Analyzing Timeliness and Effectiveness in U.S Healthcare Delivery

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ABSTRACT

The United States is home to some of the most advanced medical facilities in the world, yet patients often face delays in care such as long appointment wait times, delayed emergency room services, and slow administrative processing. This project aims to uncover systemic inefficiencies in the U.S. healthcare system by analyzing real-time data related to hospital performance using the Centers for Medicare and Medicaid Services (CMS) public datasets. By collecting, storing, and analyzing data on emergency department throughput, sepsis care, stroke care, and other performance indicators, this study seeks to provide data-driven insights into where delays are most significant and what factors contribute to them. The final deliverables will include an interactive Tableau dashboard highlighting key patterns and suggesting areas for improvement in patient care delivery.

1.Introduction

A. What is the Project About?

This project focuses on analyzing the timeliness and effectiveness of care provided by hospitals across the United States. It specifically uses the **“Timely and Effective Care–Hospital”** dataset made available by the Centers for Medicare & Medicaid Services (CMS). This dataset includes standardized performance measures reported by hospitals on various aspects such as emergency department wait times, treatment start times for life-threatening conditions like sepsis and stroke, and use of imaging services.

The core of the project is to fetch this healthcare data using APIs, store it systematically in a PostgreSQL database, and then analyze it to identify patterns of delay, inefficiencies, and variations in care delivery across hospitals, states, and regions. Visual insights are built using Tableau dashboards, offering an accessible way to interpret complex metrics.

B. Why is it Meaningful?

In emergency and critical care, time is a key factor in survival and recovery. Delays in treatment, or hospital admission can result in serious patient harm or death. Despite being a high-spending healthcare system, the United States often faces criticism for care delivery delays and outcome inconsistencies.

By analyzing how quickly and effectively U.S. hospitals deliver care, this project helps:

- Uncover geographic disparities in treatment times
- Highlight hospitals struggling with prompt care
- Offer insights that can assist in improving hospital operations and patient care quality

This data driven approach is meaningful because it moves beyond general healthcare critiques and dives into measurable, actionable insights that healthcare leaders and policymakers can use for performance benchmarking and improvement.

C. Expected Learnings from the Project?

- **Technical Learning**:
    - API integration and automation for real-time data collection
    - Efficient data storage and querying in PostgreSQL
    - Data cleaning techniques to standardize healthcare metrics
    - Creating dynamic visualizations using Tableau to surface insights for non-technical users

- **Domain Learning**:
    - Understanding how key hospital performance metrics (e.g., OP_18b, OP_18c, ED_start_1) reflect real-world care outcomes
    - Realizing how regional and facility-level disparities can impact patient experiences

2.Hardware and Software Requirements:

-Operating System: Windows/MacOS
-Database: PostgreSQL14+
-Cloud: AWS RDS
-Programming Language: Python 3, SQL
-Visualization: Tableau Public edition

3. Data Collection Using API & Data Storage Using PostgreSQL

→ Implementation Flow Diagram:

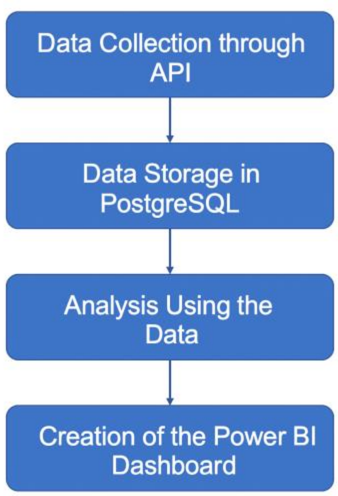


Fig-1: Implementation chart which describes different steps that are going to perform during the project

→ Dataset Selection

For this project, I selected the **Timely and Effective Care-Hospital** dataset published by CMS. This dataset provides national level performance measures across thousands of U.S. hospitals, covering care quality and delays. Key fields include facility name, measure ID, measure name, score, sample size, Hospital display,start date, and end date. I shortlisted key measures for analysis, including:

