Multimodal Technologies and Interaction

Article

Leveraging Visualization and Machine Learning Techniques in Education: A Case Study of K-12 State Assessment Data

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Abstract: As data-driven models gain importance in driving decisions and processes, recently, it has become increasingly important to visualize the data with both speed and accuracy. A massive volume of data is presently generated in the educational sphere from various learning platforms, tools, and institutions. The visual analytics of educational big data has the capability to improve student learning, develop strategies for personalized learning, and improve faculty productivity. However, there are limited advancements in the education domain for data-driven decision making leveraging the recent advancements in the field of machine learning. Some of the recent tools such as Tableau, Power BI, Microsoft Azure suite, Sisense, etc., leverage artificial intelligence and machine learning techniques to visualize data and generate insights from them; however, their applicability in educational advances is limited. This paper focuses on leveraging machine learning and visualization techniques to demonstrate their utility through a practical implementation using K-12 state assessment data compiled from the institutional websites of the States of Texas and Louisiana. Effective modeling and predictive analytics are the focus of the sample use case presented in this research. Our approach demonstrates the applicability of web technology in conjunction with machine learning to provide a cost-effective and timely solution to visualize and analyze big educational data. Additionally, ad hoc visualization provides contextual analysis in areas of concern for education agencies (EAs).

Keywords: data visualization; big data; AI; machine learning

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1. Introduction

Information processing and dissemination is a primary resource valuable to any organization. The average person processes sensory data or stimuli as images. Humans process images better than any other stimulus. When data come into the brain, the first inclination is to turn them into images or relate them to some visual experience that the person is familiar with—for example, audio stimuli such as music or screams. Immediately on reception, a person will either associate imagery related to how that stimulus makes them feel or their assumption as to what is occurring during the event. Therefore, it is a viable assumption that turning data into visualizations would have an impact on processing those data [1].

Data-driven decision making has become increasingly popular for action-based strategic planning. An organizational body or institution uses it to derive milestones for the goals, adjust operations, or provide proof of concept for its proposed action plans. The education field is no exception [2]. An increasing number of organizations are utilizing data for purposes beyond the educational outcomes of learning nowadays to improve decision making. However, there is still a gap in actualization and usage in several areas, namely data delivery, predictive analysis, visualization, and machine learning [3], to improve data-driven decision making. In this paper, we demonstrate the feasibility of actualizing these areas and improving their implementation for use in education.

While investigating the available, ready-to-deploy, or easy-to-use solutions that make use of visualization or machine learning, we found a significant lack of web-capable or web-ready solutions for K-12 school use. Although data were available in a readable format on the web, there was a notable lack of understandable and actionable visualization, predictive analytics, and functional use to utilize them for data-driven decision making in education. Thus, there is a significant need for a cost-effective and timely solution to visualize and analyze big educational data.

The major goal of this paper is to leverage data visualization and machine learning techniques to address the challenges in educational data analytics and demonstrate the utility, versatility, and usefulness of these techniques through practical implementation of reading grade-level data in K-12 education compiled from the institutional websites of the State of Texas and Louisiana. To meet this major objective, the project has several sub-objectives, as shown below:

- Goal #1: To quantify the factors in the K-12 education dataset and showcase the visualization of the results that are understandable, lacking misrepresentation, and effective in modeling the desired perspectives;
- Goal #2: To leverage ML models to showcase the utility in the educational data and understand the intent of usage of the data and their impact.

The major contributions of our work are as follows:

- We provide a proof of concept for the real-time visualization of educational data that are interpretable, lacking misrepresentation, and effective in gaining insights from them and improving data-driven decision making.
- We provide a proof of concept that demonstrates how an institution can implement solutions internally for cost-effectiveness.
- We leverage machine learning to predict the students' scores and provide the utility of it in educational assessment data.
- We leverage maps to showcase educational assessment data for all districts of Texas and Louisiana to improve the understanding of school-level data.

The rest of the paper is organized according to the following sections: Section 2 discusses related work, and Section 3 describes the methods implemented in the proposed approach. Section 4 presents the results. Finally, the paper will conclude with a discussion and summary of findings.

2. Related Work

In recent years, data have been considered a viable means of evaluating a school's effectiveness [4,5]. However, most of the existing data that an agency uses are focused on individual schools and do not leverage the widely available data from all institutions within the agency's governing body sphere of jurisdiction [3]. Even within individual local organizations, they are primarily focused on the overall comparison against the standard set by the governing agency and possibly a few similar competitors [6].

We reviewed the literature related to machine learning (ML), modeling, visualization, education, and data collection to understand the state-of-the-art technologies, datasets, and research in the education domain. The relevant knowledge helped us to understand some of the challenges in data access [7,8] and approaches to personalized metrics [9] and identify certain technologies suitable for the desired outcomes of this research [10]. Since visualization and ML are the underlying foundation of this work, these papers act as a baseline for prior work, gap analysis, and foundational theory.

The existing literature on data-driven decision making acts as a knowledge bank for educational institutions to support academic enhancement, resource allocation, or the strategic plan to increase enrollment [11]. Among these, a heavy focus on allowing the data to dictate which operational objectives are critical to the response matrices the institutions present. However, there is still a gap in the means or methods of disseminating data in a technologically innovative manner. The norm of any investigative report or analysis that provides a product outcome is either multiple versions of spreadsheets or tables for displaying the results. For administrative purposes charts, graphs, or heatmaps can act as a good visualization tool to understand the data insights.

Uyan Dur [12] discussed the importance of data visualization and infographics to communicate complex ideas and concepts in a simpler, comprehensive, and creative manner and their utility in the current education system. To efficiently share information, it is crucial to assess the conditions under which visualizations might be needed and determine the most fitting design. The reviewed literature for this paper confirms that when applied to practical use cases, the utilization of visualization can contribute to achieving desired outcomes in the field of education.

Recently, Rui and Badarch [13] deeply explored the usage of artificial intelligence (AI) in education. Their study showcases the benefits of student outcomes by incorporating AI into mainstream education. From this perspective, AI as a learning tool is highly supported. The authors discussed the design of an information-based teaching model with the purpose of displaying knowledge more intuitively in front of students. By doing this, they hope to showcase how the proposed model enriches the overall teaching and reduces the difficulty of students' learning. Since this article exclusively focuses on student learning, the authors extensively delve into how advancements in technology have proven beneficial as integrations into the methodology.

Similarly, prior works from Jones [14] and Beck et al. [15] provided an exposition of the usage of computers as a resource in education. One of the key observations regarding these articles is that limitations such as programming language compatibility, resource constraints, and inability to conduct conversations with the student in the student's natural language can now be mitigated with the technology currently available. This research specifically discusses AI and several types of computer-assisted instruction systems (CAIs) and how they may facilitate learning. Though this article focuses on the development of learning environments, it also discusses viable uses for diagnostic tools.

A more recent publication by Wang et al. [16] in 2022 pinpoints one of the gaps mentioned in education. In this article, the researchers acknowledge that current research on the visualization of educational big data lacks relevant theoretical guidance and systematic sorting and is limited to the design of informatization platforms based on the visualization of educational big data. Our paper directly aims to encourage improvement in the areas of the implementation of educational data visualization as mentioned in [16] and actively attempts to address the design of educational informatics platforms based on the visualization of education data. Our approach will be beneficial for institutional administrators as it will assist them with making data-driven decisions for institutional or organizational improvement.

As data-driven decision making has become an area of focus in education, it is important to discuss the impact of visualization and machine learning algorithms in the education domain. It is reasonable to assume that more data will lead to more complexity. Recently, Llaha and Aliu [17] discussed the application of data visualization and machine learning algorithms for better decision making in criminology. However, similar approaches can be taken in education for decision making at any level. Williamson [18] discusses cases that employ models and different implementations facilitating predictive analytics as well as increased levels of interactive use. By taking advantage of available resources, multiple uses can be found that are highly suited to an educational agency's advancement in governance, data visualization, predictive analytics, and advanced real-time strategies while safeguarding security.

Artificial intelligence exposes vulnerabilities in data security while visualization displays the degree. Therefore, sensitivity becomes a factor in displaying information. How sensitive will depend on the investment value, leading to bias and ethical issues. Programmatically, influence is injected through the lenses of perceived relevance of data or stakeholder investment values. The appropriate approach to implementing ML and visualization must at some point consider ethics and biases [19]. In the article authored by Akgun and Greenhow [20], the authors assess ethical challenges and propose means of addressing them while introducing useful resources to that end.

Overall, the previous works discussed several valid approaches to different concepts in visualization, machine learning, and educational practices. However, they did not fully address the gap found in creating and demonstrating a cost-effective in-house approach for education agencies. This is an important area of concern for institutions since the majority of their budgets tend to rely heavily on public funds and government allotments. Solutions that are replicable, cost-effective, and maintainable provide the best functionality for these institutions. While being cost-effective, it also ensures data safety or that ethics required by these institutions remain as internal as the delivery tactics chosen and are directly controlled by their delivery processes, not by contracts from external agencies. Since data-sharing agreements and software usage rights at times contain clauses for rights, we eliminate that issue by delivering in-house builds. In this paper, we provide an implementable solution for addressing this need when funds are non-existent for subscription-based products like Power BI and others.

3. Methods

This section provides a brief overview of our proposed data visualization and machine learning approach and its application to the K-12 assessment data.

3.1. Dataset

In this paper, we used GeoJSON map files and end-of-year state assessment data for the states of Texas and Louisiana, as shown in Figure 1 and Table 1. The map files we used housed the geolocations and coordinates of the districts observed within the state of Texas. These data points were used to create the district comparisons and interactive map models for our research. There was a total of three map files including the comprehensive district data file retrieved from the Texas Education Agency Public Open Data Site. The end-of-year state assessment data were obtained from publicly available sources, including the State of Texas Education Agency for students assessed in Texas, the State of Louisiana, and the National Center for Education Statistics (NCES) [21–24].

