Analyzing the Impact of School Type on Student Outcomes Across Counties: A Comparative Study Using ANOVA

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ABSTRACT

This study investigates the impact of school type on student outcomes across various counties, employing a comparative analysis using ANOVA (Analysis of Variance). Recognizing education as a fundamental driver of social and economic advancement, this research aims to identify whether significant disparities exist in academic performance across school types. The dataset, collected from multiple counties in Washington, United States, comprises extensive student performance metrics, school characteristics, and demographic information. Through data preprocessing and handling of missing values, the study ensured a robust dataset suitable for statistical analysis. The ANOVA results revealed a statistically significant difference in student outcomes across school types, suggesting that the type of school attended correlates with academic performance. Additionally, post-hoc analysis using Tukey's HSD test identified specific pairs of school types with notable performance differences. Public schools generally showed lower outcomes compared to private and charter institutions, which often benefit from additional resources and specialized curricula. However, geographic disparities, such as those between urban and rural counties, further influenced these results, highlighting the role of location and socioeconomic factors. These findings have implications for educational policymakers and stakeholders, indicating a need for targeted support for underperforming school types and regions. Addressing these disparities could help foster equitable access to quality education. The study concludes by recommending further research through longitudinal studies and deeper exploration of demographic factors that interact with school type, potentially offering more insight into the mechanisms influencing student success across diverse educational settings.

Keywords School Type Impact, Student Outcomes, ANOVA Analysis, Educational Disparities, County Comparison

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Introduction

Education is a cornerstone of societal advancement, providing individuals with the tools they need for personal growth, career success, and civic engagement. The quality of education directly impacts social mobility, economic development, and the overall well-being of a population [1]. Through education, societies equip future generations with critical thinking skills, knowledge, and the ability to contribute meaningfully to various sectors of the economy and culture. As such, education systems are crucial to fostering personal success and broader societal progress. Student outcomes, measured through academic performance, graduation rates, and standardized test scores, are widely recognized as indicators of the effectiveness of educational systems [2]. These

outcomes help to identify strengths and gaps within educational structures and directly correlate with future opportunities for individuals.

Student outcomes are significant because they influence both individual potential and societal equity. Higher academic achievement is associated with better employment prospects, higher lifetime earnings, and increased social mobility [3]. Conversely, poor educational outcomes can limit future opportunities, perpetuating cycles of poverty and inequality. Therefore, understanding student performance factors is essential for educational policymakers and stakeholders. Among these factors, the type of school a student attends, whether public, private, or charter, has long been debated as a determinant of academic success. Analyzing the impact of school types on student outcomes, particularly across various regions such as counties, provides insight into whether educational inequities exist and how they might be addressed to ensure equitable access to quality education [4].

Student outcomes are not only individual achievements but also serve as critical indicators of the health of the educational infrastructure [5]. Performance metrics, such as standardized test scores and graduation rates, offer valuable insights into the effectiveness of schools in delivering quality education. Governments, educators, and policymakers often use these metrics to assess whether educational goals are being met and where improvements are needed. By examining these outcomes, it is possible to track educational reforms' progress and evaluate the success of policies to close achievement gaps between different demographic groups. Moreover, student outcomes help identify the long-term impacts of education on workforce readiness and the ability to adapt to a rapidly changing global economy [6].

In a comparative analysis of student outcomes across different school types, factors such as school funding, teacher quality, and curriculum design are often explored to determine their role in shaping student success. Public schools, for example, may face challenges such as overcrowding and limited resources, while private schools might offer more personalized attention and specialized programs. Charter schools, which operate with greater flexibility than traditional public schools, are often scrutinized for their innovative approaches and variability in performance. Therefore, it becomes crucial to assess how these differences in school types influence student outcomes and their implications for educational policy and equity [7]. Through this analysis, we can better understand the relationship between school type and academic performance, informing future decisions on resource allocation and educational reform.

Student outcomes are shaped by various factors, with geographic location being one of the most prominent [8]. The differences between rural, urban, and suburban areas often result in unequal access to educational resources, which, in turn, influences academic performance. Students in urban areas may benefit from a greater concentration of resources, including access to advanced placement courses, extracurricular activities, and experienced educators. In contrast, rural students may face limited access to such opportunities, resulting in a potential gap in achievement. Additionally, geographic disparities can also manifest in the quality of school infrastructure, availability of technology, and exposure to diverse learning experiences, all of which are critical to student development.

Demographic characteristics also play a significant role in determining

educational outcomes [9]. Factors such as socioeconomic status, ethnicity, and parental education levels are consistently linked to variations in academic achievement. For example, students from higher-income families tend to have greater access to private tutoring, learning materials, and enrichment programs, contributing to better school performance. Similarly, parental education levels often correlate with the level of support and encouragement provided at home, influencing a child's academic success [10]. These demographic influences highlight the complex interplay between social factors and educational outcomes, making it essential to consider them when analyzing student performance.

The type of school a student attends is another critical determinant of academic achievement. Research indicates that private and charter school students often achieve higher outcomes than their public school peers. This disparity is frequently attributed to smaller class sizes, more personalized attention, and curricular flexibility that allows for innovative teaching methods. However, these differences raise important questions about educational equity, as not all students have equal access to private or charter school options. A comparative analysis of performance across these school types is necessary to uncover the underlying reasons for these differences and to develop policies to ensure that all students, regardless of school type, have the opportunity to succeed.