- **OP_18b** – Average (median) time patients spent in the emergency department before leaving from the visit A lower number of minutes is better
- **OP_18c-** Average (median) time patients spent in the emergency department before leaving from the visit- Psychiatric/Mental Health Patients. A lower number of minutes is better
- **OP_22** – Time Left before
- **ED_2_Strata_1** - Admit Decision Time to ED Departure Time for Admitted Patients - non psychiatric/mental health disorders
- **ED_2_strata_2 -** Admit Decision Time to ED Departure Time for Admitted Patients - psychiatric/mental health disorders
- **EDV –** Emergency Department volume
- **SEP_1** – Timeliness of sepsis treatment
- **STK_05** – Antithrombotic therapy for stroke patients

These indicators were chosen for their relevance to delays in emergency care, diagnostics, and treatment compliance.

→API Integration

To automate data retrieval, I used the CMS Datastore API. It supports SQL like queries, filtering, pagination, and JSON formatted responses. I wrote Python scripts using the requests module to query endpoints **https://data.cms.gov/provider-data/api/1/datastore/sql**. This approach allowed efficient ingestion of large volumes of data that update periodically monthly, quarterly, or semiannually.

→ PostgreSQL Integration

To manage the structured data, I set up a PostgreSQL database using Amazon RDS with a dedicated schema for CMS data. The schema includes three primary tables:

- **hospitals** table – facility level information
- **performance_measures** table – measure IDs, scores, and samples
- **measure_metadata** table – descriptions and classification details

The ingestion pipeline involves fetching data from the API, parsing the JSON response using pandas, and inserting it into PostgreSQL usingpsycopg2. This modular structure ensures normalization, efficient queries, and room for scalability enabling potential integration of private datasets or census information later.

→ Data Cleaning and Preprocessing

The raw hospital performance data underwent extensive preprocessing to ensure consistency, relevance, and readiness for analysis. First, data from three Excel sheets - Hospitals, Measure Metadata, and Performance Measures were loaded and validated. Facility IDs were standardized by removing leading zeros to ensure consistent joins across datasets.

Next, the dataset was filtered to include only relevant emergency department (ED) and wait-time-related measures such as OP_18b, OP_22, EDV, and others. Non-numeric or missing score values were removed. For the categorical measure EDV, scores were mapped to numeric values ranging from 1 (low) to 4 (very high) to support quantitative analysis.

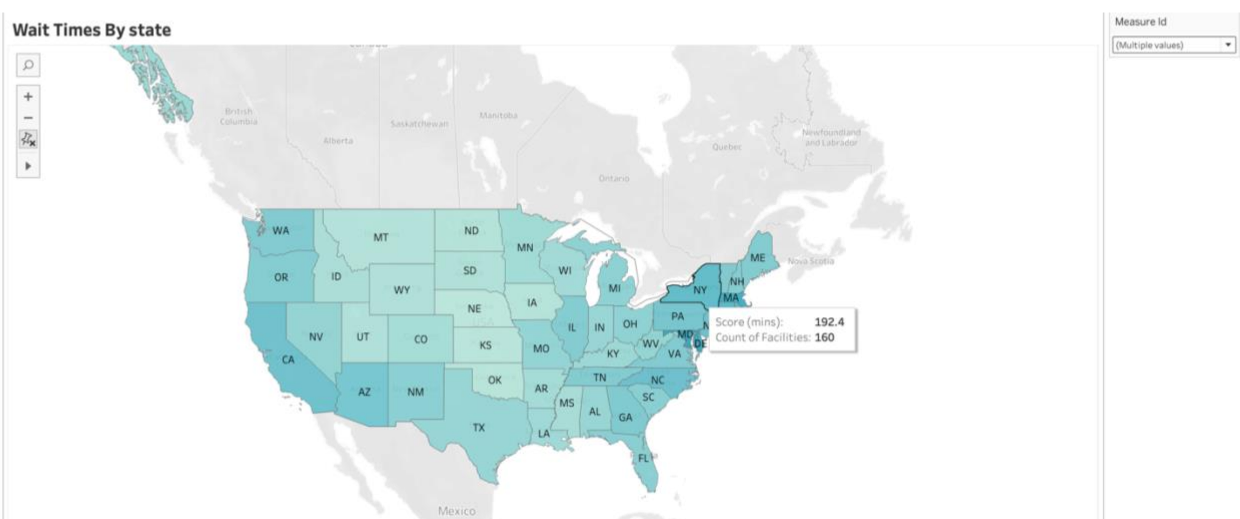
Time fields were parsed to extract start_date, end_date, quarter, and year, enabling temporal analysis. Additional fields like low_sample_flag and has_footnote were added to track reliability issues. Each hospital record was then enriched with region classification based on U.S. Census categories and given a display label combining facility name and state.