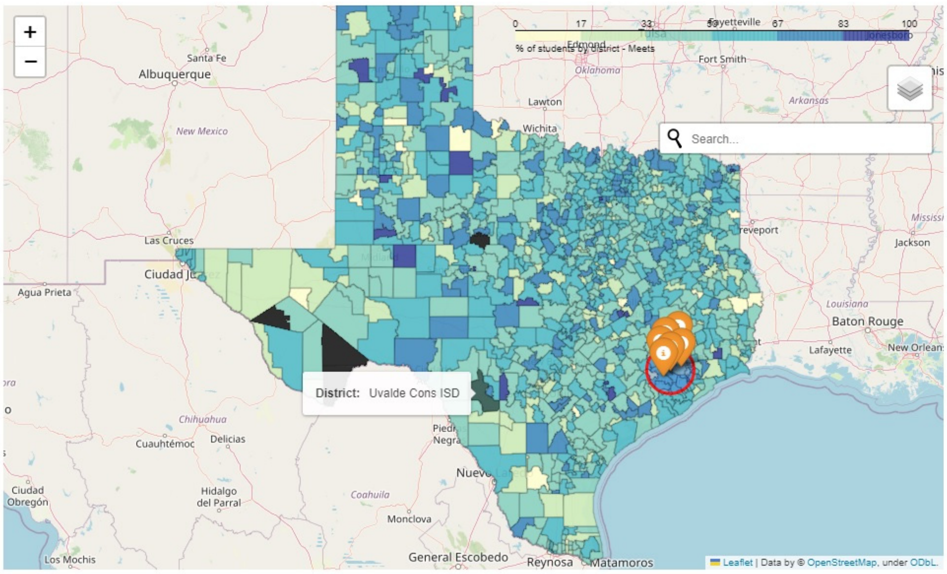

Figure 1. Implementing choropleths and interactive maps with GeoJSON files.

Table 1. Data description of Texas education assessment data.

Type	Grade Level	% of Students Did Not Meet	% of Students Approaches	% of Students Meets	% of Students Masters
Mean	3	22.39	77.18	49.80	28.23
Sd	0	13.48	14.34	16.18	12.9
Min	3	0	0	0	0
25%	3	13	70	40	20
50%	3	21	79	50	27
75%	3	30	87	60	35
Max	3	90	100	100	77

The education assessment data STAAR [21] are publicly accessible data available on the Texas Education Agency (TEA) website containing district-level data of third-grade reading performance results from assessment years 2017 to 2022. Table 1 shows the descriptive statistics of the data from Texas. Each of these datasets contains information about the district, school, class, session of the year, test type, and percentage of students meeting the proficiency level or not. These data provide an assessment of overall students within the school in the district of the state. Texas state assessment data comprise 1152 districts. Some districts lack grade-level data for specific years either because the grade level was not tested in that particular year, or the district was not actively operational during that time. These data span approximately five years of tracking and comprise a combination of numerical and textual results. Since the data are not processed, they will need to be quantified and preprocessed before being used in any of the designed models. The ingestion of collected data points included demographic data, test results, dates, and location data. The map files used for this research are in GeoJSON format and specify location-based features of the districts as well as the relative geometric shape boundary of those districts and states.

Key fields of importance extrapolated from the file include the location's size measured by area, its geometry, and its coordinates (longitude/latitude). The states' data were further parsed by district with these same data points. The assessment data for Texas schools comprise 1152 total districts. For the third-grade data used in this research, the percentage of students per performance category ranged from 22% to 77%, with the highest category of students attaining the approaches' standard (minimum passing rate).

3.2. Extraction, Transformation, and Loading

After obtaining the data, a review was conducted to ensure that each subject would have the minimum required number of variables, as shown below:

- Number of students tested;
- Percentage of students meeting the proficiency level;
- Dates of assessment;
- Location.

Our statistical models and computations took advantage of prebuilt libraries to graphically display the comparative results of the data. We removed missing values, corrected misaligned data points, and filtered non-numerical values to structure the data for extraction.

For example, Figure 2 shows the distribution of the percentage of students who fell within the Meets category in terms of the proficiency levels of students, which indicates that students have a high likelihood of success in the next grade or course but may still need some short-term, targeted academic intervention. Two challenges that this paper may tackle effectively as a side result are automating effective visualization and limiting created cognitive barriers.

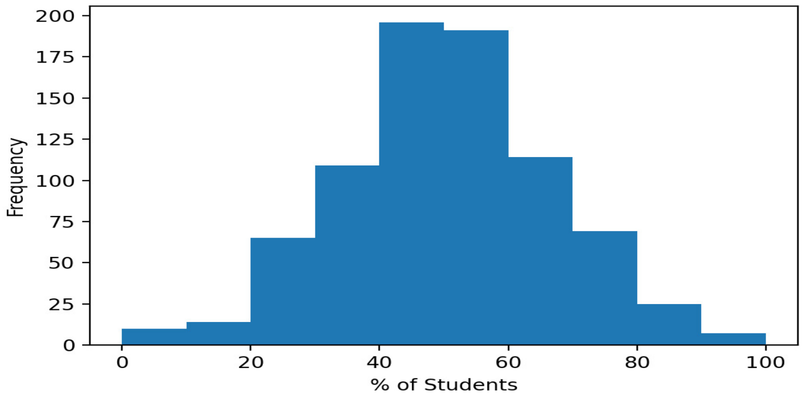

Figure 2. Distribution of the percentage of students satisfying the Meets proficiency level category.

It is easy to sometimes display data that will result in inference confusion, in which a result is concluded based on misrepresentation of data. For example, Figure 3 shows multiple trend lines for performance metrics on the same graph as the total student count. This visualization represents the data in a manner that hinders the capability to derive insights from them. It would be better to represent the percentages together on one graph or separately, as shown in Figures 4 and 5.

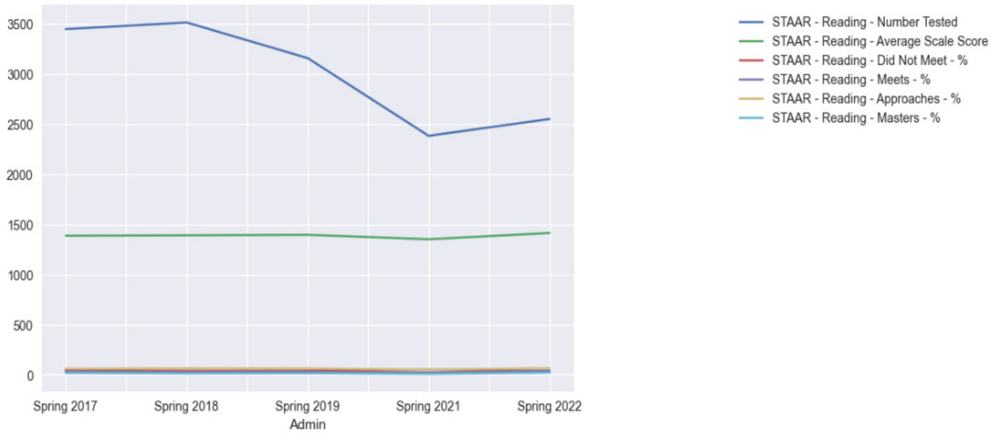

Figure 3. Example of poor graphical representation of multiple trend lines and axis misrepresentation.

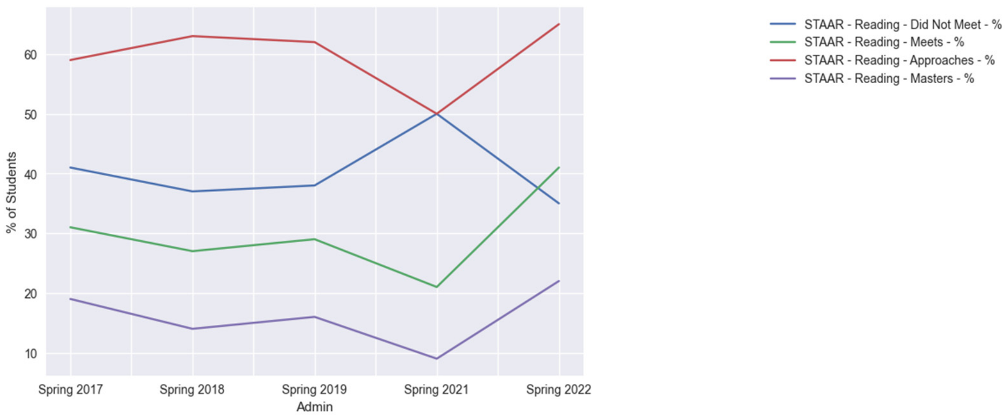

Figure 4. Example of better graphical representation for trend lines of performance standard measurement.

