Impact of Income on Student Achievement

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***Abstract* - Education is a fundamental human right and is an important factor in achieving economic and social development. [1] The quality of education and school scores may be influenced by a variety of factors, but for the sake of this project, we wish to determine whether or not resident wealth is a primary determinant. A standard score based on Standardized testing is used as a measure of educational achievement. Using standard scores, average County Income is a key determinant of educational achievement whereas Expenditures per Pupil is not. The impact of higher income counties on academic achievement is not related to they generate in the tax system or ability to fund a school system.**

Index Terms - Education, Income.

I. Introduction

Education is a fundamental human right and an important factor in achieving economic and social development. Yet, there are frequently disparities in the quality of education, with some places having schools that score higher and others scoring lower. The quality of education and school scores may be influenced by a variety of factors, but for the sake of this project, we wish to determine whether or not resident wealth is a primary determinant. Public schools in Virginia rely on a combination of state, local, and federal funding to provide education services to their students. Even though both federal and state governments have a formula to distribute state and federal funding, local funding relies on local taxes, such as property taxes and sales taxes. This indicates schools in high income areas have a higher local funding and schools from low income areas will have a lower local funding. The impact of income may not be limited to local funding; it may be a perpetual cause for other factors which affect the quality of education.

A. Background and Motivation

This project aims to examine the impact of income on education quality at the county level in Virginia. We will gather and examine data from numerous sources, including the Virginia Department of Education, the U.S. Census Bureau, and other publicly accessible datasets, in order to accomplish this purpose. In this study, while controlling for other pertinent characteristics including race, ethnicity, family structure, and family's educational background, we will apply statistical analysis tools to find correlations and causal links between income and education quality indicators.

The findings of this project can have important implications for policymakers, educators, and parents in Virginia. Identifying the impact of income and other factors that contribute to education inequality is important to improve policies and programs so that all students will have the same quality education regardless of income or their background.

Quality education has a significant impact on earning potential and therefore if higher incomes lead to better schools, then this will perpetuate income inequality.

B. Problem Statement

The relationship between income and school quality is a complex and multifaceted issue. The project is aimed to identify this relationship and also, we want to identify other factors which lead to poor school quality. Finally, we want to visualize the impact of poor school quality on students and society. In this project, we will answer the following questions.

- How does the income of society affect the education quality of schools?
- Identify the racial distribution of those counties that have lower and higher quality education. How does this distribution relate to the income of society and the quality of education?
- Which county's schools have a higher and lower number of high school dropouts?
- Which race has a higher high school dropout rate?
- Do higher expenditures for Public Elementary and Secondary Schools per Pupil of a county mean a higher education quality is in a county?

C. Related Work

Two different types of literature searches were performed. The first was on Google Scholar to determine if the topic has been addressed in academic research.

Raymond[1] research in the Journal of Human Resources indicates that teacher salary does have some impact on the overall quality of education but the assessment of education quality is difficult. Also this article was published in 1968 and while many of the results may be valid, much has changed since 1968. This study follows many others on the impact of teachers and teacher pay on the quality of education. There were also a number of articles that discussed the impact of quality education on economic impact. Overall, articles that dealt with this topic were not easily found.

There were a number of papers that discussed the equity of school funding. School finance reform, the distribution of school spending, and the distribution of student test scores paper reviews the data to determine the impact of school finance reform on the equity of test scores [2]. While this is very similar to our question, the focus of this paper is to look at the legislative environment and determine if equity of test scores is improved with legislative reform. As a side effect of this analysis, the team was not able to find a strong correlation between income and test scores but this may have been impacted by the methodology that is based around the impact of school finance reform.

School Finance Reform and the Distribution of Student Achievement paper tracked the impact of financial increases in districts over time [9]. This was in response to legal changes to school funding. Overall they found that there is an impact of school funding on student performance but the impact takes years to take hold but does eventually impact the student results.

Funding and Student Achievement: an Empirical Analysis attempts to answer a very similar question.[10] This paper is from 1981 and more than 40 years old but does find some correlation between income and school achievement but much has changed in the last 40 years including availability of data.

The relationship between School Funding and Student Achievement in Kansas Public Schools looks at relative student achievement changes after funding changes in 1997. [7] The paper, from 2010, found a weak correlation between income and student achievement but they specifically wanted to find the impact of increase in funding that occurred in 1997 over the period from 1997 to 2006.