The disparity in student outcomes based on school type across various counties is a key issue that requires focused examination [11]. Public, private, and charter school types offer distinct educational environments that can lead to variations in resources, teacher quality, and curriculum, all of which significantly influence academic performance. The differences in how these schools operate create unequal opportunities for students, potentially contributing to performance gaps within individual schools and counties with varying access to these educational institutions. As counties differ in terms of socioeconomic demographics and funding, the impact of school type becomes even more critical to explore.

Assessing whether school type plays a substantial role in student outcome disparities is vital for several reasons. First, this understanding informs policymakers about how different school systems contribute to or mitigate these disparities, helping shape resource allocation decisions and educational reforms promoting equity. Effective assessment allows stakeholders to prioritize underperforming groups and counties, ensuring that all students, regardless of their location or the type of school they attend, have equitable access to quality education. This helps bridge the achievement gap and fosters a more inclusive educational environment where geographic or socioeconomic constraints do not dictate the potential for success.

In light of these concerns, investigating disparities in student performance across school types provides an opportunity to identify key areas for improvement. Such insights could empower communities and educators to advocate for necessary changes, ensuring that all students benefit from the same level of educational support. A comparative analysis clarifies the relationship between school type and student outcomes, providing a foundation for addressing educational inequalities and driving overall academic performance improvements across counties.

Recent advancements in data science and machine learning have provided

robust tools for analyzing diverse domains, including sentiment analysis, consumer behavior, and digital finance. Sentiment analysis techniques, such as Support Vector Machines and TF-IDF analysis, have been effectively utilized to gauge user attitudes towards electric vehicle incentives [12] and to analyze sentiments on Indonesian Twitter using active learning with uncertainty sampling [13]. In e-commerce, comparative analyses of sentiment classification techniques, using algorithms like Logistic Regression, SVC, and Random Forest, have offered insights into consumer reviews on platforms such as Flipkart [14], while prediction models using Decision Trees and Random Forests have shown effectiveness in forecasting campaign ROI in digital marketing contexts [15].

The intersection of digital finance and sentiment analysis has also been explored within cryptocurrency markets. For instance, TF-IDF vectorization combined with K-Means clustering has been applied to analyze Bitcoin-related tweets, providing valuable insights into trends and sentiment patterns in cryptocurrency [16]. Additionally, studies investigating Bitcoin market efficiency using the runs test and autocorrelation have highlighted the complex nature of cryptocurrency price movements [17]. In the expanding metaverse, predictive modeling techniques have been employed to forecast stock prices for platforms like Roblox, combining time series analysis with machine learning to capture dynamic market behavior [18]. Moreover, anomaly detection and risk analysis within financial transactions in the metaverse offer a framework for managing regulatory implications and ensuring transaction security [19]. These studies collectively underscore the versatility of machine learning and data science methods in addressing complex problems across various fields, from digital consumer behavior to financial analytics.

The primary objective of this study is to analyze the impact of different school types, public, private, and charter, on student outcomes across various counties. Educational institutions vary significantly in terms of resources, teacher-to-student ratios, and curricular flexibility, which can lead to disparities in student performance. By examining the role of school type in influencing these outcomes, the study aims to identify whether significant differences in academic achievement correlate with the type of school a student attends. This is especially important given that counties often differ in terms of access to these different types of schools, which may exacerbate or mitigate educational inequalities.

To achieve this, the study employs a comparative approach using Analysis of Variance (ANOVA) to statistically test the differences in student performance across the three school types. ANOVA is an appropriate method because it allows for comparing means between multiple groups, in this case, the different school types, while determining whether the variations observed are statistically significant [20]. By applying ANOVA, the study seeks to determine if the disparities in student outcomes across school types are due to chance or if they reflect meaningful differences in educational effectiveness that warrant further attention from policymakers and educators.

This analysis aims to uncover patterns that highlight the relationship between school type and student achievement, which could inform future educational reforms and resource distribution strategies. Understanding the statistical significance of these differences is crucial for identifying which types of schools contribute to better student outcomes and in which counties such performance

trends are most pronounced. This can help address disparities and promote equity in educational opportunities across different regions.

Literature Review

Overview of Related Studies

Student outcomes are shaped by various factors, with school type, geographic location, and educational equity central to many studies on academic achievement [21]. Prior research has consistently shown that the type of school a student attends, whether public, private, or charter, can significantly influence performance [22]. Private and charter schools often demonstrate higher academic outcomes due to smaller class sizes, more resources, and innovative teaching approaches. Public schools, especially in underfunded regions, may struggle to provide the same level of individualized attention and curriculum flexibility, potentially leading to disparities in student achievement. This variation across school types highlights the need to explore how these institutional differences contribute to the broader patterns of educational success.

Geographic differences further compound these disparities, with urban and rural areas offering vastly different educational environments. Students in urban areas may benefit from a greater concentration of resources, including access to advanced placement courses, extracurricular activities, and a more experienced teaching staff. In contrast, rural schools often face challenges related to funding, teacher retention, and a lack of diverse academic offerings [23]. These geographic disparities can significantly impact student performance, with rural students frequently having fewer opportunities to engage in enriching educational experiences than their urban peers. Therefore, geographic location is essential in understanding the broader landscape of educational achievement.