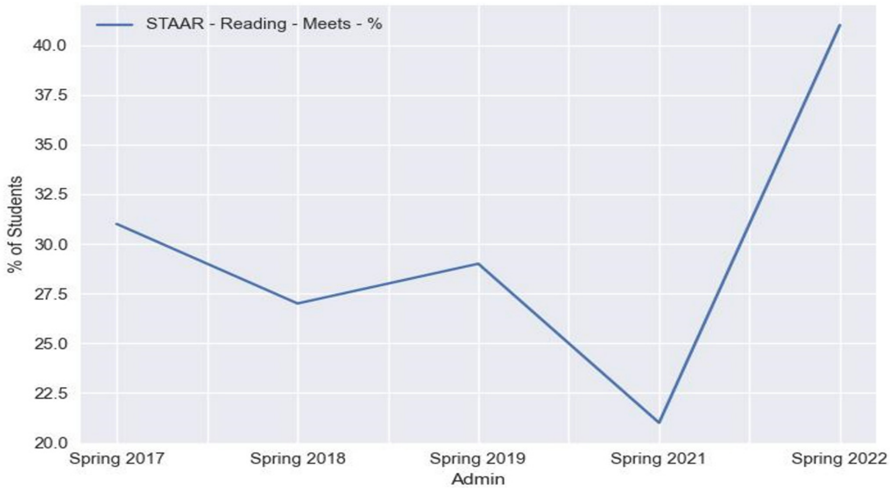

Figure 5. Graphical representation of trend line of performance standard measurement by time.

Often, how information is presented will have an effect on the outcome of any action taken or insights derived. Since this paper aims to assist in understanding data in a specific arena, the output may be useful in changing approaches or standpoints. With this work, there is space to make this a web-enabled and fully deployed solution in the future. For this research's processes, we tackled eliminating undesirable models, color correction, and adding features while maintaining accurate visualizations. Eventually, this offers the capability to combine population statistics and employment data and use data mining.

The types of visualizations that resulted from this research included several types of statistical graphs. In the bar graphs, as shown in Figure 6, we can showcase what would be useful for our story concept of how the scores are distributed across the five highest-performing school districts (of which our test district is not included) to compare with our test district's data.

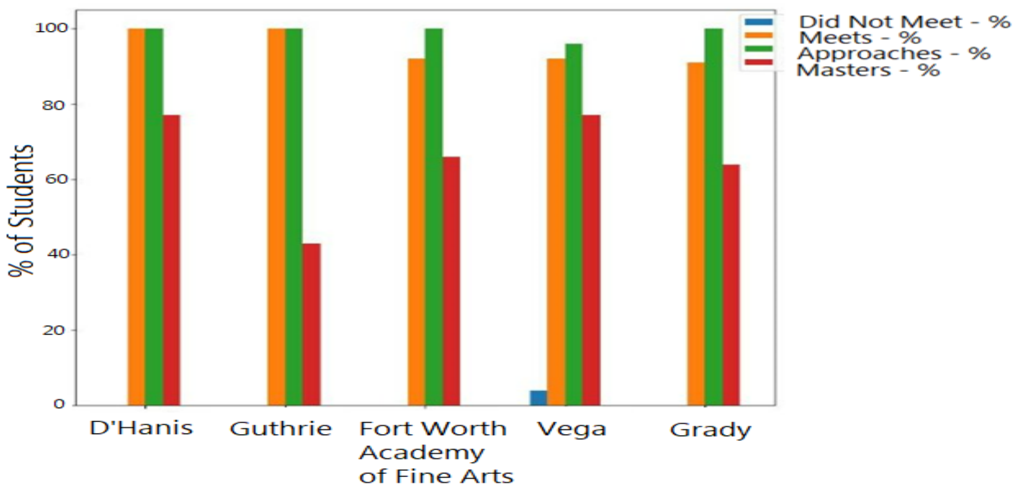

Figure 6. Graph of percentage of students within each performance standard measurement.

There were also spaces for which scatter plots such as the next infographic were useful. As shown in Figure 7, we plotted the entire statewide data and showed how our test district performed in our category of interest compared to all others.

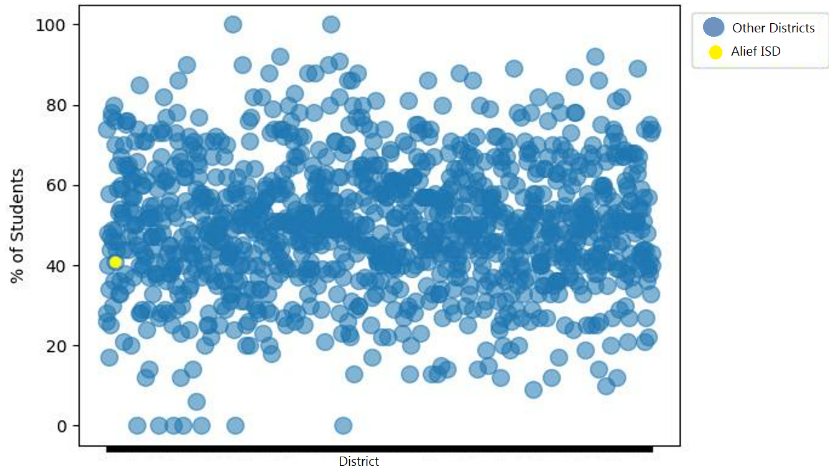

Figure 7. Plot of percentage of students of individual districts.

One of the reasons these are so effective is that schools spend a great deal of time with spreadsheets or PDFs to try to assemble something useful for deriving insights. Some of the data reports taken from the official website of the Texas Education Agency shown in Figures 8–11 demonstrate this. Figure 8 shows the reports that can be downloaded in any format from the website. Figure 9 shows a sample report of result-driven accountability (RDA) district report, which showcases the data on the performance of school districts and charter schools in selected program areas (bilingual education/English as a second language/English learners, other special populations inclusive of students in foster care, students who are homeless, students who are military-connected, and special education). Figure 10 shows the report for the proficiency level of the different subjects, and Figure 11 shows a previous Texas visually friendly tool to visualize the insights which is now decommissioned and replaced. The sources or repositories for the information are often not user-friendly (Figures 8 and 10) or they are too time-consuming to make any effective use of (Figures 9 and 11).

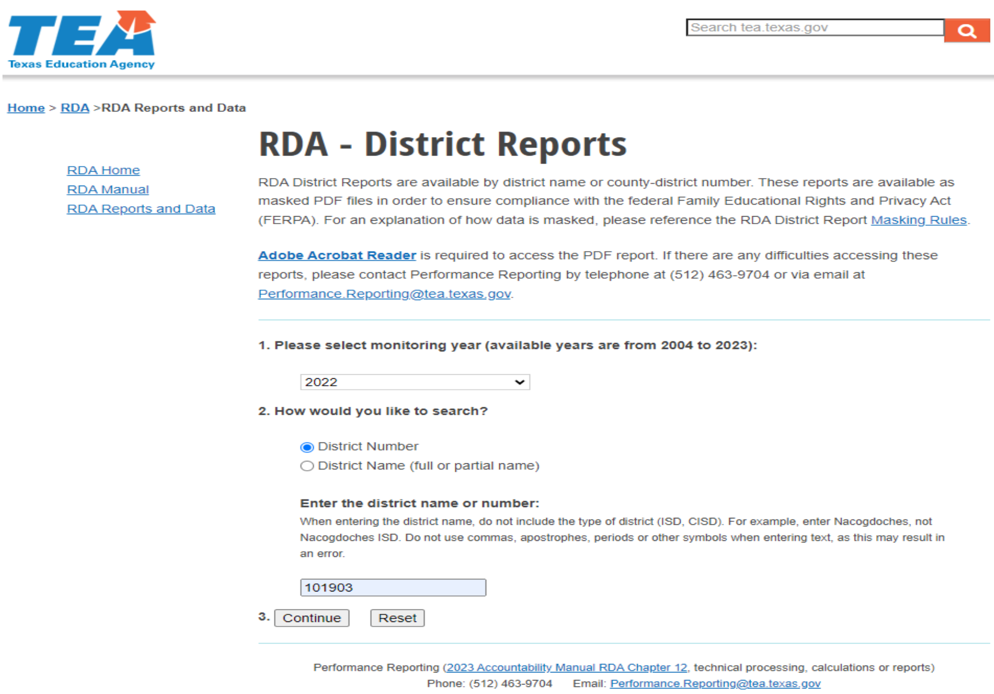

Figure 8. Example of accessible data reports [6].

Texas Education Agency

2022 Results Driven Accountability

District Report

County-District Number:
District Name:

Region: *04*

Bilingual Education/English as a Second Language & Emergent Bilingual Students (BE/ESL/EB)

Domain I – Academic Achievement (Indicators 1–9)
Domain II – Post-Secondary Readiness (Indicators 10–11)
Domain III – Disproportionate Analysis (Indicator 12)

Other Special Populations (OSP)

Domain I – Academic Achievement (Indicators 1–3)
Domain II – Post-Secondary Readiness (Indicators 4–5)
Domain III – Disproportionate Analysis (Indicator 6)

Special Education (SPED)

Domain I – Academic Achievement (Indicators 1–5)
Domain II – Post-Secondary Readiness (Indicators 6–7)
Domain III – Disproportionate Analysis (Indicators 8–18)

Figure 9. Example of output formats of data reports [6,25].

Texas Education Agency
2021-22 STAAR Performance (TAPR)
- HARRIS COUNTY

	School Year	State	Region 04	District	African American	Hispanic	White	American Indian	Asian	Pacific Islander	Two or More Races	Special Ed (Current)	Special Ed (Former)
STAAR Performance Rates by Tested Grade, Subject, and Performance Level													
Grade 3 Reading													
At Approaches Grade Level or Above	2022	76%	76%	**67%**	69%	63%	74%	100%	80%	80%	*	43%	72%
	2021	67%	68%	**53%**	57%	48%	51%	40%	71%	*	71%	29%	55%
At Meets Grade Level or Above	2022	51%	52%	**41%**	47%	35%	47%	46%	58%	80%	*	29%	50%
	2021	39%	39%	**24%**	29%	19%	24%	25%	40%	*	43%	17%	21%
At Masters Grade Level	2022	30%	31%	**22%**	26%	17%	29%	15%	37%	20%	*	12%	13%
	2021	19%	20%	**11%**	14%	8%	10%	15%	18%	*	14%	4%	7%
Grade 3 Mathematics													
At Approaches Grade Level or Above	2022	71%	71%	**60%**	56%	58%	68%	69%	79%	80%	*	39%	63%
	2021	62%	62%	**45%**	43%	41%	45%	35%	74%	*	57%	30%	48%
At Meets Grade Level or Above	2022	43%	44%	**32%**	28%	29%	41%	38%	58%	60%	*	22%	31%
	2021	31%	31%	**16%**	14%	13%	14%	15%	40%	*	29%	16%	14%
At Masters Grade Level	2022	21%	22%	**14%**	11%	12%	19%	15%	31%	20%	*	9%	19%
	2021	14%	15%	**5%**	5%	4%	6%	10%	15%	*	14%	3%	3%

Figure 10. Example of accessible data reports by interest group [25]. * represents if there are not enough students to fill that information.