Outlier detection was applied using the IQR method to flag extreme values. Both normalized (score_scaled) and standardized (score_standardized) scores were computed to support cross-measure comparison. A performance_level classification was also added based on z-scores (above average, average, below average). The final cleaned dataset was exported as clean_wait_time_data.csv, serving as the foundation for all subsequent Tableau visualizations.

4. Analysis Tasks

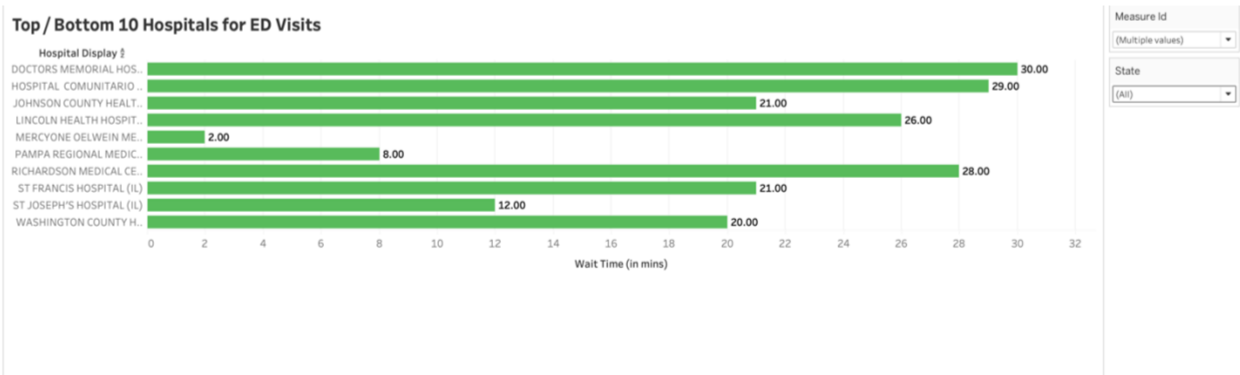
1. State-Level Delay Analysis

This analysis focused on identifying geographic disparities in emergency department wait times across the United States. Using OP_18b, ED_2_Strata_1 (non-psychiatric/mental health disorders), OP_18c, ED_2_strata_2 (psychiatric/mental health disorders) which captures the median time patients spend in the ED before departure, we created a choropleth map by state. The map was enhanced with weighted average scores to fairly represent states with large patient volumes. States with longer wait times were highlighted, and tooltips displayed both the average delay and the number of contributing hospitals. This allowed us to visually detect states with systemic delays and target regions for improvement.