In journal articles, there are a number of studies of teacher and student characteristics and student achievement. In reviewing these articles, the articles related to student characteristics provided an interesting observation. In the paper Does peer ability affect student achievement? The potential impact of a student's peer group impact on achievement is studied. [5] They find that higher expectations in peer groups leads to higher student achievement. The implication is that higher incomes lead to higher expectations and thus higher achievement.

In a web search, there were a number of articles that discussed the low level of overall funding for Virginia schools and related them to some of the potentially negative outcomes.

The commonwealth institute [3] has performed a review of Virginia education funding with respect to other states and found it to be lacking. Both the potential impacts of low funding and differential funding between high and low-income areas were discussed; there is no analysis to determine if a real outcome difference is visible.

Similarly, the Washington Post's Barbara Favola [4] has published an article highlighting the differences in education funding but the results are not analyzed but rather listed as a set of potential impacts.

An organization called the VAOurWay, published an article [11] once again discussing the low funding levels in Virginia schools and discussed the many impacts of low and differential funding but no analysis was performed to determine if the difference was actually apparent. Not much information could be found about the VA Our Way organization and while it is a 501C3 charity, charity rating websites do not provide a rating for this organization.

It is clear from these articles that education funding is highly political, and internet reporting is colored by political points of view.

II. Data Collection and Preprocessing

A.Data Sources and Variables

There were two main data sets used in this analysis. County School Score and Income and the Schooldigger data set. The income and expenditures were sourced from the County School Score and Income data set where other features were sourced from the school digger data set.

County School Score and Income: This data source was used in a study to assess school district equality but is a quality data source for this analysis.[6] This data set was in turn based on the U.S. Census Bureau and the National Center for Education Statistics. While the study was published in 2022 it does not indicate the year the source data was collected. The data set is available at the following URL and contains the features listed in Table I.. https://wallethub.com/edu/e/most-least-equitable-school-districts-in-virginia/77140.

TABLE I

County School Score and Income

Feature	Type	Description
Rank	Ordinal	The rank of the school in this list
School County	Nominal	The county name of the school district
Score	Continuous	Score of the school county
Expenditure For Schools Per Pupil	Continuous	Average expenditure per student
Income by School County	Continuous	Average family income within the county

SchoolDigger: This data was found on a website that provides parents information on schools in the United States with each state having a specific dataset. This data set is based on many of the same data sources as listed above but provides these in a single data source. The school digger data set can be acquired through the following web site. The data set contains information from 1108 Virginia primary, middle and high schools. Figure IV provides the features provided by the school digger data set for Virginia. https://schoolquality.virginia.gov/download-data

TABLE II
PUPIL DIPLOMA AND GRADUATION

Feature	Type	Description
Rank (2021-22)	Ordinal	The rank of the school in this list
School	Nominal (Categorica)	The county name of the school district
School URL	Nominal (Categorica)	The name of the school.
District	Nominal (Categorica)	District Name
District URL	Nominal (Categorica)	District URL
Address	Nominal (Categorica)	School Address
City	Nominal (Categorica)	School City
City URL	Nominal (Categorica)	School City URL
Zip	Nominal (Categorica)	School ZIP code
County	Nominal (Categorica)	School County
Phone	Nominal (Categorica)	School Phone Number
Low Grade	Interval/Ratio (Quantitative)	Lowest Grade Level Taught at this school
High Grade	Interval/Ratio (Quantitative)	Highest Grade Level Taught at this school
Is Title I	Nominal (Categorica)	Yes if this school is a Title I school. No otherwise.
Is Charter	Nominal (Categorica)	Yes if this school is a Charter school. No otherwise.
Is Magnet	Nominal (Categorica)	Yes if this school is a Magnet school. No otherwise.
Is Virtual	Nominal (Categorica)	Yes if this school is a virtual school. No otherwise.
Number Students	Interval/Ratio (Quantitative)	Number of students attending school.
Number Full-time Teachers	Interval/Ratio (Quantitative)	Number of Teachers
Student/Teacher Ratio	Interval/Ratio (Quantitative)	Student Teach Ratio
Percent Free/Disc Lunch	Interval/Ratio (Quantitative)	Percent of Students who are receiving free or discounted lunches
Percent African American	Interval/Ratio (Quantitative)	Percent of students that are African American.
Percent American Indian	Interval/Ratio (Quantitative)	Percent of students that are American Indian.
Percent Asian	Interval/Ratio (Quantitative)	Percent of students that are Asian.
Percent Hispanic	Interval/Ratio (Quantitative)	Percent of students that are Hispanic.
Percent Pacific Islander	Interval/Ratio (Quantitative)	Percent of students that are Pacific Islander
Percent Two or More Races	Interval/Ratio (Quantitative)	Percent of students that are Two or More Races.
Percent White	Interval/Ratio (Quantitative)	Percent of students that are White
Average Standard Score (2021-22)	Discrete	The standard score achieved in the school year 2021-2022.
Average Standard Score (2020-21)	Ordinal	The standard score achieved in the school year 2022-2023.
Rank (2020-21)	Ordinal	Rank in the 2021-2022 school year.
Rank Change from (2020-21)	Ordinal	Rank in the 2022-2023 school year.
SchoolDigger Star Rating	Ordinal	SchoolDigger School Rating out of five stars
SchoolDigger Star Rating	Ordinal	SchoolDigger School Rating out of five stars

