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Transforming Healthcare Data into Actionable Insights for Budget Allocation

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Abstract:-In the realm of healthcare expenditure, understanding the distribution of funds, particularly within Medicare, is crucial for policymakers, researchers, and healthcare providers alike. However, the complexity of raw data often presents significant challenges, hindering stakeholders' ability to make informed decisions regarding resource allocation. This paper explores the gap between data availability and practical utility, highlighting the need for comprehensive solutions to transform raw data into actionable insights. By leveraging sophisticated visualization tools and dashboard solutions in Tableau software, stakeholders can navigate complex datasets, identify expenditure patterns, and optimize resource allocation within hospital budgets. Furthermore, collaborative features within these solutions promote transparency and accountability, facilitating collective decision-making and consensus-building among stakeholders. Ultimately, the adoption of advanced visualization tools empowers hospitals to optimize resource allocation and drive positive healthcare outcomes, enhancing both efficiency and effectiveness in budget allocation processes.

Keywords: *Tableau, Budget allocation, Data visualization, Healthcare, Interactive dashboard.*

1. Introduction

The issue of healthcare expenditures has garnered considerable attention on a global scale in recent times, with researchers, policymakers, and healthcare providers attempting to comprehend the fundamental drivers of this spending. Policymakers and stakeholders in the healthcare industry must comprehend how Medicare money is distributed among various medical procedures, therapies, and geographic areas. The allocation of healthcare resources and the efficacy of different medical interventions can be understood by examining the detailed overview of Medicare spending provided per claim.

In the realm of hospital budget allocation, stakeholders and budget allocators face a formidable challenge: the limitations posed by raw data. Despite the wealth of information available regarding Medicare spending and other financial aspects, this data often remains disparate and unstructured, making it difficult for decision-makers to derive meaningful insights. As a result, stakeholders are hindered in their ability to understand expenditure patterns, identify areas for improvement, and make informed decisions regarding resource allocation. This deficiency in data utilization not only hampers the efficiency of budget allocation processes but also undermines the overall effectiveness of healthcare management within hospitals.

The crux of the problem lies in the inability of raw data to provide stakeholders with the clarity and actionable insights necessary for informed decision-making. Without the aid of sophisticated visualization tools and dashboard solutions, stakeholders are left grappling with complex datasets that are challenging to interpret and analyze effectively. Consequently, there exists a significant gap between the availability of data and its practical utility in guiding budget allocation decisions within hospitals. This gap not only impedes the optimization of resources but also poses a barrier to achieving optimal healthcare outcomes for patients.

To address this pressing issue, hospital administrators and decision-makers must prioritize the implementation of comprehensive solutions that bridge the gap between raw data and actionable insights. By leveraging sophisticated visualization tools and dashboard solutions, stakeholders can transform disparate data into dynamic visual representations that facilitate deeper understanding and analysis. These solutions enable stakeholders to explore expenditure patterns, identify trends, and uncover opportunities for cost-saving and optimization within hospital budgets. Moreover, by incorporating interactive features such as filters and drill-down capabilities, decision-makers can delve deeper into the data, extract valuable insights, and make informed decisions with confidence.

Furthermore, the adoption of collaborative features within dashboard solutions fosters communication and cooperation among stakeholders, facilitating collective decision-making and consensus-building. By providing a centralized platform for sharing findings, discussing strategies, and aligning priorities, these solutions promote transparency and accountability in budget allocation processes. Through enhanced collaboration, stakeholders can leverage collective expertise and insights to develop more robust and inclusive budget allocation [13] strategies that align with organizational goals and priorities. In essence, by embracing sophisticated visualization tools and dashboard solutions, hospitals can empower stakeholders with the actionable insights necessary to optimize resource allocation and drive positive outcomes in healthcare delivery.

Moreover, collaborative features within these dashboard tools enable stakeholders to share findings, discuss strategies, and collectively optimize budget allocation decisions. In essence, while the data serves as the backbone, it's the integration of user-friendly dashboard interfaces and interactive tools that empowers budget allocators to make informed decisions that drive positive outcomes within the Medicare system.

Hence, there is a critical need to transform raw data into visual representations to enhance comprehension and uncover insights. Utilizing interactive dashboard tools, derived from raw data, becomes imperative for improving budget allocation processes [1][11]. These tools enable budget allocators, stakeholders, and policymakers to discern expenditure patterns effortlessly, understanding which departments, states, periods, or hospitals utilize budget resources effectively. Conversely, they facilitate the identification of areas where resources are underutilized or misallocated, streamlining decision-making processes with minimal effort.

2. Proposed Methodology

The suggested model utilizes Tableau software to provide better understanding of data for stakeholders and budget allocators. The visuals, interactive dashboard and story telling are developed with the help of Tableau.