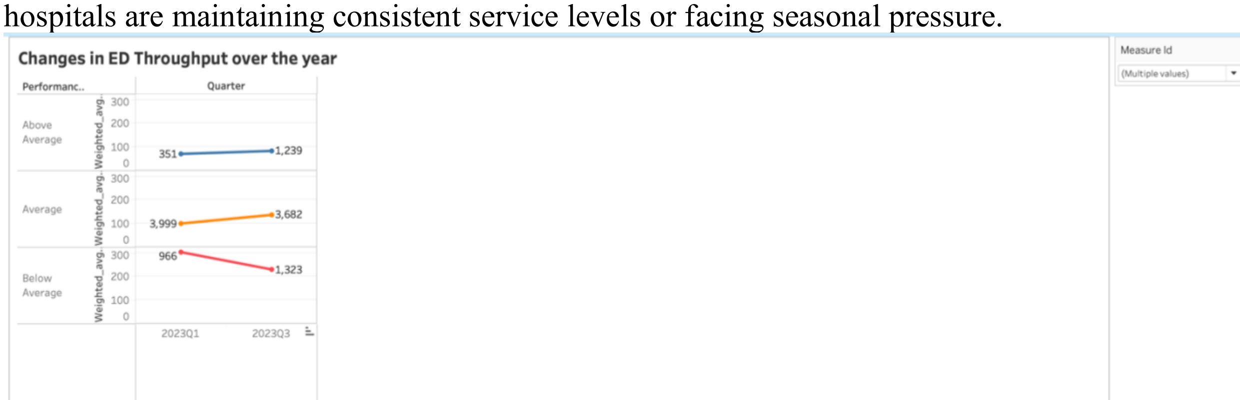
2. Hospital-Level Performance Analysis

This chart ranks hospitals within each selected state based on their weighted average ED wait times. The top or bottom 10 hospitals are displayed using a horizontal bar chart, enabling direct performance comparison. Filters allow users to isolate specific states and measure_ids (e.g., OP_18b or OP_18c). Tooltips reveal additional context like sample size and Name of Facility. The analysis helps identify high-performing hospitals.



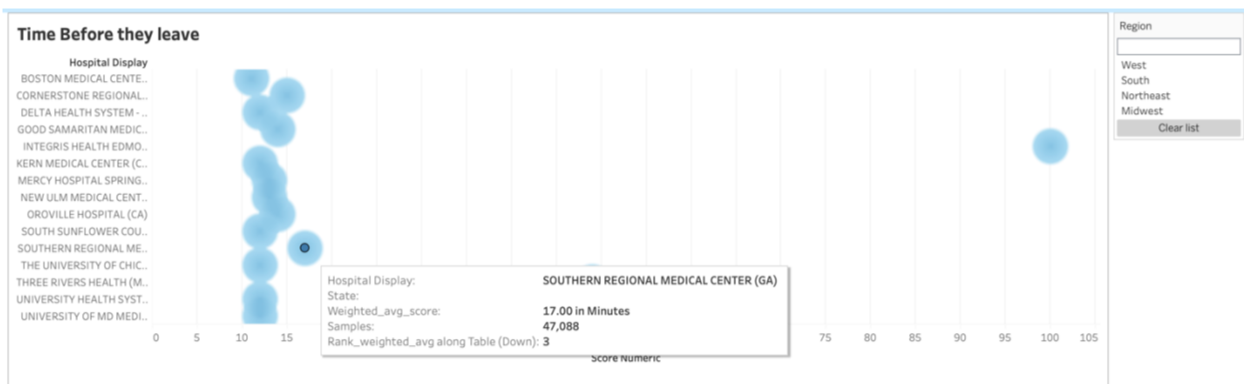
3. Quarterly Trends in Wait Times

To evaluate how emergency wait times changed over time, we analyzed trends across Q1 and Q3 of 2023. Weighted average scores different measure_id's were plotted against each quarter, segmented by hospital performance levels. This line chart helped visualize overall improvement or degradation in throughput. Performance disparities became more apparent when layered by "Above Average," "Average," and "Below Average" tiers. The analysis emphasized whether hospitals are maintaining consistent service levels or facing seasonal pressure.