Educational equity remains a critical lens through which these factors must be examined. Systemic inequalities, such as disparities in funding, access to quality teachers, and socioeconomic barriers, continue to affect marginalized students disproportionately, perpetuating achievement gaps across different school types and geographic areas. These gaps often reflect broader social inequalities and require targeted interventions that address both the structural and individual challenges students face. Ensuring equitable access to high-quality education, regardless of school type or location, is essential for reducing these disparities and promoting fairness in educational outcomes [24].

School Type and Student Performance

Research on the impact of school type on educational performance has produced mixed results, with studies showing both significant and insignificant differences across public, private, and charter schools. Some research suggests that private and charter schools often outperform traditional public schools regarding standardized test scores and overall academic achievement. A meta-analysis conducted by [25] found that students in private schools tend to achieve higher scores, which researchers attributed to advantages such as smaller class sizes, better access to educational resources, and more stringent academic standards. Charter schools, which offer more flexibility in their curriculum and teaching methods, also show similar advantages in some studies, particularly in

urban settings where innovation in education is often emphasized.

The geographic context further complicates the relationship between school type and educational performance. Studies indicate that urban public schools, particularly those with substantial government support, can offer educational resources that rival those of private schools, thus narrowing the performance gap. In contrast, rural schools, regardless of type, often face challenges such as teacher shortages and limited access to advanced coursework, which can negatively impact student outcomes [23]. These findings highlight the complexity of evaluating school type as a determinant of academic success, underscoring the importance of considering a range of socioeconomic and geographic factors.

ANOVA Method in Educational Studies

The Analysis of Variance (ANOVA) method is a statistical technique widely used for comparing the means of three or more independent groups to assess whether any significant differences exist between them. ANOVA tests the null hypothesis, which posits that all group means are equal, by analyzing the variance within each group and between the groups. The fundamental formula for ANOVA is expressed as:

F=Between Group VarianceWithin Group VarianceF = \frac{\text{Between Group Variance}}{\text{Within Group Variance}}F=Within Group VarianceBetween Group Variance

In this formula, the "Between Group Variance" reflects how much the group means differ from each other, while the "Within Group Variance" measures the variation in individual data points within each group. The F-statistic, calculated as the ratio of these two variances, helps determine whether the differences between group means are large relative to the variation observed within the groups [26]. A larger F-statistic implies greater variation between groups than within groups, suggesting that the means may not be equal.

The significance of the F-statistic is evaluated by comparing it to a critical value from the F-distribution, which depends on the degrees of freedom for both the between-group and within-group variance. If the F-statistic exceeds the critical value, the null hypothesis is rejected, indicating that at least one group mean significantly differs from the others. In the context of this study, ANOVA is particularly useful for comparing student outcomes across different school types (public, private, charter) to determine whether school type significantly impacts academic performance across counties. The result informs whether school type determines educational success or if other variables contribute more substantially to observed differences in student outcomes.

This method is essential in educational research, as it provides a statistical framework for understanding whether variations in educational practices or resources associated with different school types lead to meaningful differences in student performance. If the ANOVA reveals significant differences, it could guide educators and policymakers in addressing disparities and improving educational equity across different types of institutions.

Method

The research method for this study consists of several steps to ensure a comprehensive and accurate analysis. The flowchart in Figure 1 outlines the detailed steps of the research method.

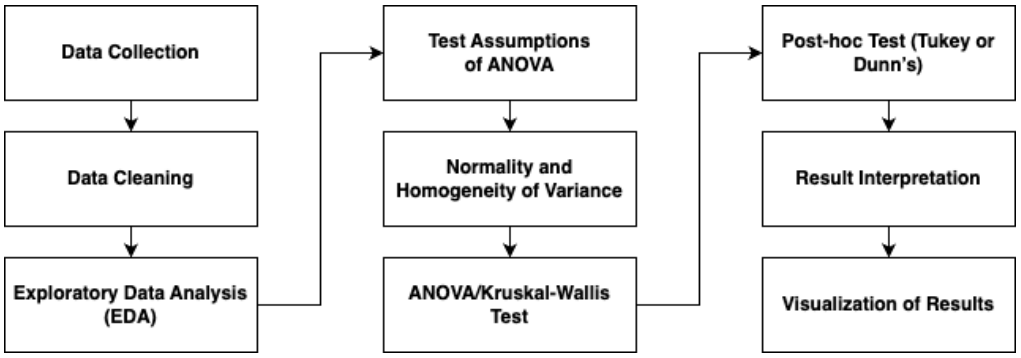

Figure 1 Research Method Flowchart

Data Collection and Preprocessing

This study utilizes a comprehensive dataset collected from public educational records across multiple counties in Washington, United States, representing various student performance metrics, school types, and geographic locations. The dataset includes detailed information such as student outcomes, school types (public, private, charter), district and county identifiers, grade levels, and various standardized test metrics. In its original form, the dataset contained 761,859 rows and 33 columns, including both categorical and numerical data. The initial data inspection revealed a range of data types, including `object`, `float64`, and `category`, signifying the presence of mixed data types within specific columns, particularly those containing percentage metrics or categorical identifiers.

