6 | 75.8 | Q41-7 | 81.42 | Q17-6 | 89.65 |
|  | Q17-7 | 70.84 | Q41-6 | 79.99 | Q49-5 | 53.1 |
|  | Q53-2 | 67.19 | Q49-6 | 69.25 |  |  |
|  | Q17-6 | 67.03 | Q17-5 | 69.04 |  |  |
|  | Q41-6 | 63.84 | Q21-5 | 60.12 |  |  |
|  | Q17-5 | 51.84 | Q21-6 | 57.52 |  |  |
|  | Q52-2 | 51.78 | Q49-5 | 54.49 |  |  |
| Mississippi (MS) | Q21-6 | 86.85 | Q49-5 | 100 | Q41-5 | 77.47 |
|  | Q89-4 | 72.19 | Q21-5 | 94.54 | Q17-7 | 66.41 |
|  | Q47-6 | 69.18 | Q89-4 | 88.2 |  |  |
|  | Q52-2 | 67.35 | Q17-8 | 76.14 |  |  |
|  | Q21-5 | 63.89 | Q47-5 | 70.18 |  |  |
|  | Q41-6 | 63.06 | Q89-6 | 69.33 |  |  |
|  | Q17-4 | 62.48 | Q47-6 | 63.93 |  |  |
|  | Q49-6 | 60.37 | Q87-3 | 60.37 |  |  |
| Nebraska (NE) | Q41-6 | 94.32 | Q17-8 | 100.00 | Q17-8 | 81.22 |
|  | Q47-5 | 78.55 | Q41-6 | 85.21 | Q89-7 | 76.66 |
|  | Q17-5 | 59.37 | Q87-3 | 79.09 | Q7-3 | 61.62 |
|  | Q21-4 | 56.70 | Q47-5 | 66.80 | Q41-7 | 55.38 |
|  |  |  | Q89-7 | 55.47 |  |  |
|  |  |  | Q17-5 | 52.82 |  |  |
| Oklahoma (OK) | Q17-6 | 100.00 | Q17-6 | 81.70 | Q89-4 | 50.82 |
|  | Q17-7 | 53.65 | Q17-8 | 64.25 |  |  |
|  |  |  | Q89-4 | 58.23 |  |  |
|  |  |  | Q17-5 | 53.24 |  |  |
| Pennsylvania (PA) | q17-7 | 100.00 | q17-7 | 81.69 | q21-6 | 60.65 |
|  | q21-6 | 58.17 | q17-6 | 72.77 | q50-2 | 50.22 |
|  | q17-6 | 55.77 | q89-5 | 70.93 |  |  |
|  | q89-5 | 53.65 | q49-5 | 61.95 |  |  |
|  |  |  | q50-2 | 55.79 |  |  |
|  |  |  | q17-5 | 55.61 |  |  |
| South Carolina (SC) | q17-6 | 100.00 | q17-6 | 94.06 |  |  |
|  | q52-2 | 59.37 | q52-2 | 53.33 |  |  |
|  | q17-8 | 51.76 |  |  |  |  |
|  | q50-2 | 51.76 |  |  |  |  |
| West Virginia (WV) | q89-7 | 100.00 | q89-7 | 84.34 | q49-5 | 65.77 |
|  | q89-6 | 93.99 | q89-6 | 80.94 |  |  |
|  | q17-6 | 57.84 | q17-6 | 69.58 |  |  |
|  | q49-5 | 56.82 |  |  |  |  |

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Table. 6 variable importance table for each local school district, variable importance > 10** | | | | | |  |
|  | **Class 1** | **Importance value for class 1** | **Class 2** | **Importance value for class 2** | **Class 3** | **Importance value for class 3** |
| Broward County, FL (FT) | None | 0 | None | 0 | None | 0 |
| Chicago, IL (CH) | q49-4 | 100 | q41-4 | 15.28 | None | 0 |
| Eaton Consortium, MI (EA) | None | 0 | None | 0 | None | 0 |
| Fort Worth, TX (FW) | None | 0 | None | 0 | None | 0 |