This data set was primarily used and therefore the calculation of the Average Standard score requires additional explanation.The score is based on the Virginia Standards of Learning (SOL) tests. The SOL tests used are those administered in all grades from primary, middle and high schools. SOLs are a good indicator of academic achievement as they are standardized across all schools in Virginia.

In order to create a Standard score combines a number of different tests into a single score that represents an average or standard score. Since the means and standard deviations are different for different tests, each school's result is normalized by mapping them to a Standard Normal Distribution. The z-score is calculated for each of the school's results on the SOL test.

Z-Score Calculation: $z = \frac{x-\mu}{\sigma}$

This Z-score is then applied to the results to calculate a standard score for the schools performance on an SOL. The standard scores for each SOL test administered during the school year are then averaged to achieve the school's standard score for the school year.

III. Tools and Processes Used

Initially Weka was used to explore and understand the data sets. Once the data was better understood, excel was used to view and modify the data. This processing was used to verify the problems and solutions to missing data and data format issues. Once the data was understood, the processing moved to the following technologies.

A number of different tools were used to process the data, generate models and create visualizations. Preprocessing was performed in Python using the pandas and numpy packages replacing the initial work completed in Weka and excel.

Modeling except the decision tree analysis was performed in R using the caret, ggcorplot, ggplot2, dpylr and glmnet. Decision Tree and Exploratory Data Analysis was completed in SAS Jump along with the visualizations.

IV. Data cleaning and preprocessing

While the School Digger was relatively clean with the following two problems. The Fredericksburg City Public Schools were missing Percent School Lunch and racial data. The data for Fredericksburg City Public Schools was removed.

Other random fields were missing from individual schools. These were filled with the average value for the feature.

Once the initial data cleaning was complete, the data was summarized into county level data. The schools were combined into a single county row by performing the following functions. School, School URL, District, District URL, Address, City City URL, Phone, Low Grade and High Grade columns were all dropped as they had no meaning at the county level.

A weighted average based on the number of students. For example, the Percent African American percent was multiplied by the school's number of students. This was summed for each school then divided by the number of students in the county to create a weighted average. This weighted average was applied to the following features Percent African American, Percent American Indian, Percent Asian, Percent Hispanic, Percent Pacific Islander, Percent Two or More Races, Percent White, Average Standard Score (2021-22), Average Standard Score (2020-21)', 'Rank (2020-21), Rank Change from (2020-21), Percent Free/Disc Lunch,and SchoolDigger Star Rating.

The number of teachers column was summed to provide a total number of teachers in the county. The Yes/No attributes, Is Title I, Is Charter, Is Magnet and Is Virtual, were converted to a 1 (yes) or 0 (No) and then averaged across the county schools.

This data was then merged with the County School Score and Income data set and to add Expenditure For Schools Per Pupil and Income by School County.

The data preprocessing was completed in python using pandas and numpy.

V. Summary statistics and exploratory data analysis

A number of data visualizations were created to obtain a better understanding of the data. The following visualizations provide interesting observations on the data

FIGURE I
Income by County in Virginia

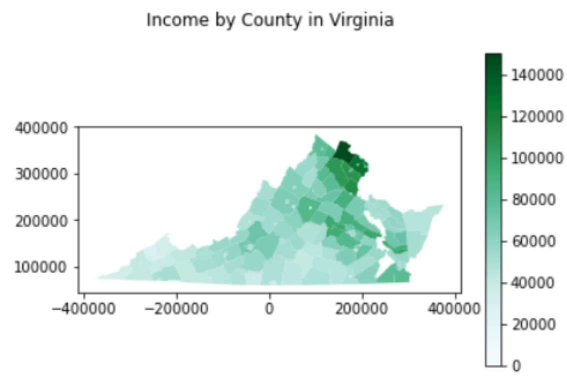


Figure.I shows that the northern counties of Virginia, such as Fairfax, Loudoun, and Arlington, have the darkest shades of color, indicating higher median household income. This is consistent with the fact that these counties are generally considered to be more affluent than other parts of the state.