A. Software Requirements

- Operating System: Operating systems compatible with the system include Mac, Windows 7, Windows 8, or any higher version. Versions of Windows preceding Windows 7 may not be supported due to potential limitations in handling large datasets and executing commands compatible with newer versions.
- Python 3: Developer: Anaconda – Jupyter notebook or Google Colab. This is required for data wrangling, cleansing and manipulation purposes before creating visuals and dashboards.
- Libraries: Python libraries like Pandas, NumPy, Seaborn, Matplotlib and Statsmodels are used for data manipulation and preprocessing.
- Microsoft Excel: Excel is used to find relationships between variables in the data which helps in understanding data to create graphics.
- Solver: A solver package needs to be installed in Excel from Ad ins. This helps to do data analysis like correlation, regression, descriptive statistics [16] etc.
- Tableau Software: Tableau is used as a data visualization tool for creating visuals, dashboard, and storyline. Interactive actions can be developed for a more user-friendly experience in Tableau. Data manipulations can also be done in Tableau.

B. Hardware Requirements

- RAM: A desktop or laptop with 8GB of RAM or more is recommended for efficient handling of large datasets. Lower RAM capacities may struggle to manage extensive data and could result in errors. Given the substantial size of the datasets involved, opting for a computer with higher RAM ensures smoother processing.

- Storage: A minimum of 64GB of storage space or higher is necessary due to the extensive datasets involved. Having more space on the laptop or desktop will facilitate smoother execution of the code. Alternatively, a hard disk with a capacity of 40GB or greater can also be utilized to store both the data and CSV files used in the code.

3. Dataset

A comprehensive collection of data on healthcare [9] spending under the US Medicare program is provided by the Medicare spending by claim dataset. It includes a broad range of information, such as specifics about hospital names and its provider numbers, their states, claim types, average spending, and percentage per episode of hospitals, states, and whole nation. This dataset is an important tool for studying the patterns of healthcare spending across various medical specializations and geographical areas for researchers and policymakers. Furthermore, the dataset makes it easier for stakeholders to compare various healthcare providers and geographical areas, allowing them to spot differences in the distribution of resources and availability of service.

Table 1. Dataset variables data type and description

Variable	Data Type	Description
Hospital Name	Categorical	The hospital's name linked to the claim.
Provider Number	Numerical	The unique identifier assigned to each hospital.
State	Categorical	The geographical location of the hospital, denoted by the state.
Period	Categorical	The period associated with the claim.
Claim Type	Categorical	The category of claim attributed to the hospital.
Avg Spending per Episode (Hospital)	Numerical	The mean expenditure per episode incurred by the hospital.
Avg Spending per Episode (State)	Numerical	The mean expenditure per episode observed at the state level.
Avg Spending per Episode (Nation)	Numerical	The mean expenditure per episode documented across the nation.
Percentage of Spending (Hospital)	Numerical	The percentage of expenditure attributed to the hospital.
Percentage of Spending (State)	Numerical	The percentage of expenditure allocated to the state.
Percentage of Spending (Nation)	Numerical	The percentage of expenditure accounted for at the national level.
Measure Start Date	Date	The initiation date of the measure.
Measure End Date	Date	The termination date of the measure.

Given the diverse range of factors available within this dataset, we identified it as an optimal choice for our visualizations. These visualizations serve as effective tools for stakeholders and novice learners engaged in budget allocation tasks, empowering them to make informed decisions based on insights derived from the data.

4. Analysis

Upon commencing our analysis, we noticed that most rows in the "Measure start date" and "Measure end date" columns contained identical values. Consequently, we conducted a cardinality test with the help of python in

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Google Colab laboratory, which revealed that there was no variability present in these two columns. Given that the cardinality was determined to be 0, indicating no distinct values, we concluded that these columns had no impact on other variables. Consequently, we opted to remove these columns due to their null cardinality.

The below output from the below Python code [10] executed in Google Colab confirmed our findings, showing that there was indeed no variability in the values of these columns.

```
categorical_var = list(set(df.dtypes[df.dtypes == object].index))

zero_cardinality = []

for i in categorical_var:
    if len(df[i].value_counts().index) == 1:
        zero_cardinality.append(i)
print(zero_cardinality)

['Measure End Date', 'Measure Start Date']
```

Fig. 1 Test for cardinality.

After the removal of start and end dates due to identical values, we have done some preprocessing of data using python libraries like pandas, numpy and seaborn. After that, our analysis led us to make a correlation matrix in excel. Below is the correlation matrix of our data.