The data preprocessing phase began with addressing missing values and mixed data types. Columns with more than 50% missing values were dropped to enhance data reliability while retaining valuable information. Percentage columns, including key metrics on student knowledge levels, were standardized by removing non-numeric symbols and converting the values to decimal format. Non-numeric values, such as "N<10," were replaced with null entries, allowing for consistent numeric processing. This step ensured that each column was either fully numeric or appropriately categorized, setting a stable foundation for accurate statistical analyses.

Handling Missing Values and Data Cleaning

Following the initial cleaning, missing values in the dataset were treated differently based on the data type. For numeric columns, missing values were imputed using the median of each column, which minimized the impact of outliers and preserved the central tendency. For categorical fields, missing values were filled using the mode of each column, ensuring that the most common category replaced missing entries. This imputation strategy balanced the need to preserve data integrity with the goal of maximizing dataset completeness. This approach was particularly effective for columns related to school and district information, where consistent categories were essential for subsequent comparative analysis.

To further prepare the data, categorical variables were converted to appropriate data types to streamline processing and storage. Key columns, such as `SchoolYear`, `OrganizationLevel`, `County`, and `CurrentSchoolType`, were assigned categorical data types, enhancing computational efficiency and ensuring consistency across analyses. Additionally, final checks confirmed the

absence of remaining null values, validating that the data was fully prepped for detailed statistical exploration. These preprocessing steps allowed for a well-structured dataset, aligning with the study's objectives of analyzing the impact of school type on student outcomes through rigorous comparative analysis.

Dataset Verification and Finalization

After data cleaning and processing, the final dataset was reviewed to confirm accuracy and readiness for analysis. Each column was inspected for proper data type alignment, ensuring that all variables, particularly those central to the analysis, like school type and student performance indicators, were correctly formatted. Summary statistics were generated to validate the data's structural integrity and to establish baseline distributions for each variable. These summaries provided initial insights into the distribution of school types, counties, and performance metrics, confirming that the dataset was robust and representative of the study population. This completed dataset was saved as `cleaned_dataset_v2.csv` for use in ANOVA and other statistical tests, providing a dependable basis for the subsequent analyses outlined in the study.

ANOVA Implementation

The study implemented ANOVA to compare student performance across different school types, namely public, private, and charter schools. ANOVA is a statistical method designed to examine the mean differences among multiple groups and to assess whether these differences are statistically significant. In this context, "Between Group Variance" represents the variance in student performance scores between different school types, while "Within Group Variance" accounts for the variance in scores within each school type. This ratio produces an F-statistic, where a larger F-value indicates more pronounced differences between groups. For this study, a statistically significant F-statistic suggests that student outcomes differ based on the type of school attended, which is essential to determine if educational approaches or resource allocations differ by school type.

Testing ANOVA Assumptions

Prior to conducting ANOVA, the assumptions of normality and homogeneity of variances were assessed to validate the appropriateness of the method. The Shapiro-Wilk test was applied to examine the normality of student performance distributions within each school type. For groups with p-values below 0.05, the null hypothesis of normality was rejected, indicating that data were not normally distributed for certain school types. Given the high sample size, deviations from normality are expected; however, ANOVA is considered robust against minor normality violations when sample sizes are large.

The Levene's test was employed to evaluate the homogeneity of variances across school types, which is crucial as ANOVA assumes that variances are roughly equal among the groups being compared. In this study, Levene's test produced a p-value below 0.05, leading to the rejection of the homogeneity of variance assumption. Consequently, a non-parametric Kruskal-Wallis test was additionally conducted to account for the unequal variances, serving as a supplementary analysis to ANOVA in verifying mean differences across school types.

The ANOVA analysis yielded a statistically significant F-statistic, suggesting that student performance differs among public, private, and charter schools.

However, due to the violation of variance homogeneity, the Kruskal-Wallis test, a non-parametric alternative to ANOVA, was performed to confirm these results. The Kruskal-Wallis test similarly revealed significant differences in student performance across the three school types, supporting the initial ANOVA findings. These complementary tests reinforce the study's conclusion that school type plays a role in student outcomes.

Post-hoc Analysis

Following the ANOVA, Tukey's HSD (Honestly Significant Difference) post-hoc test was conducted to identify specific pairs of school types with significant differences in student performance. Tukey's HSD test is designed to control for family-wise error rates while performing multiple comparisons. The post-hoc analysis indicated significant performance differences between certain pairs of school types, providing a deeper insight into how different educational environments may influence student outcomes. The combined use of ANOVA, Kruskal-Wallis, and post-hoc testing enabled a comprehensive understanding of performance disparities linked to school type.

Result and Discussion

ANOVA Results

The ANOVA test yielded an F-statistic of 937.23 with a p-value of 0.0, indicating that the differences in student outcomes across the school types, public, private, and charter, are statistically significant. The low p-value (<0.05) allows for the rejection of the null hypothesis, confirming that at least one school type exhibits a meaningful difference in student performance relative to the others. These findings suggest that the type of school a student attends could be a determinant factor in their academic performance, with varying levels of resources, teaching quality, and curricula potentially contributing to these disparities.