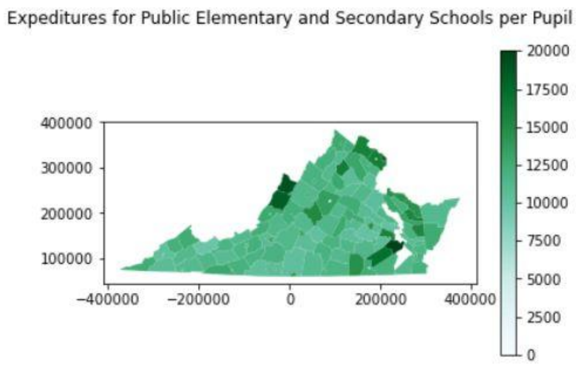
On the other hand, we can see that the southern and western parts of Virginia, such as Lee County, Wise County, and Buchanan County, have lighter shades of color, indicating lower median household income. This is consistent with the fact that these areas are generally more rural and economically disadvantaged compared to the more urbanized northern part of the state.

Overall, the visualization provides a quick and easy way to see the geographic distribution of median household income in Virginia and highlights the disparities that exist between different parts of the state.

From Figure II. We see that Surry County, Arlington County, Falls Church City, and Highland County have higher expenditures per pupil than other counties in Virginia. This means they are spending more money on each student's education, possibly resulting in higher-quality education for those counties. On the other hand, Appomattox County, New Kent County, Chesterfield County, Tazewell County, and Norton City have lower expenditures per pupil compared to other counties.

FIGURE II

Expenditure for publicElemtary and Secondary Schools per Pupil



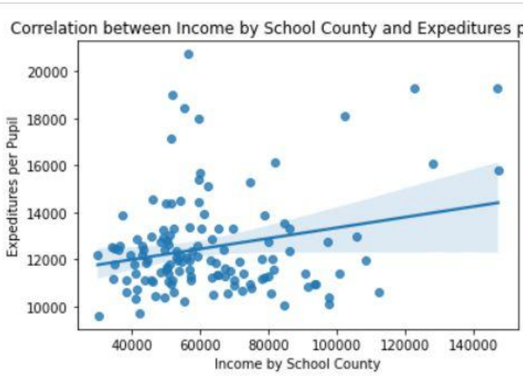

```
count        132.000000
mean       12481.287879
std         2089.969146
min         9600.000000
25%        11146.500000
50%        11962.500000
75%        12974.750000
max        20729.000000
Name: Expeditures for Public
```

It's important to note that there may be various factors influencing the expenditure per pupil, such as the local tax base, state funding, and demographic factors, among others. As we see on figure III it has a direct correlation to the income of residents.

The expectation was that expenditures per student would be highest where the income was the highest but this is not the case. Figure.III shows there is little correlation between income and expenditure per pupil. This low correlation is even more problematic when considering the cost of living in counties with higher income levels is higher. The ability to adequately pay teachers is lower in higher income counties.

FIGURE III

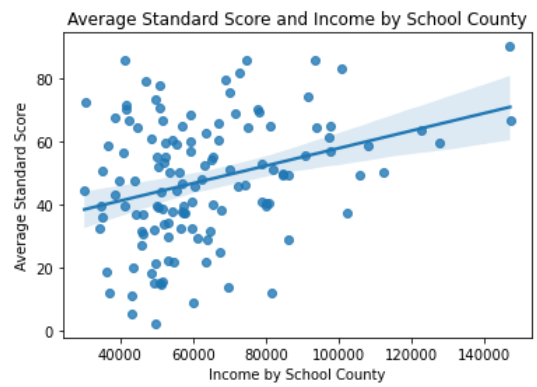
Correlation between Income by County and Expenditure Per Pupil



From Figure.IV as we move from left to right on the x-axis, which represents the income by county, we can see an increase in the average standard score of students on the y-axis. This suggests that there is a positive correlation between the income level of a county and the academic performance of its K-12 students. However, it is important to note that correlation does not necessarily imply causation, and there may be other factors at play that influence academic performance.