Deploying methods similar to the implementation used in this research allows for not just the visual representation of the data but also interactive dashboarding that is suitable for stakeholders invested in school operations. As shown in Figure 12, multiple points of interest can be compiled to actualize relevant storyboards for stakeholders' use for decision-making. In this figure, the results of the regression models are stored as images in a dedicated file directory and through coding techniques deployed as a browser compatible html file.

Data Interaction™
for Texas Student Assessments

Group Summary: Performance Levels: STAAR 3-8, Grade 3

Group	Admin	Grade	STAAR - Reading Number Tested	Average Scale Score	Did Not Meet %
A W BROWN LEADERSHIP ACADEMY	Spring 2017	3	221	1326	56
Hispanic/Latino	Spring 2017	3	8	1326	50
Black or African American	Spring 2017	3	213	1326	56
A W BROWN LEADERSHIP ACADEMY	Spring 2018	3	193	1387	37
Hispanic/Latino	Spring 2018	3	3	-	-
Asian	Spring 2018	3	1	-	-
Black or African American	Spring 2018	3	188	1386	37
White	Spring 2018	3	1	-	-
A W BROWN LEADERSHIP ACADEMY	Spring 2019	3	145	1381	43
Hispanic/Latino	Spring 2019	3	5	1316	60
American Indian or Alaskan Native	Spring 2019	3	1	-	-
Black or African American	Spring 2019	3	135	1381	44
Two or More Races	Spring 2019	3	3	-	-

Figure 11. Example of a visually friendly, low functionality data viewer [21]. This data portal has since been disabled and replaced as of school year 2023–2024 [21,26].

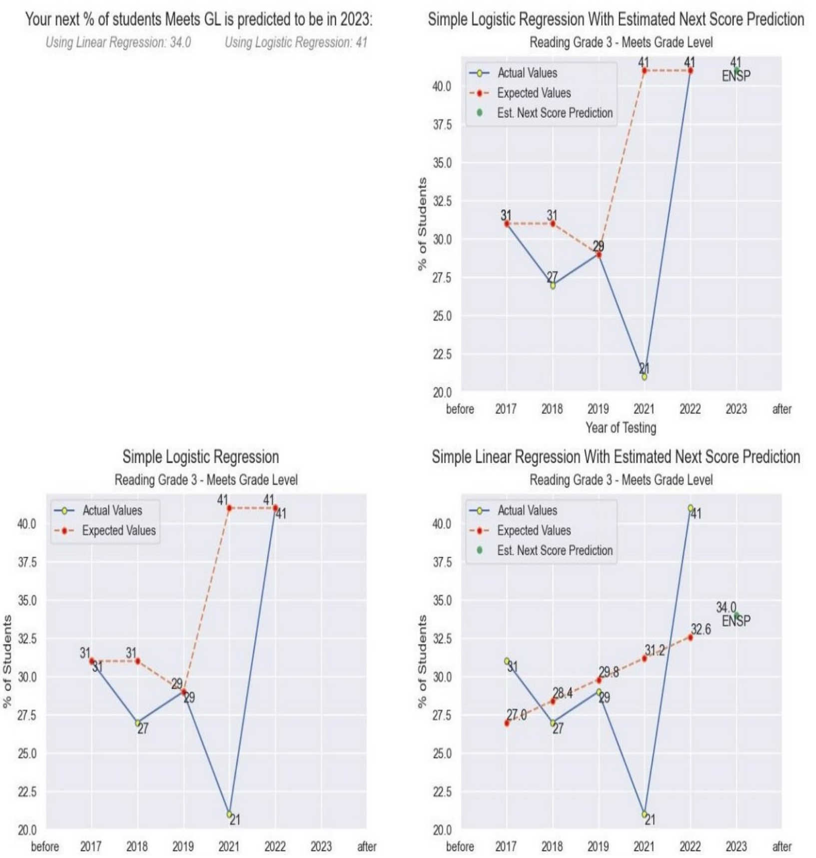

Figure 12. Example of creating analytic solutions for web deployment through dashboarding.

3.3. Learning Models

Machine learning is a field of artificial intelligence that allows for the learning of systems, computers, or other devices through experience with data or algorithms. We can use machine learning to project situational outcomes given the various data inputs and to make predictions and/or decisions. Machine learning minimizes the error/biases generated, by allowing the data to define rules for predicting the most probable outcome and then modeling that result across different domains. Employing various machine learning algorithms will yield varying impacts on the strengths of the relationships within the model. Machine learning practitioners also can make use of correction algorithms combined with their predictor algorithms to increase effectiveness and accuracy. When including machine learning as a component to support data-driven objectives in education, there is a noticeable difference in turnaround time in providing results that are actionable and valuable. We made use of two machine learning algorithms. Although there are other applicable types such as k-means clustering or SVM algorithms, in this study, we used linear regression followed by logistic regression as these are the most appropriate learning algorithms for our case study outcomes. This research focused on simple regression using single-variable analysis. It is possible to use multivariate regression techniques, but we used single-variable analysis in this paper.

Linear regression is a modeling technique that approaches prediction by drawing a relationship from one variable based on the value of another. The data are structured in a manner in which a line is used to approximate the relationship between the variables, serving as an estimation function to estimate a new value when provided with test input, similar to how we estimate the next point on a line by using the slope-intercept formula in mathematics. Logistic regression is a modeling technique that produces a probability of a discrete outcome given an input variable.

This research uses linear regression and logistic regression [27,28]. The models will take the grade-level data for the test district and use the data from the prior years to train and make a prediction for the next estimated score. Our test case uses the performance standard category "Meets grade level" and uses the percentage of students per year to make an estimate.

Expected Results

We expect our research to provide visualizations that are intuitive of the retrieved data. The results we expect from the research are to create visualizations that will be able to be used with the data from which the visualizations were created. They will be understandable, lacking misrepresentation, and effective in modeling the desired perspectives. The approach we take will produce results because one of the processes in the design model is removing biases and first modeling the statistical reference before inferring relationships. It is expected to have precision to the degree of completeness of the data and, where appropriate, adjustment for missing data and new models to represent those missing data. This paper's requirements can be used to provide the following results:

1. Financial Benefits
   - Result #1: Reduce expenditure of funds on resources to generate products;
   - Result #2: Inexpensive data evaluation to interested entities.
2. Technical Benefits
   - Result #1: Computerized modeling of data and correlations;
   - Result #2: Additional hands-on usage of data visualization;
   - Result #3: Evidentiary support/background research used as preliminary for future work.
3. Other Benefits

   These benefits are those that are specific to the stakeholders:
   - Result #1: Increased stakeholder investment and satisfaction;
   - Result #2: Opportunity to be used in conferences and research presentations.

4. Experiments and Results

In this section, we describe the experimental setup, results, and evaluation.

4.1. Experimental Setup

Several technologies were leveraged to showcase this research. The bulk of the language used was Python with some batch scripting to showcase different deployment options to be discussed later. Additionally, this research used machine learning in the form of regression for modeling and predictions. While this research employed simple linear and logistic regression of univariate stats, it is not limited in capability and can support multivariate analysis. The web tool for deployment that was used was StreamLit version 1.24.0. After creating the Python code used in the implementation, a batch script was used to call for the code and run it through a simple command line interface. In this way, if necessary, any minute changes that would need to be made could be made during testing or execution. It was saved and would even offer the ability to change the default image icon if one wanted to distinguish it from other programs stored on the device. To simply create the code file used to generate the data and the results, the steps presented in Table 2 were followed.

Table 2. Simple packaging and scripting methods for deployment.

Steps	Tasks
Step 1:	Determine the data used in the implementation.
Step 2:	Create the Python code to generate the desired data analysis.
Step 3:	Save the Python code in a specified location and make note of the file path.
Step 4:	Create a batch script file to execute the data to the web browser of choice through StreamLit. Use the file path of the saved Python file for the run command.
Step 5:	Save the batch script preferably in an easy-to-manage location for instant access or deployment.
Step 6:	Assign an image icon to the batch script.

We experimented on a system with an Intel(R) Core(TM) i7-10610U processing unit running with a 1.80 GHz processor with 16.0 GB RAM, 8 cores, and 1 TB of hard disk. The software and programs used in this research included a general 64-bit operating system for the device (Windows 10), Python 3.1 version release, natively built text editor (Notepad for creating batch scripts), and StreamLit framework install. For this research, the data and technology components were acquired by the research team. Data gathering, data processing, data model design, and data model programming and testing were included in the design process. This is useful to any agency or institution that may intend to remain relevant in those functional areas. In the event that the data were unavailable for any district, we ensured that the related models accounted for them and reflected accurately.

4.2. Evaluation Metrics

We evaluated the expected models against the actual observed scores and, based on the difference, identified the most likely model for the implementation. The criteria for the success of predictions is that the estimate must be within $\pm 1\%$ of the observed value, the error rate accepted by most institutions. The utility set of criteria includes the level of complexity related to implementation, cost-effectiveness, and level of value they will bring to the user and the organization.