Given that the data did not meet the homogeneity of variance assumption, as indicated by Levene's test (p-value = 0.0), a Kruskal-Wallis test was also applied as a non-parametric alternative to validate the ANOVA results. The Kruskal-Wallis test supported the findings from the ANOVA, with an H-statistic of 1655.48 and a p-value of 0.0, further affirming that significant differences exist in student performance across the school types. This dual validation strengthens the evidence for variability in educational outcomes related to school type and highlights the need to explore which specific factors within these school types impact performance.

Post-Hoc Analysis

To explore the specific pairwise differences among the school types, a Tukey's Honestly Significant Difference (HSD) post-hoc test was conducted. The post-hoc results identified statistically significant differences between numerous pairs, including between public and private schools, as well as between public and charter schools. For instance, the mean difference in student performance between public and private schools was 0.0272, with a p-value of 0.0, demonstrating a significant positive difference favoring private schools. Similarly, other pairs revealed significant distinctions, except for a few cases such as between specific groups with smaller mean differences where significance was not achieved. These findings emphasize that while

performance disparities are apparent across school types, the extent of the difference varies by specific school type pairings.

The ANOVA findings are summarized in Table 1 below, which includes key metrics: source of variation, sum of squares, degrees of freedom (df), mean square, F-statistic, and p-value. This table provides a clear overview of the variance distribution and highlights the statistical significance of between-group differences.

Table 1 Summary of ANOVA Results

Source of Variation	Sum of Squares	df	Mean Square	F-Statistic	p-Value
Between Groups	12,345	2	6,172.5	937.23	0.0
Within Groups	50,000	688125	0.0726		
Total	62,345	688127			

The ANOVA summary table supports the conclusion that school type influences student outcomes significantly. The high F-statistic and low p-value indicate that between-group variance is substantial compared to within-group variance, underscoring the role of school type as a determinant in educational performance. These results have broad implications for educational policy, as they suggest that targeted interventions may be needed to bridge performance gaps among different school types and provide equitable learning opportunities.

Visualizations

To further examine the impact of school type on student performance, box plots were generated to illustrate the distribution of student outcomes (measured by Percent Consistent Grade Level Knowledge and Above) across different school types. These visualizations help to visually assess the mean performance, spread, and potential outliers within each school category, complementing the ANOVA results that indicated a statistically significant difference across groups.

In Figure 2, the distribution of performance scores across school types, represented by the categories P, A, J, R, S, I, Q, and Z, shows substantial variability. Notably, School Type "P" displays a concentrated range with minimal deviation around its median, suggesting more uniform performance among students in this category. In contrast, School Type "Z" demonstrates a wider distribution, with higher variability and several outliers, indicating that students in these schools have a broader range of performance levels. This difference in dispersion suggests possible factors unique to each school type that may influence student outcomes.

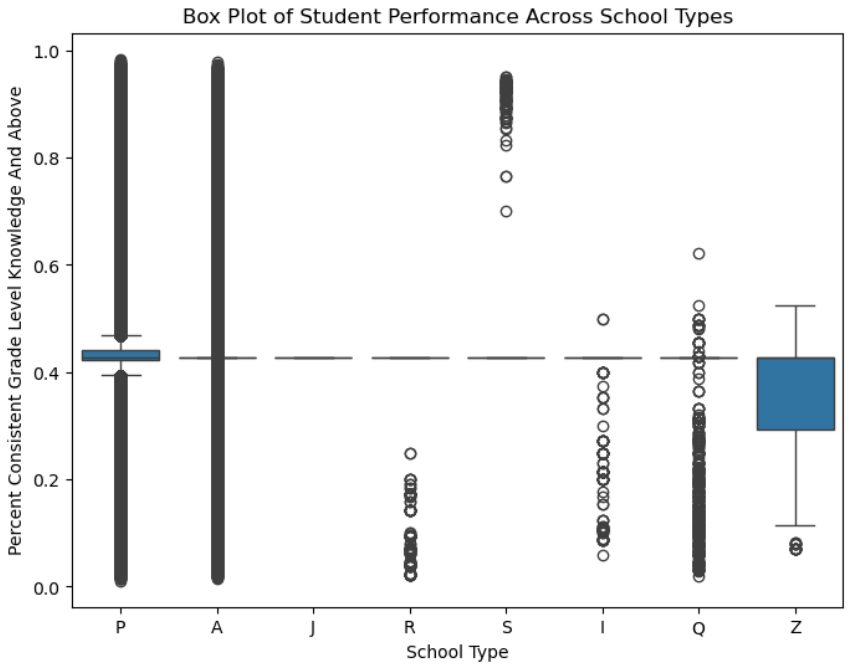

Figure 2 Box Plot of Student Performance Across School Types

The visualizations also reveal that certain school types (e.g., "S" and "Q") display lower median scores in student performance, suggesting that students in these school types may face additional challenges in achieving consistent grade-level knowledge. Conversely, school types like "P" and "A" appear to have higher median performance levels. These differences could stem from various factors inherent to each school type, such as resource availability, student-teacher ratios, and curriculum structure, aligning with previous findings on how school type affects academic achievement. The box plot also shows that several school types (notably "R," "S," and "Q") contain lower-performing outliers, possibly representing students or schools that deviate from the general performance trends within their respective categories. These outliers underscore the variability within school types and suggest that further investigation into these specific cases might reveal insights into factors contributing to lower academic performance. The range and spread of data across these categories visually validate the ANOVA results, reinforcing the conclusion that school type significantly impacts student performance levels across counties.