FIGURE IV

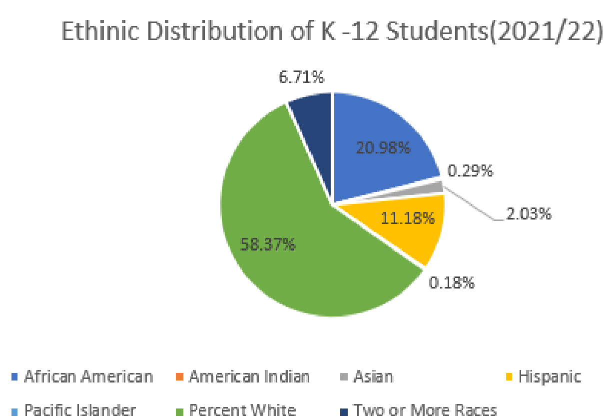
Correlation between Income by County and Average Standard Score



Other information provided by the data set included racial diversity of the student population. Figure VI provides an overview of the racial diversity of the schools.

FIGURE V

Ethnic Distribution of K - 12 Students year 2021/22



The above piechart shows the ethnic distribution of K-12 students in Virginia. The largest ethnic group is White, making up 45.8% of the total student population, followed by Black or African American at 21.8%. Hispanic students make up 18.1%, while Asian or Asian/Pacific Islander students make up 7.4%. Two or More Races and American Indian/Alaska Native students make up 6.5% and 0.3%

respectively. Nat. Hawaiian or Other Pacific Isl. students make up the smallest percentage at 0.2%

VI. Analytical Techniques

In this analysis, Standard Score from the SchoolDigger data set will be used as a measure of academic achievement. The following attributes will be used as predictors Percent African American, Percent American Indian, Percent Asian, Percent Hispanic, Percent Pacific Islander, Percent Two or More Races, Percent White,Is Title I, Is Charter, Is Magnet and Is Virtual,Expenditure For Schools Per Pupil and Income by School County.

As an initial step of the analysis, a Primary Component Analysis (PCA) is used to provide insights into the underlying structure of the data and assist in the next steps of clustering, regression, or classification.

Linear regression is a statistical technique that can be used to examine the relationship between one or more predictor variables and an outcome variable. While it may not be the most powerful predictive algorithm, linear regression provides valuable insights into the correlation and statistical significance of the predictors on the outcome variable. Therefore, it will be the primary method for gaining a deeper understanding of the underlying relationship between the predictors and the outcome.

K Means clustering will be used to determine clusters of data and if those clusters have significantly different relationships between the predictor variables and academic experience.

Finally decision tree analysis will be used to provide a different view of the results.

B. Primary Component Analysis

The results of the PCA analysis shows the cumulative proportion of variance shows that the first two components explain a majority of the variation at 0.7, and it takes up to 11 components to explain 99.9999% of the variation. These results suggest that two components will be the primary predictors of the output but the first 11 components have some less practical significance. Table V provides the details of the PCA analysis. The linear regression results match this analysis.

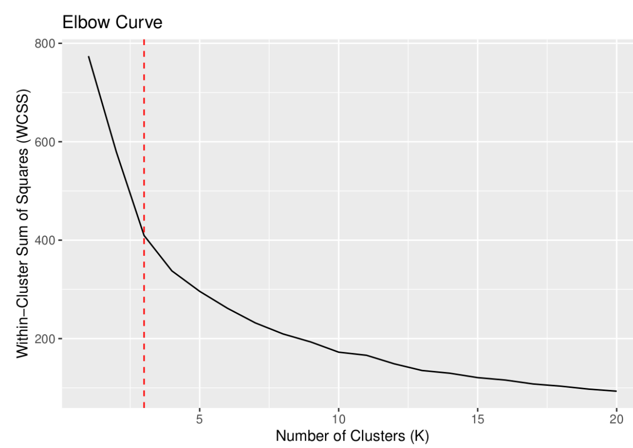
TABLE V
Primary Component Analysis Results

	Standard deviation	**Proportion of Variance**	**Cumulative Proportion**
Comp.1	0.9173	0.5168	0.5168
Comp.2	0.5468	0.1836	0.7004
Comp.3	0.3534	0.0767	0.7771
Comp.4	0.3379	0.0701	0.8473
Comp.5	0.2924	0.0525	0.8998
Comp.6	0.2455	0.0370	0.9368
Comp.7	0.2279	0.0319	0.9687
Comp.8	0.1649	0.0167	0.9854
Comp.9	0.1098	0.0074	0.9928
Comp.10	0.0920	0.0052	0.9980
Comp.11	0.0571	0.0020	1.0000
Comp.12	0.0009	0.0000	1.0000
Comp.13	0.0000	0.0000	1.0000