4.3. Results

As a result of this research, we were able to achieve several deliverables. There were four successful groupings of models derived from implementing this research's approach. Visual Model Group 1 generated visual models of relevant data under uncorrelated conditions such as histograms and scatter plots. Visual Model Group 2 generated visual models of relevant data under correlated conditions such as multiyear data and bar charts. Visual Model Group 3 generated visual models of relevant data under predicted conditions of the next event such as line graphs with and without the estimated predictions. Visual Model Group 4 generated visual models of relevant data under the assumed impact of the implemented approach such as web deployment tools and the multifunction choropleth maps.

After compiling the data, a typical scenario was run through of how a school may approach this usage if they were to use data-driven decision making. In this dataset, the results from third-grade participants across all the school districts from the states of Texas and Louisiana were used. Then, we delved into how that representation looked for district performance, used that to run comparisons at certain proficiency levels, and then tracked the data across time and implemented predictions based upon the data. This allowed for further analysis to be run on a comparison of an individual district's performance with reference to statewide results. While implementing this research, we wanted to focus on valid use cases for this paper that would be relevant to demonstrate our concept. To that end, we introduced the following storyboard:

> "At any given time, a school district will make attempts to evaluate their institutional effectiveness. At times, that can include evaluating themselves against other districts; either in their surrounding area that may be competitors for enrollment or across a geographic area that has similar distributions of demographics within their population(s) served."

These evaluations were analyzed not only at an organizational level as a whole (district) but also at an institutional level (school). The prevalent analyses often delve further by disaggregating by demographics or special populations. Priorities of doing so are usually to attain insight into whether or not there is improvement in a desired focus area such as enrollment or assessment outcomes. Statewide results are more relevant for an institution when population size is a parameter. It offers the benefit of having the ability to see how many institutions there are in the total comparison group for any comparison made (see Figure 13). Comparing the results across groups with like populations is typical in assessing overall academic performance in institutions.

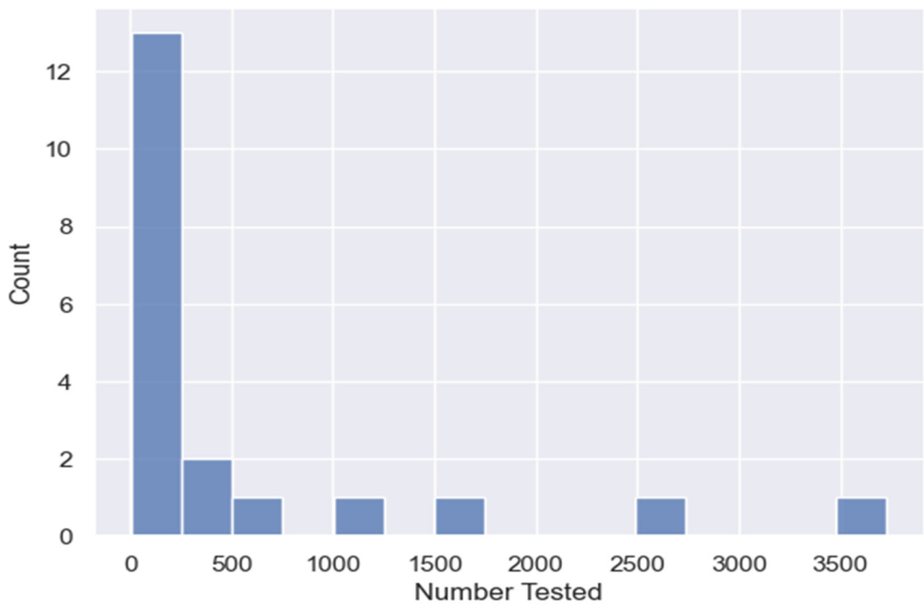

Figure 13. Number of districts per group of number of students tested.

One of the measures for evaluating baselines or successful learning organizations is the ability to review and disaggregate performance data regarding the proficiency of state-mandated assessment results. As these assessments measure the learning of students in content areas, schools use them in data-driven decision making in curriculum and content for instruction. Furthermore, the data allows them to review the success of the instructor in delivering content effectively for students to demonstrate satisfactory progress.

Being able to accurately use data to derive insights becomes the most important outcome at the organizational level. At the stage in which the data are the most effective, it also requires quick turnaround and accuracy while being delivered most efficiently across multiple audience types. Visualizing the data serves to meet this need as we can quickly view results from any distribution or measured standpoint. This involves the creation of images, diagrams, or animations of data for visual representations in order to provide information. Visualization helps to quantify results in the most meaningful and appropriate focus area. Effective, high-impact, practical evidence that can be received on time is the best way to measure the cause and effect of learner outcomes and the relationships between organizational objectives, students, and teachers. Providing this through visualization makes the information digestible and interpretable while also connecting the material to the audience. Take a look at how simply using visualization to showcase statistical measures or data trends can be implemented in the examples shown in Figures 14 and 15.

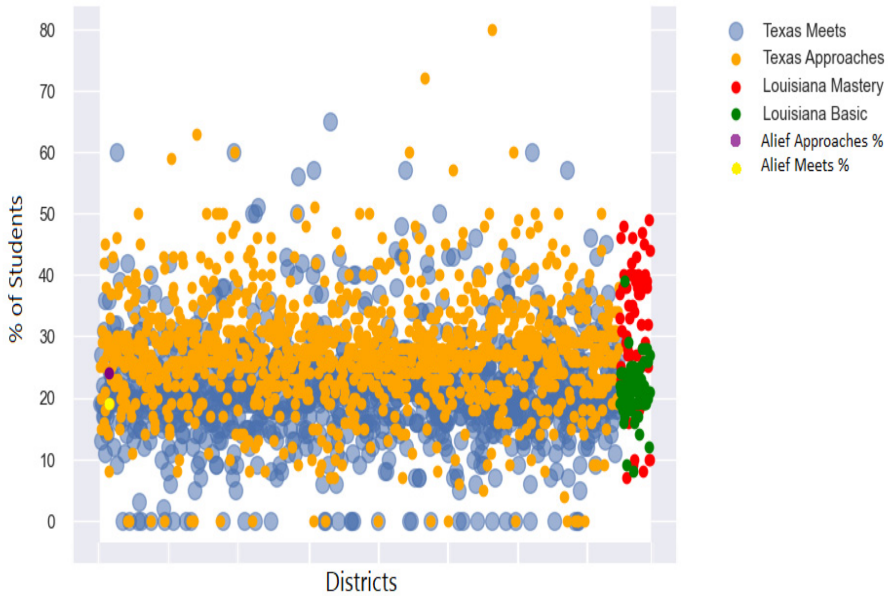

Figure 14. Plot of education assessment data comparisons per performance measure by state.

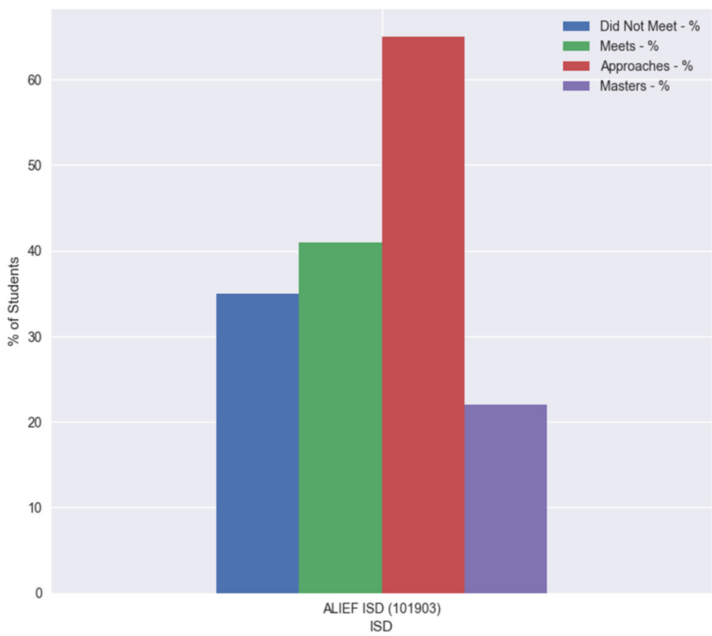

Figure 15. District's percentage of students for the state assessment in reading for third grade.

In Figure 14, we showcase how state assessment results are distributed across all districts in Texas against agencies in Louisiana. The scatter plot shows two performance measures and where our test district lies within the distribution of those performances. This distribution shows the distribution of the overall school population percentage of students tested in third-grade reading for the state's assessment for each performance measure. In Texas, the minimum passing standard is the "Approaches" performance standard (orange), while in Louisiana, the minimum standard is "Basic" (green). The Texas "Approaches" standard does not assume that the student is proficient at their grade level. The Texas "Meets" performance standard (blue) correlates to proficiency at the grade level. By comparing these categories with each other, we can understand the difference between assessments and student performances between the two states. The comparisons are often used to determine where an institution falls in the range of performances, as seen by the example district's performance ratings in Figure 15 (purple—Approaches, yellow—Meets).

For the case of this paper's scenario, we used the results for Alief Independent School District in Houston, Texas, as our district of interest. In Figure 15, the district's percentage of students receiving differing designations across the district for the state assessment in reading for third grade is shown. With these types of visualizations, we can view how certain areas of interest are distributed within the organization of interest and make summative comparisons against similar organizations.

In addition to measuring or showing data distributions, often, education agencies make plans based on "what-if" scenarios. These scenarios give a sample guide of how situations are addressed or affect an outcome. They are basic analytic tools that are used quite frequently in education for decision making. They can be further thought of as specific types of trends or projection analysis which can also be modeled through machine learning.