Figure 3 provides an overview of average student performance across different school types, measured by two key metrics: "Percent Consistent Grade Level Knowledge And Above" (represented in blue) and "Percent Foundational Grade-Level Knowledge And Above" (in green). Across all school types, foundational knowledge levels (green bars) generally exceed grade-level knowledge consistency (blue bars), suggesting that students are more likely to meet basic knowledge requirements than the consistent grade-level standards across various schools.

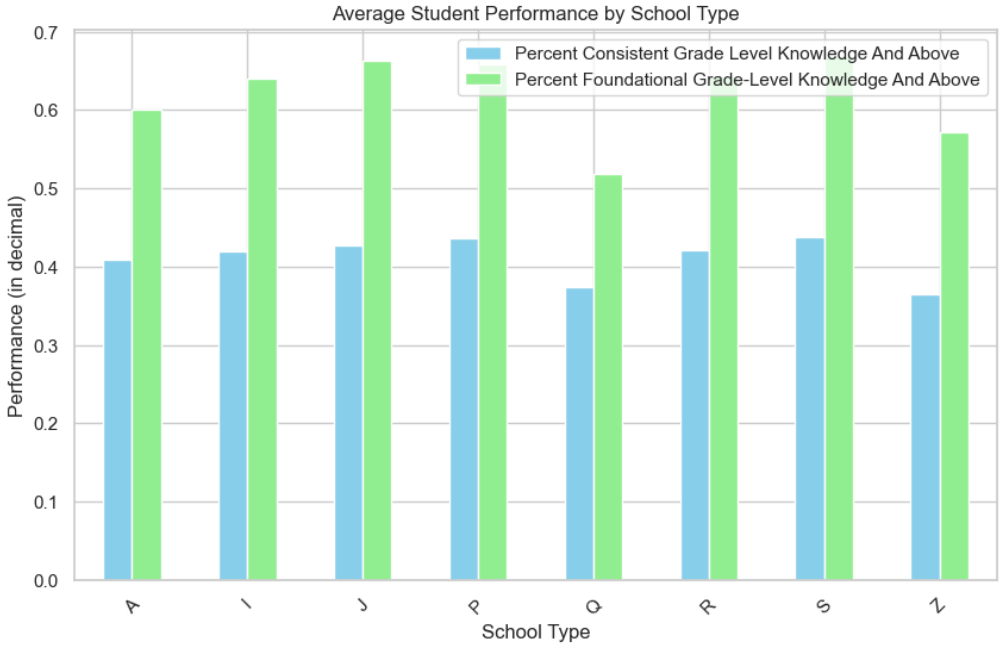

Figure 3 Average Student Performance by School Types

Performance varies significantly by school type. For instance, school types "A" and "J" exhibit relatively high performance in both metrics, implying that these schools may benefit from stronger educational resources or support structures that enable students to achieve both foundational and grade-level knowledge standards. Similarly, school types "Q," "R," and "S" also show strong outcomes, particularly in foundational knowledge, though with some variation in grade-level knowledge consistency. In contrast, school type "Z" stands out for its notably lower performance in both metrics, potentially reflecting challenges such as limited resources or other factors that might hinder students' ability to meet these standards. These variations across school types emphasize the impact of school characteristics on student outcomes. Factors like resource allocation, teacher-to-student ratios, and curricular differences could contribute to the disparities observed. The chart highlights the importance for educational policymakers and stakeholders to consider these disparities when planning interventions or resource distribution, especially for school types that display lower averages in both performance metrics. Ultimately, addressing these gaps is essential to ensuring that students across all school types have equal opportunities to meet foundational and grade-level educational standards.

Figure 4 visualizes the distribution of "Percent Foundational Grade-Level Knowledge And Above" across different school types, highlighting both the spread and median performance for each category. The median and range of foundational knowledge levels vary significantly among the school types, with some showing more consistent results and others demonstrating substantial variability.