A. K Means Clustering

A K Means clustering was generated to see if the predictors formed clusters. In order to determine the best set of clusters, K was varied between 1 and 20 and the Within-cluster Sum of Squares "elbow" method was used to determine the optimum number of clusters. Performing a K Means cluster with all variables resulted in a graph that contained no discernible elbow. Reducing the variables to Expenditures per Pupil, Income by School District, Percent White, Percent African American, Percent Asian, Is Title I and Is Charter

FIGURE VI
K Means Elbow Curve



While not very prevalent, the best cluster was determined to be between 3 and 5 clusters. The best "elbow" is a K=3 and therefore this was chosen to perform the analysis.

The following four plots Figure 8-11, show scatter plots of the variables Is Tile I, Percent African American, Percent White, and Percent Asian vs Income of School District. While some clusters appear, none of the plots show a clear cluster that would be useful for analyzing Income impacts. For this reason, further analysis on the clusters was not pursued.

FIGURE VII

Cluster Plot Income vs Is Title I

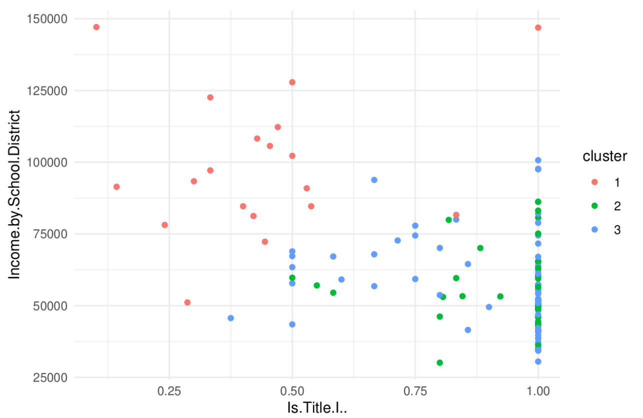


FIGURE VIII

Cluster Plot Income vs Is Percent African American

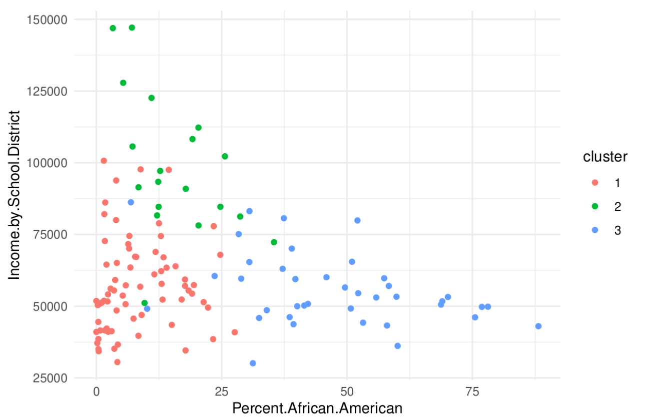


FIGURE IX

Cluster Plot Income vs Is Percent White

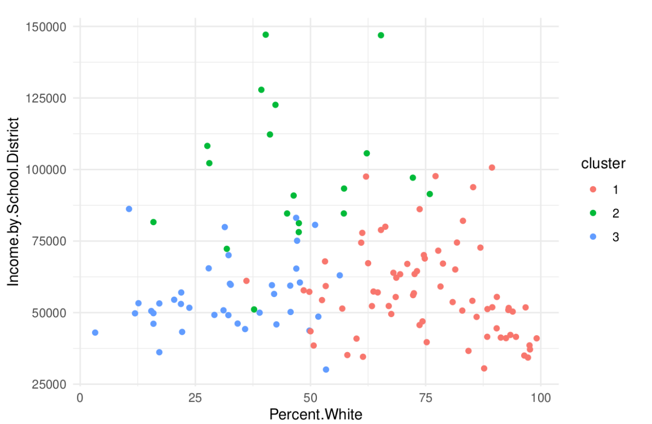
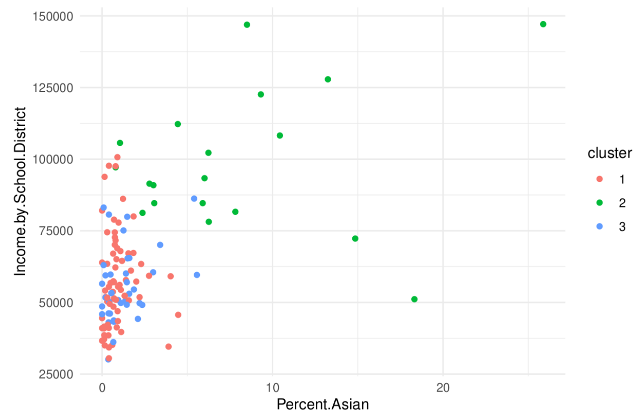