As shown in Figure 16, the variable we focused on for regression analysis is the performance metric for grade-level standards. It is the "Meets" category that defines how the student performed on an assessment content area. The value for each student's assessment score is placed into this category using true/false indicators to denote whether the student has fulfilled the requirements of the exam to demonstrate proficiency in the content on the grade level assessed for that content. As such, not only does the student "pass" the exam, but it is also at the grade level of proficiency, as indicated in the subject assessed by the exam.

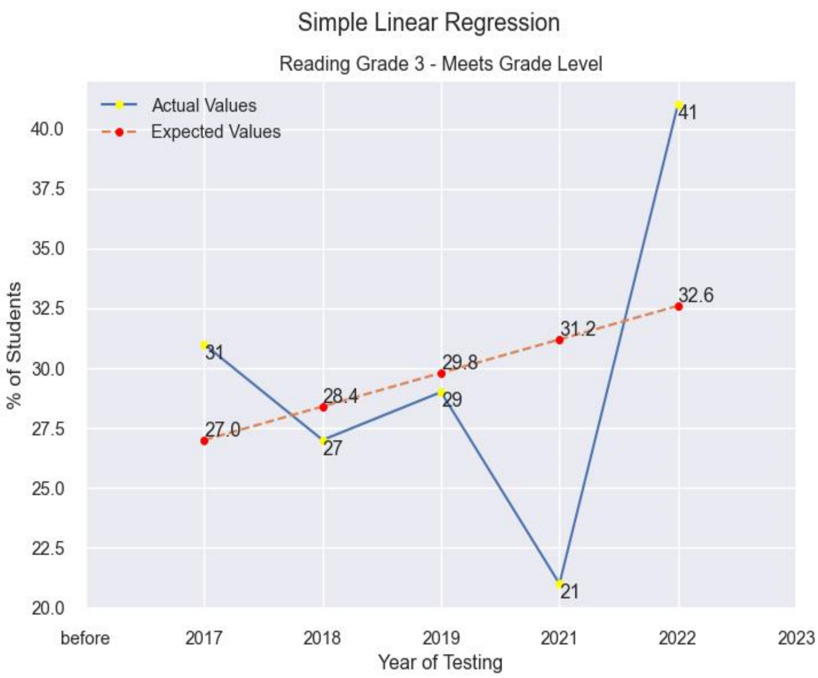

Figure 16. Linear regression modeling for education assessment data.

As previously mentioned, the content and grade level chosen to demonstrate the concept of using MLAs is third-grade reading. The given dataset imports all of the STAAR results at the district level for all of the school districts in the state of Texas. These publicly available data found on the Texas Education Agency (TEA) website comprise third-grade reading performance results from assessment years (where existing) 2017 to 2022. From there, we used this single variable under the "Meets" category and, following the rules for implementing linear regression, fit a line to the data to predict the estimated percentage expected to receive for the example district in 2023. For our test district, we used the linear regression package built in the scikit learn library to create our regression model. At the time of the initial version of this report, the expected value for our example district using linear regression was 34, as shown in Figure 17.

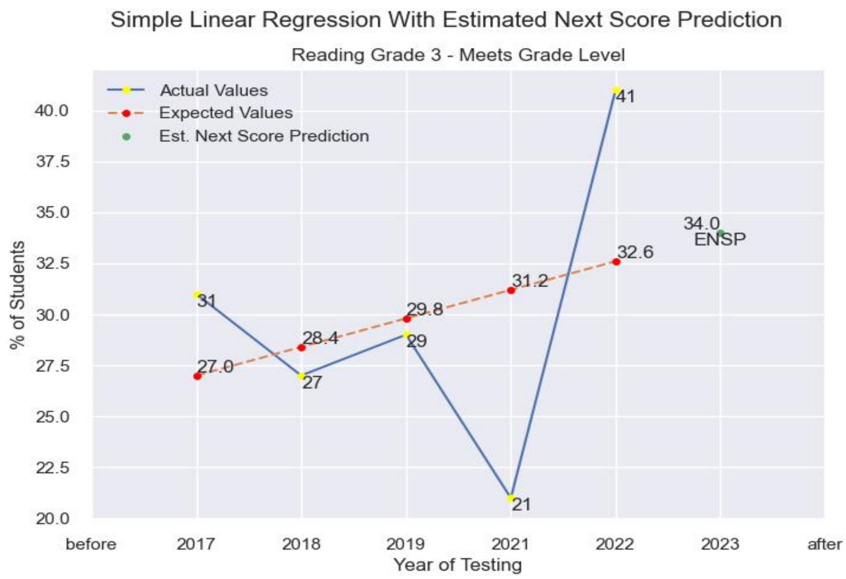

Figure 17. Predictions for education assessment data using linear regression.

This was, of course, assuming no other variables were associated or would have a large enough effect that would necessitate the need to include them in the regression model. The results that schools sometimes calculate themselves tend to be within $+/-$ one percentage point of the official published data usually published sometime later, after the schools have used their data to make administrative decisions. Being able to implement this type of predictive analysis much quicker and to some degree of accuracy allows for better response time for districts to improve their operations. Note that the official published data for our sample district noted the results to be at 35%, which is within the accepted margin of $\pm$ one percentage point districts accept, proving the validity of the usefulness of MLAs to enhance decision making.

Similarly, with linear regression, we used the same variable and conditions to run our test case under logistic regression shown in Figure 18. In this study, only one variable was used, and following the procedure for logistic regression, an estimate was made for the predicted value. As with linear regression, the values also assumed no other variable influenced the result in order to show the possibility of regression analysis. Using logistic regression, the estimated next score prediction was computed to be 41%, which can be seen in the Figure 19.

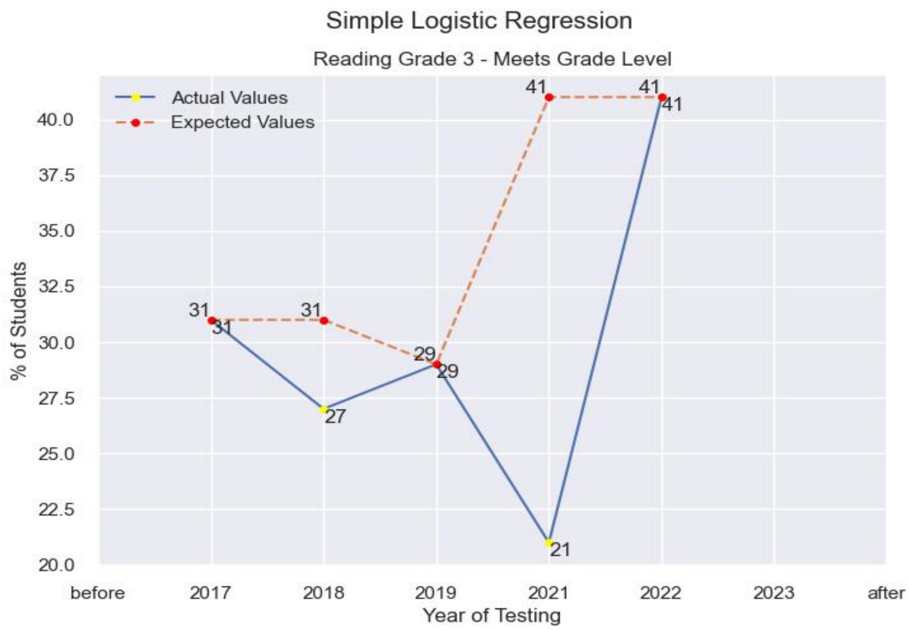

Figure 18. Logistic regression modeling for education assessment data.

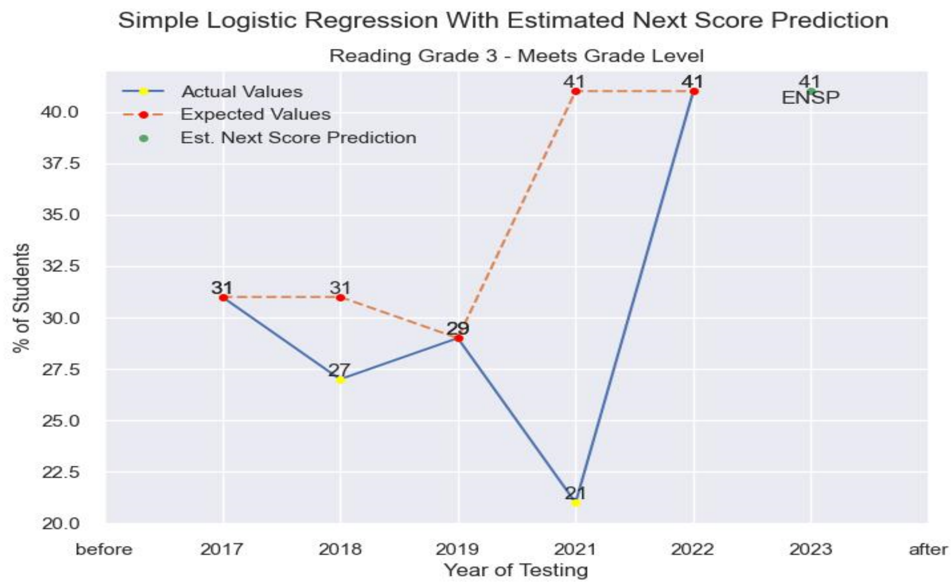

Figure 19. Logistic regression predictions of the next score.