| Genesee Consortium, MI (GE) | q17-7 | 100.00 | q49-6 | 72.61 | q49-4 | 43.78 |
|  | q53-2 | 89.72 | q41-5 | 72.05 | q17-4 | 22.79 |
|  | q21-3 | 72.04 | q17-5 | 42.66 |  |  |
|  | q21-5 | 67.37 | q89-4 | 39.12 |  |  |
|  | q87-2 | 35.14 | q41-4 | 33.77 |  |  |
|  | q65-4 | 34.62 | qnothhpl-2 | 32.85 |  |  |
|  | q23-2 | 31.05 | q41-2 | 32.56 |  |  |
|  | q49-4 | 18.93 | q49-3 | 27.81 |  |  |
|  | q17-2 | 18.34 | q89-7 | 27.60 |  |  |
|  | grade-2 | 16.36 | q47-4 | 25.29 |  |  |
|  |  |  | q49-2 | 25.03 |  |  |
|  |  |  | q47-2 | 21.74 |  |  |
|  |  |  | q52-2 | 18.98 |  |  |
| Hillsborough County, FL (HL) | None | 0 | None | 0 | None | 0 |
| Los Angeles, CA (LO) | None | 0 | None | 0 | None | 0 |
| Newark, NJ (NW) | qnothhpl-2 | 23.34 | q47-6 | 100.00 | q87-3 | 82.23 |
|  | q49-4 | 10.09 |  |  |  |  |
| Orange County, FL (OL) | qnothhpl2 | 36.47 | q213 | 76.12 | q896 | 100.00 |
|  | q895 | 34.02 | q474 | 35.63 | q474 | 21.83 |
|  | q654 | 25.25 | q475 | 24.85 | q872 | 16.35 |
|  | q633 | 22.42 | q496 | 16.33 |  |  |
|  | age6 | 13.31 | race43 | 11.22 |  |  |
| Palm Beach County, FL (PB) | qnothhpl-2 | 10.67 | q21-4 | 100.00 | q17-6 | 30.71 |
|  |  |  | q17-6 | 57.22 | q87-2 | 18.93 |
|  |  |  | q49-6 | 36.09 | q47-2 | 11.51 |
|  |  |  | q63-3 | 22.22 |  |  |
|  |  |  | q89-4 | 20.08 |  |  |
|  |  |  | q17-4 | 19.50 |  |  |
|  |  |  | q89-7 | 17.55 |  |  |
|  |  |  | q53-2 | 12.42 |  |  |
| Pasco County, FL (PS) | q17-8 | 100.00 | qnothhpl-2 | 14.87 | q47-5 | 74.58 |
|  | q49-3 | 17.75 | q50-2 | 14.04 |  |  |
|  | sex-2 | 17.38 |  |  |  |  |
|  | grade-4 | 12.55 |  |  |  |  |
|  | q30-2 | 10.61 |  |  |  |  |
| Philadelphia, PA (PH) | None | 0.00 | None | 0.00 | None | 0.00 |
| Portland, OR (PO) | qnothhpl-2 | 90.60 | age-7 | 100.00 | None | 0.00 |
|  | sex-2 | 75.05 | grade-2 | 95.15 |  |  |
| San Francisco, CA (SF) | q17-8 | 92.36 | qnothhpl-2 | 70.66 | q49-2 | 100.00 |
|  | q41-5 | 85.03 | q30-2 | 44.69 |  |  |
|  | q47-4 | 42.31 | age-4 | 42.26 |  |  |
|  | q17-5 | 40.17 | q49-5 | 33.95 |  |  |
|  | age-6 | 15.93 | q65-3 | 21.01 |  |  |
|  | age-4 | 15.75 | q21-2 | 19.26 |  |  |
|  | q87-3 | 12.80 |  |  |  |  |
| Shelby County, TN (ST) | q17-6 | 86.44 | q47-2 | 41.69 | q21-6 | 100.00 |
|  | q41-4 | 78.60 | q89-7 | 25.18 | q17-8 | 41.63 |
|  | sex-2 | 18.16 | race4-2 | 23.41 |  |  |
|  | q47-3 | 15.50 | q47-3 | 13.75 |  |  |