	Provider Number	Avg Spending Per Episode (Hospital)	Avg Spending Per Episode (State)	Percent of Spending (Hospital)	Percent of Spending (State)
Provider Number	1				
Avg Spending Per Episode (Hospital)	0.002687632	1			
Avg Spending Per Episode (State)	0.002039743	0.978570787	1		
Percent of Spending (Hospital)	3.63568E-07	0.982092496	0.994077991	1	
Percent of Spending (State)	-6.00076E-06	0.97683843	0.999073076	0.994950296	1

Fig. 2 Correlation matrix for variables

Upon analyzing the correlation matrix [4], we noted a robust correlation between average spending and the percentage of spending at both the hospital and state levels. This observation led us to infer that hospitals with higher spending tend to be situated in states with elevated spending. Consequently, it suggests a need for increased investment in regions with lower spending to enhance medical services or infrastructure, while regions with higher spending may benefit from initiatives focused on optimizing resource allocation and improving cost efficiency without compromising quality. Inspired by these insights from the correlation analysis, we decided to leverage Tableau's mapping capabilities for a geospatial analysis of hospital spending across different states. Consequently, we crafted a spatial map depicting period-wise average spending per episode at the state level and a tree map illustrating percentage spending at the state level.

This exploration prompted further questions about the influence of other categorical variables, such as claim type and period, on our dataset. To address this, we employed various visualizations, including packed bubble charts, highlight tables, and bar charts. Subsequently, we applied clustering algorithms in Tableau to unveil distinct groups or clusters of hospitals based on spending patterns. This analysis prompted concerns about outliers among hospitals in each state, leading us to construct box and whisker plots to identify and examine these outlier hospitals in each state. Simultaneously, identifying cost-efficient medical services provided valuable insights into opportunities for enhancing cost efficiency in healthcare delivery. In essence, these findings collectively underscore the pivotal role of data-driven decision-making in optimizing resource allocation and elevating healthcare quality and efficiency on a national scale.

5. Results

A. Period-Wise Spending For Each State

Mapping the period-wise spending for every state provides a thorough knowledge of how healthcare costs are distributed across time. Each state is shown in this visualization as a geographic area on a map, and color gradients show the amount spent during a certain period. Stakeholders can determine temporal patterns and variations in healthcare expenditures among states by charting spending data over time. The map provides a visual representation of how healthcare spending evolves over time within each state, allowing policymakers, healthcare administrators, and researchers to discern patterns and variations in expenditure patterns. Darker shades on the map indicate higher spending, while lighter shades represent lower spending, enabling stakeholders to quickly identify states with significant changes in healthcare utilization and expenditure over different periods.

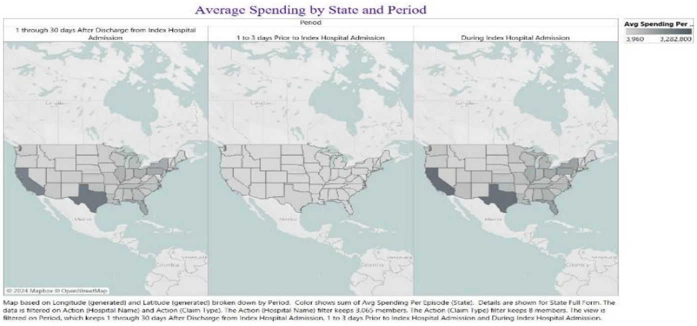


Fig. 3 Period Wise Spending for each State

For example, stakeholders can easily observe from the visualization that Texas and California demonstrate the highest spending during the hospital admission period, highlighted by the darker color shading. Additionally, the data illustrates that expenditure peaks during admission and after discharge, while it tends to be lower prior to hospital admission.

B. Average Spending by Claim Type

In this visualization, each bubble represents a specific type of claim, with the size of the bubble indicating the typical amount of money associated with that claim type. Smaller bubbles signify lower average spending, while larger bubbles indicate higher average spending. Additionally, each bubble is assigned a unique color corresponding to its claim type. Using packed bubbles, stakeholders can quickly understand the relative contribution of different types of claims to the overall cost of healthcare. Different bubble sizes produce a visual hierarchy that makes it easier for legislators and healthcare providers to pinpoint the primary Medicare program spending drivers.

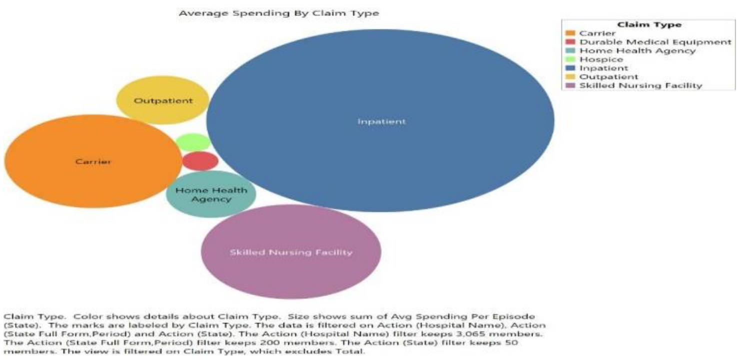


Fig. 4 Average Spending by Claim Type

From this visualization, stakeholders can readily discern that the Inpatient claim type incurs the highest expense, while Hospice claims have the lowest expenditure. This insight enables stakeholders to prioritize interventions and resource allocation strategies to manage and optimize healthcare spending within the Medicare program effectively.