The robustness of the experiment is replicable at multiple levels. Often, as previously mentioned, districts may want to perform comparisons at a demographic or population group level. Similar to district data, states, districts, and even schools have the ability to compare across different subpopulations. To date, the most popular comparisons are usually by racial groups, gender, language, and economic groups. Following the same procedure as with our other visualizations and regression techniques, you can derive insights based on your criteria of interest for datasets like the one retrieved from the TEA website shown in Figure 10. Although in our example, we used Python for the practical implementation of our concept, many other tools serve this purpose. Additionally, with the progressive movement to dashboarding tools, education is expected to slowly join in the collective effort of stakeholders investing in them. Other means include using R, Tableau, Power BI, Julia, etc., which vendors and companies are taking advantage of to customize solutions to sell and deploy products. Each method has its own considerations for usage in the education space. As long as the infrastructure and resources are clearly understood, you can effectively duplicate, streamline, improve, or further develop your avenues for showcasing deliverables within the data-driven space.

One of the driving forces for this paper is the possibility of making something of this nature web-deployable. To make this research a fully functional product that education institutions and other stakeholders would find useful, we focused on using tools that they would be able to acquire. It is worth emphasizing that besides the publicly available data, the other tools utilized to develop this solution were also freely accessible, thereby constraining the costs associated with its creation. This means that individuals willing to invest time and effort into production can replicate it. With agencies limiting funding to education institutions in the US, this becomes increasingly important to consider in their budgets.

To showcase the scenarios that use comparisons across locales, we made use of Python libraries to incorporate map and mapping functions with geolocations as shown in Figure 20.

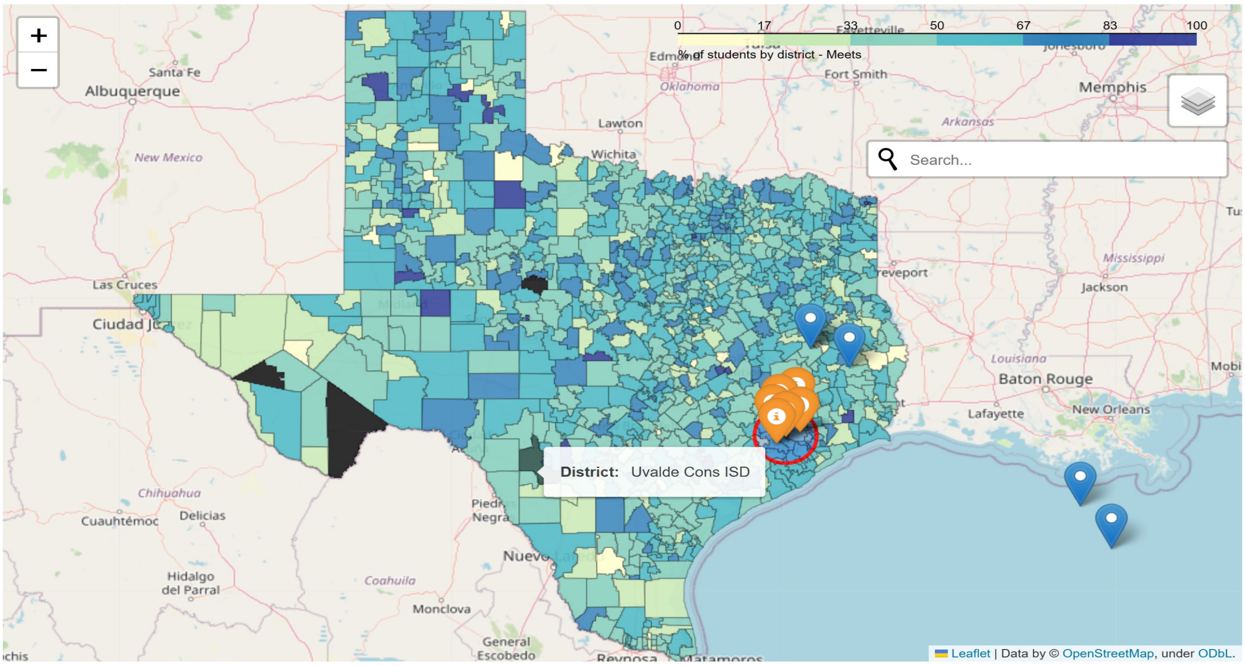

Figure 20. Districts across Texas—interactive choropleth.

This served as a way of not only providing the ability to compare data across locales but also interacting with the maps to perform useful functions such as searches, radius marking, and multilevel information relay. We can hide features that would be important to have them ready for users on rollover or click function and embed those qualities into the map so that each location has its own specific detailing according to the information available (see Figure 21). The web-deployment criteria were successfully implemented using StreamLit, a powerful tool allowing for the results to be transferred to a web browser that is typically the preferred method of information display. StreamLit allowed the flexibility to take any visualizations, documents, videos, etc., to build an interactive site. We tested this by creating Python HTML document-ready pages for our visualizations and linking them as subpages. Some of the data were output as tables that were directly read from our data files into StreamLit. Even the interactive maps were able to find their home on the site page with full functionality intact as shown in Figure 22.

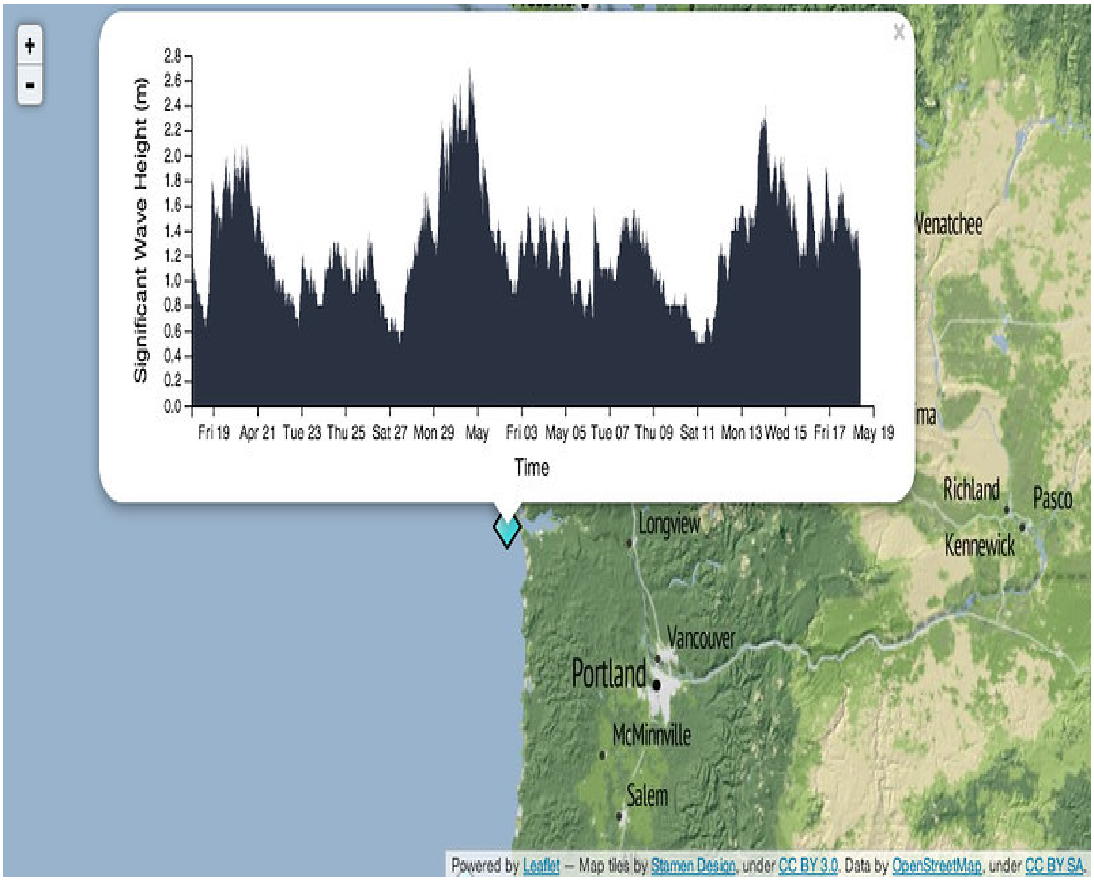

Figure 21. Example of optional features for maps using Folium.