FIGURE X

Cluster Plot Income vs Percent Asian



C. Regression and Correlation Analysis

An initial regression analysis was performed using all 13 predictor variables. The results indicated that five of the variables had weak to strong statistical significance.

TABLE VI

Linear Regression Analysis

Variable	**Estimate**	**Std. Error**	**t value**	**Pr(>|t|)**	
(Intercept)	7.216	20.72	0.348	0.7283	
Expenditures.per.Pupil	-0.0011	0.0007	-1.621	0.1078	
Income.by.School.District	0.0003	0.0001	3.47	0.0007	***
Total.Number.Students	-0.0011	0.0022	-0.496	0.6208	
Percent.White	0.7808	0.1157	6.746	0.000	***
Percent.African.American	0.3175	0.1331	2.387	0.0186	*
Percent.American.Indian	-2.997	2.74	-1.094	0.2763	
Percent.Asian	1.207	0.688	1.754	0.0821	.
Percent.Pacific.Islander	0.5071	9.204	0.055	0.9562	
Number.Full.time.Teachers	0.0168	0.0302	0.555	0.5799	
Student.Teacher.Ratio	-0.338	0.7809	-0.433	0.666	
Is.Title.I..	-13.36	7.165	-1.865	0.0647	.
Is.Charter..	-305.2	300.2	-1.016	0.3116	

Is.Magnet..	10.98	15.82	0.694	0.4889	
Is.Virtual..	NA	NA	NA	NA	

D. Hypothesis Testing and Significance Analysis

The linear regression model was fitted using 13 predictor variables and 1 response variable. The adjusted R-squared value for the model is 0.5245, indicating that about 52.45% of the variability in the response variable can be explained by the predictor variables included in the model.

Income by School District and Percent White are both statistically significant at a 0.001% level (p-value = 0.000732 and 6.28E-10), with a positive coefficient.

Percent African American is statistically significant at a 5% level (p-value = 0.018624), with a positive coefficient of 3.175e-01.

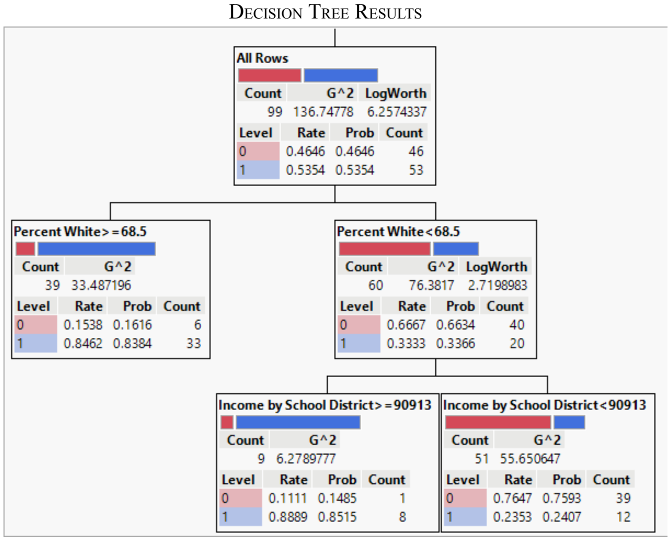
Percent Asian and Title I are marginally significant at a 10% level (p-value = 0.082110 and 0.064656), Percent Asian has a positive coefficient of 1.207e+00 and Is Title I has a negative coefficient of -1.336e+01.

Other predictor variables were not significant. The F-statistic is 11.94 with a p-value of 4.654e-16, indicating that the model is statistically significant overall.

E. Decision Tree Analysis

To create a decision tree using SAS JMP for predicting education quality in counties, we labeled counties that scored below average as Low-Quality education (0) and those that scored above average as High-Quality education (1). The decision tree revealed that the percentage of white students in a county is the most significant predictor of education quality, followed by income by the district.