C. Percentage of Claims Associated with each Hospital

An area chart depicting [15] the distribution of claims among various hospitals provides an accurate overview of healthcare utilization patterns. The x-axis represents different claim types, while the y-axis displays the percentage of spending for each hospital. Each hospital's proportional share of Medicare claims is illustrated by the area under the curve, with larger areas indicating higher utilization. To facilitate analysis, we have incorporated hospital filters, allowing users to examine a specific hospital's claim type expenditure by selecting it from the options. The filter encompasses all hospitals in the United States, enabling users to search for a particular hospital by name and explore its claim type distribution. Additionally, state details have been included, allowing users to identify the location of a hospital when hovering over its area on the chart.

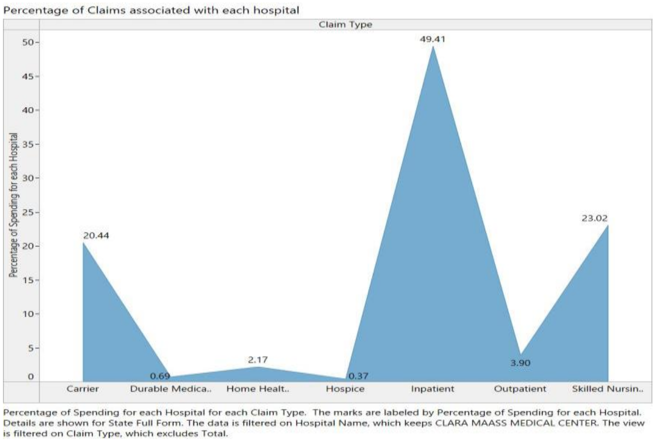
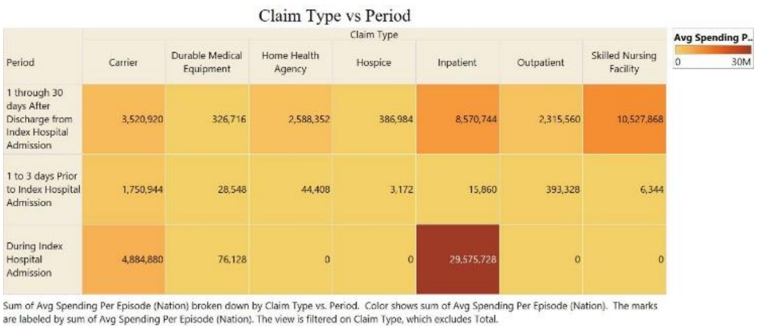


Fig. 5 Percentage of Claims associated with Clara Maass Medical Center

The above visualization enables stakeholders to swiftly identify hospitals with the highest and lowest Medicare claim volumes. For example, a quick glance at the chart reveals that Clara Maass Medical Center, located in New Jersey, allocates 49.41% of its funds to the Inpatient department and only 0.37% to Hospice. Users can easily select any hospital of interest to scrutinize its fund allocation.

D. Claim Type vs Period

The below highlighted table displays time periods (prior, during hospital admission, and after discharge) arranged in rows, while claim types are listed along the columns. Each cell in the table denotes the cost, with color gradients indicating the intensity of Medicare expenditures for each claim type across different periods. Stakeholders can swiftly discern temporal trends and variations in healthcare costs across various claim types using the highlighted tables.



Claim Type vs Period

	Claim Type						
Period	Carrier	Durable Medical Equipment	Home Health Agency	Hospice	Inpatient	Outpatient	Skilled Nursing Facility
1 through 30 days After Discharge from Index Hospital Admission	3,520,920	326,716	2,588,352	386,984	8,570,744	2,315,560	10,527,868
1 to 3 days Prior to Index Hospital Admission	1,750,944	28,548	44,408	3,172	15,860	393,328	6,344
During Index Hospital Admission	4,884,880	76,128	0	0	29,575,728	0	0

Avg Spending P..
0 30M

Sum of Avg Spending Per Episode (Nation) broken down by Claim Type vs. Period. Color shows sum of Avg Spending Per Episode (Nation). The marks are labeled by sum of Avg Spending Per Episode (Nation). The view is filtered on Claim Type, which excludes Total.