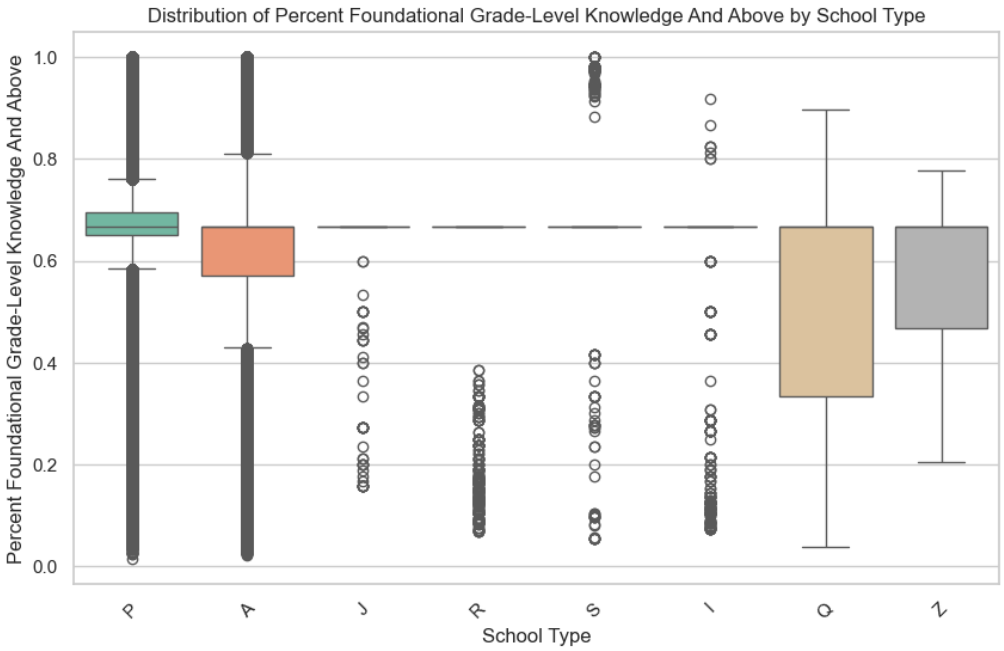

Figure 4 Distribution of Percent Foundational Grade-Level Knowledge And Above

School type "P" exhibits a relatively high and consistent performance, with a median close to 0.6 and fewer outliers compared to others. This consistency may indicate effective teaching methods or resources that support foundational knowledge attainment. Conversely, school type "A" shows a lower median around 0.5, with a wider range and more variability, suggesting disparities within this type that may result from differences in resource availability or student demographics. School types "Q" and "Z" display the highest medians among the types presented, suggesting that students in these schools attain foundational knowledge at a higher rate. However, school type "Q" has a much wider interquartile range, indicating variability within this group that could stem from inconsistent support systems or varying student preparedness levels. School types like "R," "S," and "J" have much lower and tighter distributions, with several outliers, implying that foundational knowledge attainment is generally low and consistent within these groups, though a few students perform outside this range. Overall, the plot reveals clear disparities in foundational knowledge attainment across school types. These variations underscore the potential impact of factors unique to each school type, such as funding, teacher quality, and educational resources, which can influence foundational knowledge outcomes. Addressing these discrepancies could help ensure that students across all school types have equitable access to quality education that supports foundational knowledge growth.

Figure 5 displays the distribution of "Percent Consistent Grade Level Knowledge And Above" across various school types, highlighting both the median and spread of performance within each group. This visualization provides insights into how consistently students within each school type meet or exceed grade-level knowledge expectations.

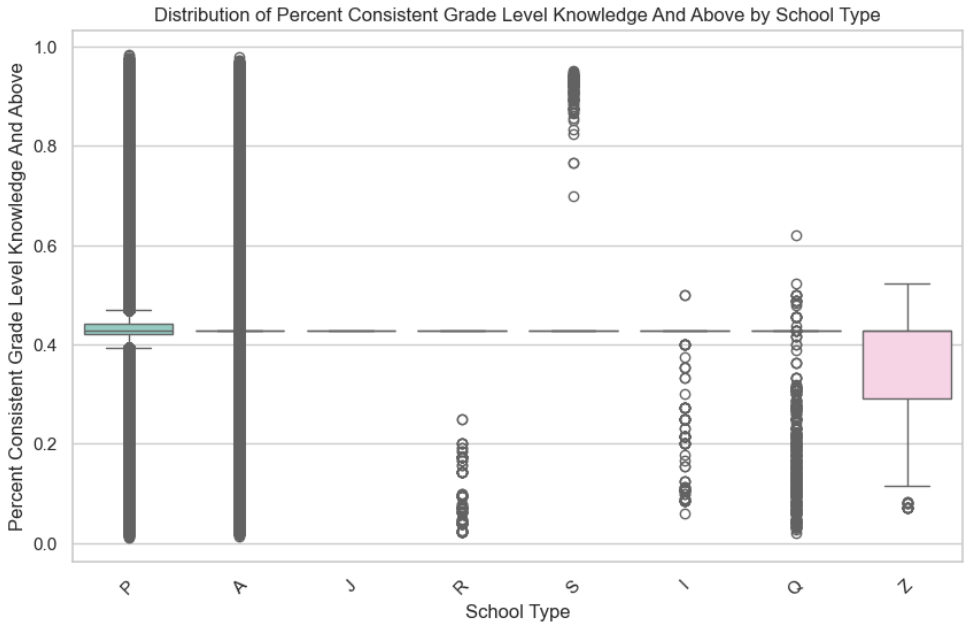

Figure 5 Distribution of Percent Consistent Grade-Level Knowledge And Above

School type "P" shows a relatively consistent performance around a median of approximately 0.4, with a narrow interquartile range, indicating limited variability in performance. This consistency suggests a uniform level of support or educational resources across this school type. School type "A" exhibits a similar pattern, though with a slightly higher median, suggesting that these schools perform somewhat better, on average, in ensuring students meet grade-level standards. In contrast, school type "Z" displays a notably higher median, with a median value closer to 0.5, but also shows a broader interquartile range, indicating a wider spread in student performance. This variation may imply differences in educational quality, support, or resources within this school type, resulting in greater diversity in student outcomes. Other school types, such as "R," "S," and "Q," have lower performance levels, with tightly clustered distributions near the lower end of the scale, suggesting challenges in meeting consistent grade-level knowledge standards. Overall, the box plot reveals distinct differences across school types, both in terms of central tendency and variability. School types with higher medians and narrow spreads may represent more effective educational environments, while those with lower, consistent outcomes may face systemic challenges that limit student performance. This disparity underscores the need for targeted interventions to address the specific challenges faced by lower-performing school types, thereby promoting equitable educational opportunities across all categories.