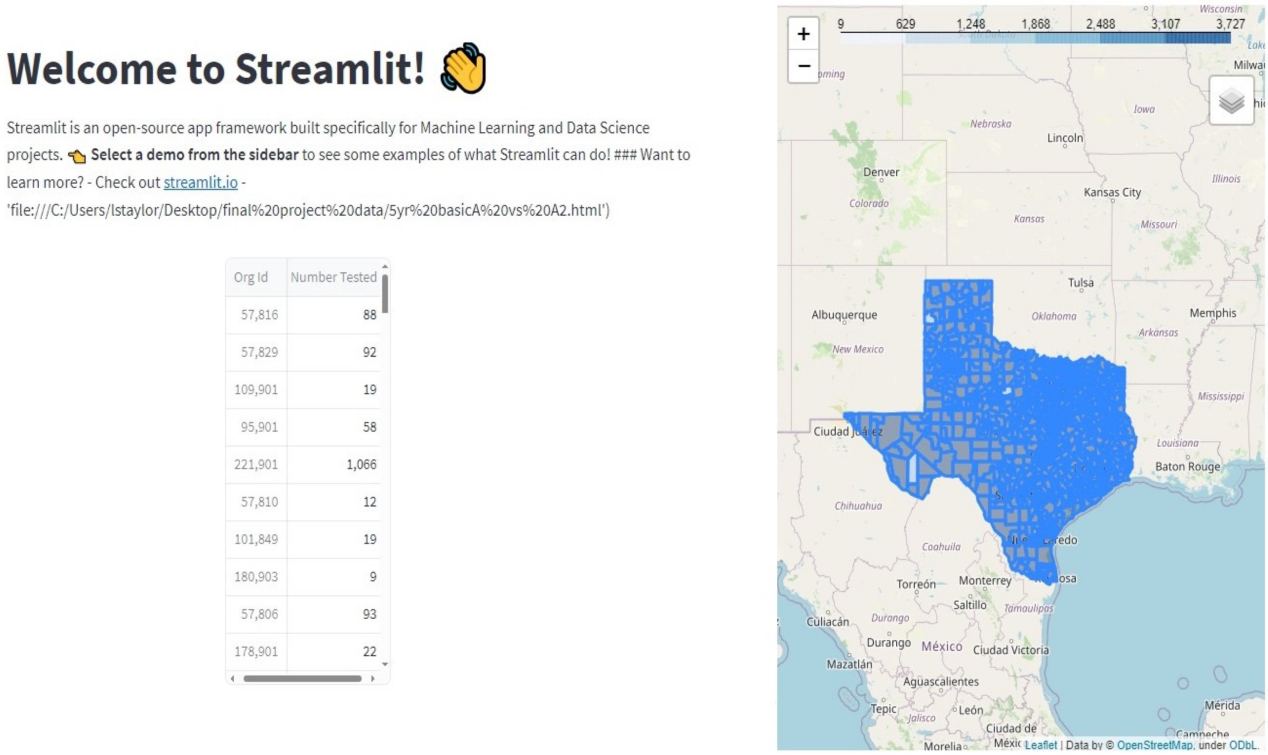

Figure 22. Deploying the visualizations to functional websites using StreamLit.

Since our approach required the use of command line code to run StreamLit, it also provided an excellent method for packaging as a runnable software package. By creating a simple executable or batch file to run the code(s) required, you have an easy and simple way to deploy this solution as an in-house product for an institution.

The solution can be housed on any server and deployed from any station or imaged into an institution's endpoint configuration. Python, RStudio, Dash, and other tools have the ability to interact and deploy web solutions proving that this is not only useful but also sustainable in the education space. There are numerous avenues through which this product can deploy and live within an environment, and what makes it flexible is that it is also able to be delivered through systems such as Altiris, SCCM, or ServiceNow, if group policy management determining device management were of consideration. Further improvements would allow for the use of automation through Selenium to incorporate action-based scripting. With the completion of this research and paper, this could be used for the presentation of modernizing decision making in education for multiple levels of education. While this research was implemented on K-12 data, it also has the versatility to be used in higher ed. As in the case with other programs such as "My Brother's Keeper", we could also integrate multiple sources of data to increase the types of information presented to stakeholders with the more granular requests.

One example is local disciplinary data or epidemiological records that would then showcase education results and the level of relationship between them. Since there are very few programs available providing these types of complete and comprehensive visualizations, especially those that are useful as case management tools, if our solution is worked to its fullest potential, we can actually derive cross-functional insights from several correlational studies.

Within this paper, we have demonstrated use cases implementing univariate regression models. The case for these models only uses a single feature and serves the overall purpose of demonstrating practicality. However, as previously mentioned, other algorithms using these data are possible. While we chose to use only a single feature by selecting one of the performance categories, any researcher could tune their results by adding additional features to the design. Doing so will open avenues to other models that use more complex analysis, which could have varying effects on the accuracy of their predictions. The resulting models in this paper show that linear regression performs more favorably in the prediction versus logistic regression. The average error is larger for the input year set (4.96% difference) but gives a smaller difference in individual year estimations. The predicted outcome comes closer in range (1% point lower). This is expected as the model only uses a single performance category as feature input. Choosing these two algorithms for demonstration allowed us to explore the differences in the applicability of the different models based on desired outcomes. In our case, since we wanted to estimate the following year's score, linear regression proved to be the better choice given the expected versus observed values. The linear regression algorithm's performance overall maintained a close range between the expected and observed values except in cases where there were extreme circumstances unaccounted for by the algorithm, such as in the 2020 school year in which testing was suspended due to the coronavirus pandemic and 2021, where remote learners were not forced to sit for an assessment that at the time was not administered virtually. In contrast, logistic regression either reached the observed values or predicted vastly greater outcomes (inflated scores), which implies unreliability. The average error is smaller for the input year set (4.8% difference) but fluctuates too much in individual year estimations. The predicted outcome comes further in range (6% points higher). If an institution or agency relied on such a model, they would face difficulty in areas such as staffing as they would assume their enrollment would increase due to better performance and hiring more teachers for the students.

5. Discussion

School improvement and accountability are a driving force in competition for enrollment between schools. To this end, schools have several needs to address in order to remain abreast of operational ability. These needs include equity, proficiency, expenditures, and economic determinants as well as others [29]. Schools are one of the places where we spend time learning about ourselves and the world. As such, there is often a need to choose an institution of learning based on what is culturally valued. One of the most agreed-upon baseline metrics is educational proficiency and performance in academics [30–32].

As institutions begin to take further advantage of data to drive improvement [33], one of the useful approaches to gaining insight is to use current technology to visualize the data, provide an avenue for analyzing statistical trends, and use artificial intelligence by machine learning to predict events [34]. The background of the basis of this research stems from a noticeable lack of material and easily accessible means of providing user-friendly and actionable data to schools, specifically in the state of Texas. Often, schools comb through unfriendly/unwieldy reports that are time-consuming to make any real use of. While the state is improving its ability to work toward creating effective dashboards and other useful tools, this research demonstrates how schools can take the initiative to work toward that goal with greater independence [35].

In this paper, we hoped to set a base for the future usage of artificial intelligence (AI) and use cases of visualizations associated as an outcome of the design. As AI intends to build mimicked cognitive function, the use of this research can enable to some degree a response-type product in the future primarily in the scope of analytics or image processing. In AI, the computer, system, or inorganic (artificial) component is endowed with capabilities assumptive of human ability (intelligence). The process components of AI essentially involve teaching a system; the system then learns, judges, or makes decisions, and then finally, it acts or performs a task based on the previous input. One of the examples of the application that was explored here was in machine learning (ML) and algorithms. In machine learning, the intent is to teach a computer, system, or machine to learn through algorithms. To leverage these effectively in education, the appropriate visualizations must also accompany it [36].

It is effective to leverage machine learning and visualization for education. However, the approaches taken are dependent upon the preferred outcomes of the institution or agency deploying the solution. While this may seem negligible, it increases the risk of biases as feature selection will depend upon interpretations of relevancy to the outcome. For example, given our scenario, if it is expanded to include multiple features, such as language of assessment, demographic, testing accommodations, and funding spent on computing resources, the result of the prediction will vary based on whether a student requires testing accommodations (text to speech, braille, etc.) and whether the associated computing resources (desktop, laptop, Chromebook, hotspot vs. LAN) received poor or good quality resources. If that funding expenditure is poor, and the resources are subpar, then the expectation is that the student will perform poorly. However, if the agency prizes human capital over technology resources, they may assume that it is immaterial to the cause and effect of the predictions over time and may not include this element in the analysis. It will bleed into the modeling as feature selection would be manually chosen as a result of the supervised learning process. In unsupervised learning, the associated risk forces low-value inputs to be discarded even if they are a contributing factor. So, while the funding may not show a direct correlation, if it is not understood by the algorithm that the agency is underfunded or serves underprivileged communities, it would mistakenly assume equity where none exists. While no one model accounts for all fluctuations without overfitting, the acceptable margins are determined by the functional areas of concern agencies have.

6. Conclusions

This research will serve to offer a second look into data elements and determine if there is cause to explore other options. This paper can offer conclusive evidence on the approaches and help solve lingering issues. With the benefit of years of experience in computation, programming, and simulation, as well as the close ties to this subject, one can combine the visualizations produced with data science to make relevant meaning for not just the administration but also other stakeholders who may get involved as a result.

One can look forward to working further on this research to model and create unbiased visualizations. Some invested stakeholders have expressed a high interest in the work of the initial research with the openness to pursue future outcomes. By creating and providing supporting visualizations, we could potentially improve efforts to rehabilitate the currently used processes and prevent the side effects of data lag in education. There is a very high level of confidence that this approach can effectively provide a route to pinpointing areas of concern within the desired research range, and if unable to retrieve enough data, alternate usable data can be used in its place. The plan put forth is a rough estimate of feasibility, and it is believed this model will work to drive a successfully completed implementation.

This research employed statistical analysis, interactive maps, density metrics, etc., as tools to engage stakeholders in investigating metrics across target data. Although data preprocessing was employed to streamline some of the visualizations for the purpose of this demonstration, these strategies are effective for modeling and predicting data under any desired condition. Additionally, through this implementation, we were able to effectively provide insight into how negatively an inaccurate representation can affect a user. Quite a few tools are available for use; they are not limited to the ones presented here, and some can work with various network organizations and deployment requirements (cloud, batch, and network image deployment). One of the ones that are common and popular to use and that has been gaining ground is machine learning. Others include open source tools and programming languages that use statistical functions. The usage of these tools in the education space to drive decision making and school improvement instead of tools that focus on content needs greater consideration with a focus on implementation. By learning the concepts central to visualization and compounding that knowledge with understanding applicable implementation, we can provide reasonable use cases while still providing readable and usable images for users.

Overall, this paper is geared toward showcasing visualizations, AI/ML, and their effective usefulness in education. Our test case proves that there is a comparative advantage in applying their concepts and web technology to enhance data-driven decisions and instruction. We were able to successfully use the data to show that the distributions differ and look for future work to apply other studies to bolster our analysis. Additionally, these data and their accompanying results afford the ability to consider utilizing machine learning as a tool for the identification of delineating factors.

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