Fig. 6 Claim Type vs Period

This visualization [12] serves as a valuable tool for users and newcomers (potentially new stakeholders), in grasping the dynamics of healthcare expenditure. For instance, it demonstrates that during hospital admission, expenditure for home health agencies, hospice, outpatient, and skilled nursing facilities amounts to zero. Conversely, during this period, the inpatient claim type records the highest spending compared to other periods. Following discharge, the skilled nursing facility claim type exhibits a darker shade, indicating the highest spending during that timeframe. This intuitive table format aids in the quick understanding of temporal and categorical patterns in healthcare expenditure.

E. Outliers of Hospitals for each State

Box and whisker plots, employed to visualize hospital outliers for each state, offer crucial insights into the distribution of healthcare usage across various locations within the US Medicare program. These plots depict outliers as individual data points lying outside the whiskers of the box plot, indicating hospitals with notably high or low claim volumes relative to the state's average. Stakeholders can swiftly identify hospitals that significantly deviate from the typical healthcare usage patterns within their respective states by leveraging box and whisker plots.

The below visualization includes [5] whiskers, hinges, and medians for all hospitals within each state, with each hospital distinguished by a distinct color. Additionally, a sliding filter allows for easy state selection, facilitating enhanced observation. A sliding filter will be available to select the state for which the user wants to see outliers. For example, on selecting the state of Kansas, there are four outliers identified. Upon closer examination, it becomes evident that Doctors Hospital LLC and Kansas Spine and Specialty Hospital LLC lie above the upper whiskers, indicating significantly higher average spending compared to other hospitals in the state. Conversely, Bob Wilson Memorial and Modern County Hospital fall below the lower whiskers, suggesting lower average spending relative to other Kansas hospitals.

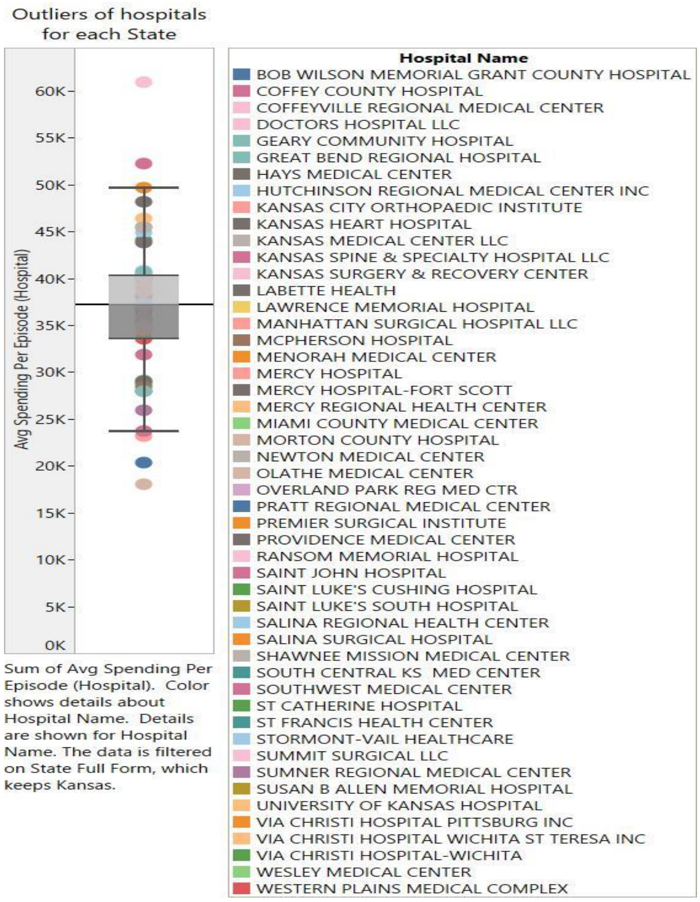


Fig. 7 Outliers of Hospitals for Kansas State

Upon hovering on the outliers, users can see the name and average spending for that hospital. These outliers may suggest unique characteristics of the hospital, such as patient demographics, referral networks, or specialized treatments, warranting further investigation to determine the factors influencing their consumption patterns.

F. Percentage of Spending for each state

In this tree map visualization, each state is represented as a tile, with the color intensity of each tile indicating the state's proportion of the overall Medicare cost. Lighter tones signify higher percentages of spending, while darker shades indicate lower percentages. We have also added average spending per episode by state in details so that when we hover on any tile it shows that state spending data information. This graphic facilitates stakeholders in discerning the relative share of total Medicare spending across different states. By comparing the colors of the tiles, decision-makers and medical professionals can swiftly identify regions with higher or lower healthcare spending and utilization.