FIGURE XI
DECISION TREE RESULTS



According to the decision tree figure (10), if the percentage of white students in a county is above 68.5%, there is an 84.62% chance that the county will have a higher education quality. On the other hand, if the percentage of white students is less than 68.5% and the income by school district is above $90,913, the probability of good education quality in that county or district increases to 88.9%. From the confusion matrix of validation data the model is predicted quite well and the ROC curve (figure 11) of validation data proves that the model predicts 69.17 percent accurately based on the given attributes.

TABLE VII
DECISION TREE CONFUSION MATRIX

Confusion Matrix

Training

Actual	Predicted Count	
Edu_Quality	0	1
0	39	7
1	12	41

Actual	Predicted Rate	
Edu_Quality	0	1
0	0.848	0.152
1	0.226	0.774

Validation

Actual	Predicted Count	
Edu_Quality	0	1
0	12	4
1	6	9

Actual	Predicted Rate	
Edu_Quality	0	1
0	0.750	0.250
1	0.400	0.600

FIGURE XII
DECISION TREE ROC CURVE

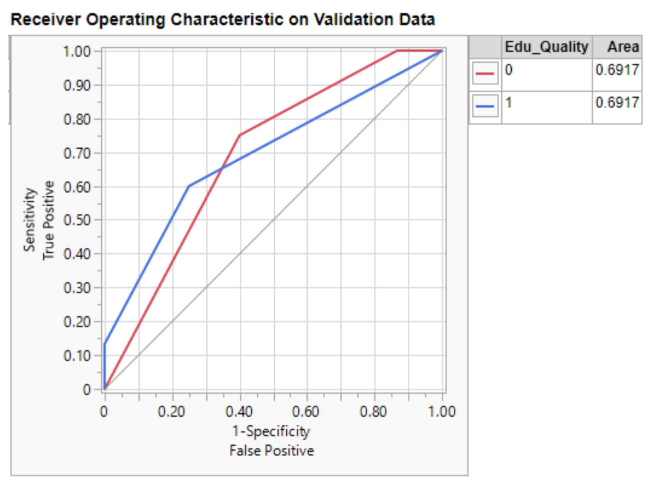


TABLE VIII
DECISION TREE LEAF REPORT

Leaf Report

Response Prob

Leaf Label	0	1
Percent White>=68.5	0.1616	0.8384
Percent White<68.5&Income by School District>=90913	0.1485	0.8515
Percent White<68.5&Income by School District<90913	0.7593	0.2407

The above leaf report informs that percent white greater than 68.5% is the most pure leaf prediction high education quality in the district with probability of 83.84%.

TABLE IX

COLUMN CONTRIBUTION TO DECISION TREE

Column Contributions

Term	Number of Splits	G^2	Portion
Percent White	1	19.6434487	0.5123
Income by School District	1	18.7012445	0.4877
Total Number Students	0	0	0.0000
Percent African American	0	0	0.0000
Percent American Indian	0	0	0.0000
Percent Asian	0	0	0.0000
Percent Hispanic	0	0	0.0000
Percent Pacific Islander	0	0	0.0000
Percent Two or More Races	0	0	0.0000
Student/Teacher Ratio	0	0	0.0000
Number Full-time Teachers	0	0	0.0000
Is Title I %	0	0	0.0000
Is Charter %	0	0	0.0000
Is Magnet %	0	0	0.0000
Is Virtual %	0	0	0.0000
Expenditures for Public Elementary and Secondary Schools per Pupil	0	0	0.0000

VII. CONCLUSIONS AND FUTURE WORK

The purpose of this analysis was to determine if income of county residents impacts academic achievement. There is a clear correlation between Income of School District and Standard Scores in those school districts. These two variables are correlated but causal mechanisms are not clear. The assumption is that higher incomes lead to higher tax revenues which provides for higher school funding and therefore better educational outcomes. For this causation to be true, there would be a strong relationship between Expenditures per Pupil and Standard Scores which was not seen. Also, there is a correlation between Income of School District and Expenditures per Student. This correlation is statistically significant at the .01 level but only accounts for 5% of the variance in Expenditures per Student. .

The connection between income and student achievement is real but the causal mechanism is not clear. It was also impossible to ignore the racial aspects of this analysis as it appears in the linear regression, clustering and decision tree analysis. Once again, the exact mechanism for these relationships is unclear and was not the focus of this analysis.

Further analysis is needed to understand the mechanism that underpin these statistical relationships and determine ways to mitigate or reverse them. It is likely that additional data will be necessary to understand the causes. Maximizing human capital should be at the heart of both state and local government policy.

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