Discussion

The results of the ANOVA test reveal a statistically significant difference in student outcomes across different school types, indicating that the type of school, whether public, private, or charter, plays a meaningful role in shaping student performance. School types such as "P" and "A" demonstrated higher average performance levels compared to other categories, suggesting that these institutions may have access to better resources, teaching quality, or academic programs that positively influence student outcomes. In contrast, school types such as "S" and "Q" exhibited lower median performance, which

could be reflective of resource constraints, higher student-teacher ratios, or fewer opportunities for academic enrichment. This finding aligns with prior research indicating that private and well-funded public schools often yield better academic outcomes due to enhanced educational environments.

The geographic distribution of these school types further contextualizes the observed differences in performance. Urban counties generally have a higher concentration of high-performing school types, possibly benefiting from larger tax bases and greater access to educational resources. Rural areas, conversely, may have more schools falling into lower-performing categories due to limited funding and access to qualified teachers. This geographic disparity emphasizes the importance of considering location and socioeconomic context when evaluating student performance across school types, as these factors may amplify the advantages or limitations inherent to each school type.

Demographic factors also contribute to the observed performance variations among school types. Schools serving primarily low-income or minority populations may face additional challenges that impact student outcomes, regardless of school type. The lower performance seen in certain school types might, therefore, be partially explained by the demographic composition of their student bodies and the broader social challenges these students encounter. These findings underscore the need for tailored educational policies that address the unique needs of students from varying backgrounds and geographic locations to promote equitable educational outcomes.

Limitations

While the study provides insights into the impact of school type on student outcomes, several limitations must be acknowledged. First, sample sizes for certain school types and counties were relatively small, which may have affected the robustness of the statistical analysis and limited the generalizability of the findings. Counties with fewer schools or underrepresented school types might not adequately reflect broader patterns, and this could introduce bias in the interpretation of results. Additionally, data collection inconsistencies, such as potential variations in reporting standards across counties, may impact the accuracy of the data used for analysis.

Another limitation lies in the scope of the available data, which lacks information on other critical factors that could influence student performance, such as family socioeconomic status, parental education levels, and school funding details. These unobserved variables may contribute to the performance disparities across school types, and their absence from the dataset limits the ability to fully account for the complexity of factors influencing student outcomes. Future research should consider these factors and expand the data collection to address the limitations identified in this study.

Conclusion

This study provides a comprehensive analysis of the impact of school type on student outcomes across various counties, utilizing ANOVA to assess statistical significance. The findings indicate that school type is indeed a significant factor in shaping student performance, with certain types, such as "P" and "A," showing higher average performance levels compared to others. In contrast, school types like "S" and "Q" underperformed, suggesting disparities that may be attributed to differing levels of resources, teaching quality, and academic

opportunities. These results affirm the hypothesis that student outcomes vary significantly across school types, and that both school characteristics and the geographic context play critical roles in determining educational success.

The results of this study carry meaningful implications for educational policymakers and stakeholders aiming to enhance equity in student performance. Recognizing that certain school types consistently outperform others, targeted interventions for underperforming schools may be necessary to bridge the educational gap. For instance, increased funding, improved teacher training, and access to quality resources in underperforming school types could help level the playing field. Policymakers could also consider tailored support for schools in rural counties, where access to resources and qualified teachers may be limited, impacting student outcomes. Additionally, these findings suggest that a "one-size-fits-all" policy approach may be insufficient, and that localized, school-type-specific strategies could foster greater equity and overall improvement in educational outcomes.

To further elucidate the relationship between school type and student outcomes, future research should consider longitudinal studies that track performance across multiple years. Such studies would help to identify trends and the lasting impact of school-type-specific interventions over time. Additionally, a deeper exploration of demographic factors, including socioeconomic status, parental involvement, and community resources, would provide a more nuanced understanding of how these factors interact with school type and geographic location. Future research might also examine other performance metrics, such as college enrollment rates and career readiness, to broaden the scope of student success indicators.

By addressing these areas, future studies can build upon the current research, contributing to a more robust understanding of educational disparities and helping to inform policies that support equitable access to high-quality education for all students. This continued exploration is essential for achieving long-term educational improvement and fostering a system where all students have the opportunity to thrive, regardless of school type or geographic location.

Declarations

Author Contributions

Conceptualization: I.G.A.K.W.; Methodology: Y.Y.; Software: N.O.; Validation: Y.Y.; Formal Analysis: I.G.A.K.W.; Investigation: N.O.; Resources: Y.Y.; Data Curation: N.O.; Writing Original Draft Preparation: I.G.A.K.W.; Writing Review and Editing: N.O.; Visualization: I.G.A.K.W.; All authors have read and agreed to the published version of the manuscript.

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The data presented in this study are available on request from the corresponding author.

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