For instance, the visualization reveals that Texas accounts for 9.96% of total available funds, while California accounts for 9.42%, and so forth. The varying shades of colors enable stakeholders to easily identify states with the highest and lowest spending, and by the percentages of each state they can also estimate the remaining funds available for other states, thereby aiding in the efficient allocation of budgets across different regions.

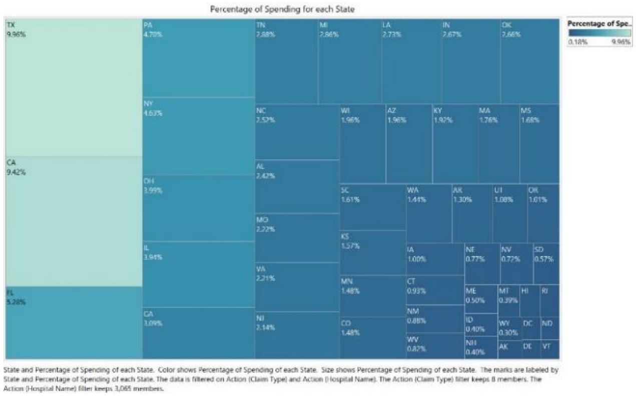


Fig. 8 Tree map for percentage of spending for each state

G. Overall Percent of Spending for different States as well as Period

In this graph, the y-axis represents the total percentage of Medicare spending, while the x-axis displays the periods of expenses, including during hospital admission, prior to admission, after discharge, and the overall total expense. The chart illustrates the contribution of each state to the overall spending as segmented areas, with the height of each segment indicating the share of spending attributed to that state at each specific time point. Different colors and rhombus shapes distinguish each state.

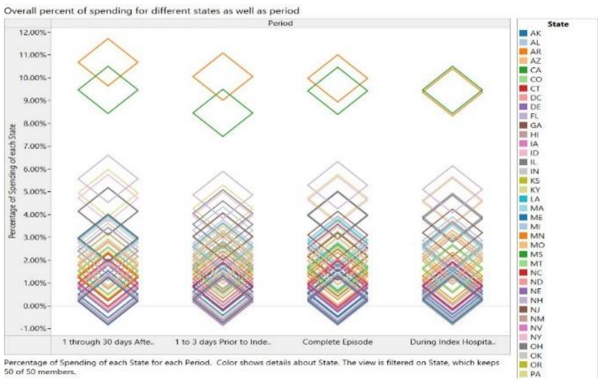


Fig. 9 Overall percentage of spending for different states as well as period

This visualization [8] technique empowers stakeholders to discern patterns, monitor changes, and make well-informed strategic decisions for optimizing budget allocation and improving healthcare delivery and outcomes across states. The visually appealing depiction of spending trends over time enhances the understanding of how each state contributes to the overall Medicare spending landscape.

H. Claim Type Spending for each State

The accompanying image displays the distribution of claim types across states, employing color gradients to represent each claim type. This visualization tool [14] enables stakeholders and policymakers to swiftly identify states where specific healthcare services are utilized disproportionately. Furthermore, a bar chart is utilized to depict the relative prevalence of different healthcare services within each state. Claim types are categorized by color, with expenditure or utilization data represented on the y-axis.

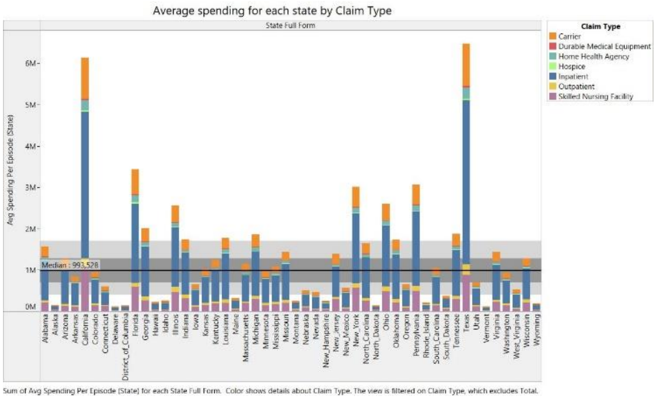


Fig. 10 Average spending for each state by claim type

From the above visualization, we can observe that for every state inpatient claim type has more expense. Texas and California have the highest spending of all the states. We have also added median (90% confidence interval), upper quartile and lower quartile for all states.

I. Hospital Clusters based on their spending

This illustration can be made by using cluster analysis, which separates hospitals with similar spending patterns into distinct clusters for comparison. Similar patient demographics, specialty, or approaches to healthcare delivery may be shared by hospitals in the same cluster. This can offer crucial insights into the factors affecting healthcare utilization and spending.

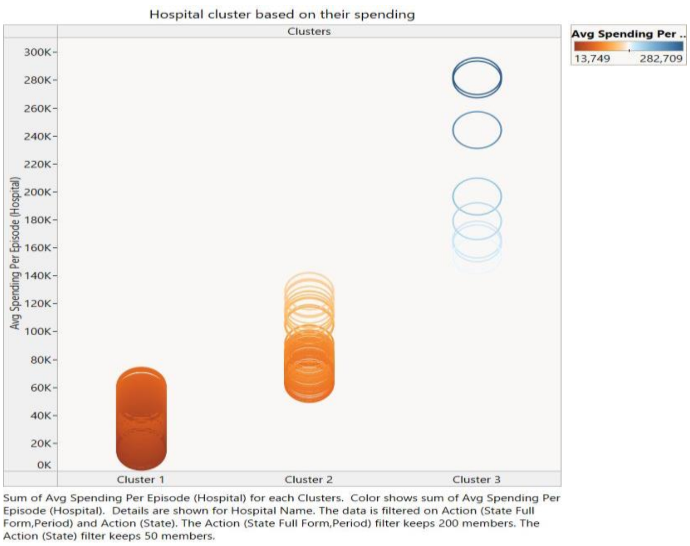


Fig. 11 Clusters for hospitals based on their average spending.

The visualization shows three distinct clusters to classify hospitals into lower, moderate, and higher levels of spending. Hospitals in Cluster 3, depicted in shades of blue, represent those with the highest per-episode spending across the country. Cluster 2 comprises hospitals with moderate budgets, highlighted in orange, while the lowest-cost hospitals are found in Cluster 1, depicted in brown. Notably, there is a significant decrease in the number of hospitals from Cluster 1 to Cluster 3. By examining spending trends both inside and across clusters, stakeholders can identify inefficiencies, efforts to reduce costs, and develop commercially sustainable healthcare delivery models.

J. Interactive Dashboard

We've developed a user-friendly dashboard tailored for both stakeholders and new users, incorporating data through intuitive actions, buttons, and visualizations.

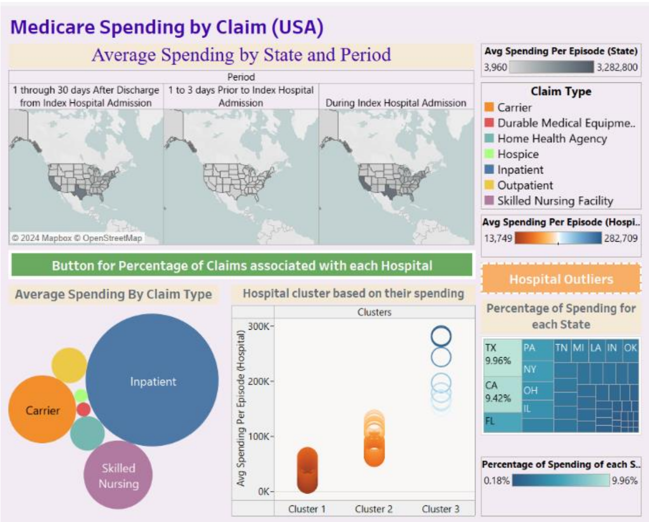


Fig. 12 Dashboard for Medicare Spending by Claim (USA)

The dashboard [2] provides an in-depth understanding of healthcare spending, covering various states in each period, the percentage of spending in each state, claim types, and hospital clusters. To enhance user engagement, interactive elements such as buttons for accessing hospital outliers [3], the percentage of claims associated with each hospital, and links to Google Maps and hospital directories are seamlessly integrated, fostering a more immersive and informative exploration experience.We've incorporated interactive features into our dashboard to enhance the user experience.

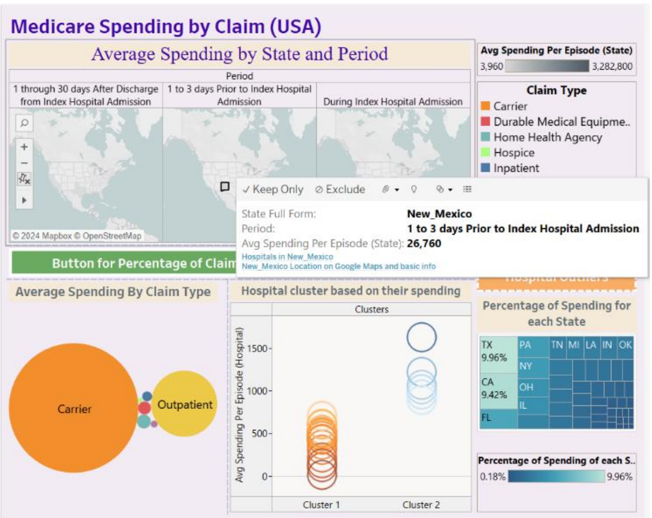


Fig. 13 Interactive action for New Mexico state.

Clicking on a specific state during a particular period triggers dynamic changes in average spending by claim type and hospital clusters, tailoring the data to the selected period and state. For instance, if New Mexico is chosen in the 1 to 3 days prior to the index hospital admission period, the dashboard displays the corresponding average spending by claim type and hospital clusters for that specific period and state. Furthermore, selecting the entire period, regardless of the state, results in an automatic adjustment of the data below to reflect the chosen period for all states. Additionally, clicking on a state on the map provides convenient links to the list of hospitals in that state and the Google Maps location, offering users a more detailed and informative exploration. In the presented image, choosing New Mexico on the map reveals links to the hospitals in New Mexico and the Google Maps location for added insights.

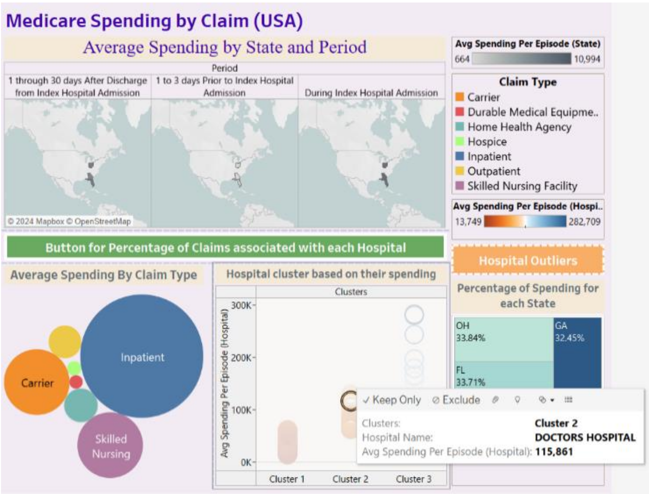


Fig. 14 Interactive action Doctors Hospital

In addition, we've implemented actions [7] for hospital clusters based on their spending. When a specific hospital is selected, all other visualizations in the dashboard dynamically adjust to reflect data related to that hospital. This means that whichever hospital is chosen, its relevant data is prominently displayed throughout the dashboard. For example, selecting "Doctor’s Hospital" prompts the dashboard to showcase the corresponding data for that hospital. Similarly, we've integrated actions for other visuals to further enrich the user experience, ensuring seamless navigation and tailored insights for users.

K. Story Telling

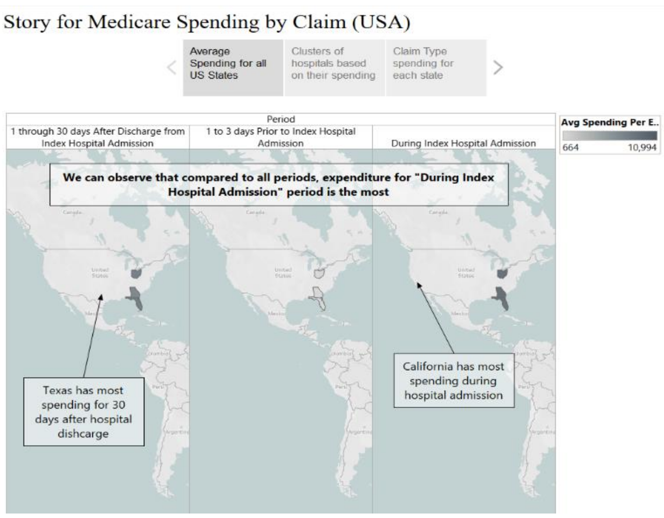


Fig. 15 Story telling for Hospitals expenditure.

In Tableau, storytelling [6] has been created which explains and annotates the story of provided visualizations. Stories for average spending for all US states, clusters of hospitals based on their average spending, and claim type spending for each state has been created. These story lines provide additional information for users while going through the visual.

6. Limitation of Study and Conclusion

Although the Medicare program's healthcare spending data analysis offers insightful information about resource allocation and utilization trends, it's crucial to recognize some inherent limitations in the dataset and visualization techniques. The possibility of insufficient data is one drawback. For instance, this data is only for one single year. So, we could not forecast future data with the help of this data. It would be easier to forecast future data if we had similar data for several years. Moreover, if the user wants to know the county or street location of the hospital, it is unavailable.

In the cluster chart in dashboard, if a user wants to select a particular hospital, then he/she must zoom in data to find that hospital, which may be inconvenient for some users.

Notwithstanding these drawbacks, researchers, healthcare administrators, and legislators can all benefit from the analysis and visualization of healthcare spending trends. Stakeholders can lead initiatives to enhance healthcare access, quality, and efficiency within the Medicare program, as well as educate evidence-based decision-making and optimize budget allocation by identifying trends, discrepancies, and areas for improvement.

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