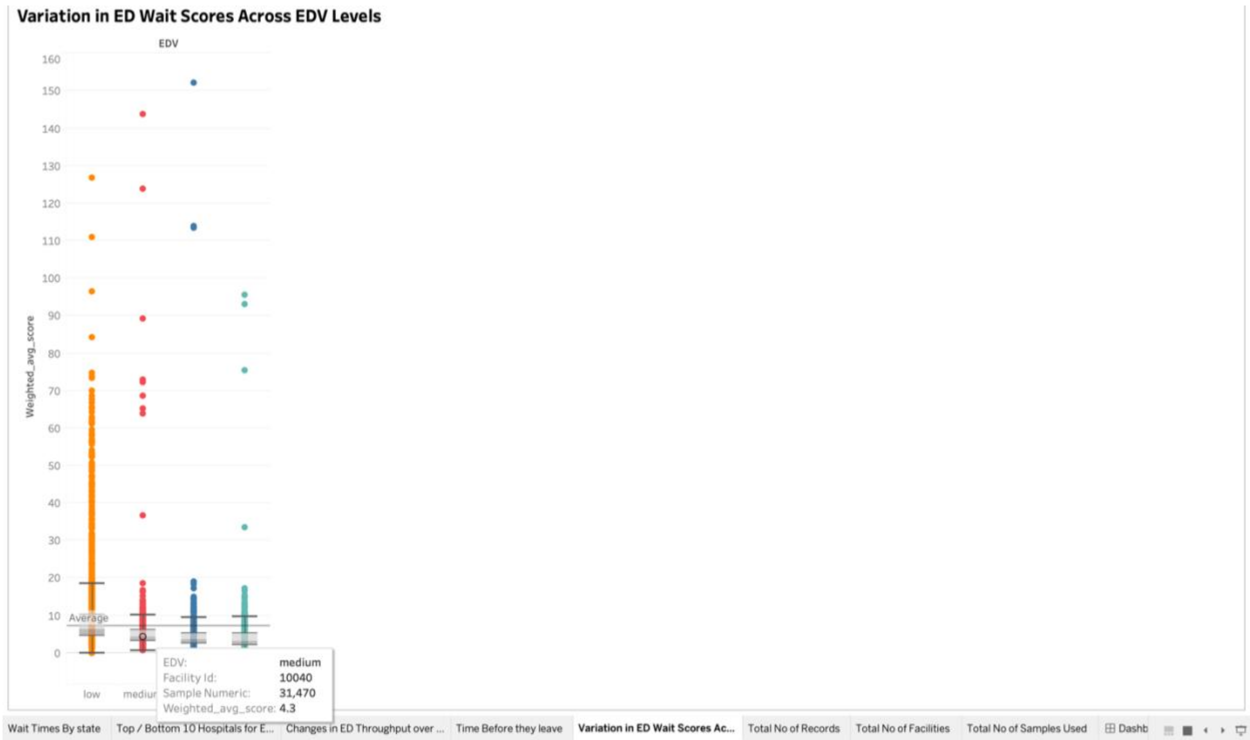
4: Time Before Patients Leave Without Being Seen (OP_22)

This analysis focuses on OP_22, which measures the percentage of patients who leave the Emergency Department (ED) before being seen by a healthcare provider , a key indicator of patient dissatisfaction and ED congestion. The scatter plot visual highlights facilities where patients are more likely to walk out without receiving care, sorted by weighted average scores. Hospitals with high walkout rates and longer wait times before leaving stand out distinctly, such as Southern Regional Medical Center (GA) with an average of 17 minutes before patients leave. This insight signals potential inefficiencies in triage or staffing. The visualization also filters by region, offering an opportunity to compare walkout behaviors across different parts of the U.S., which can guide targeted operational improvements and regional policy interventions.



5. Emergency Department Volume (EDV) Category Analysis

This analysis examines whether hospitals with higher emergency volumes suffer from longer wait times. EDV, a categorical metric (very high, high, medium, low), was extracted using a Level of Detail (LOD) calculation and applied to all hospital rows. Using box plots, we compared the distribution of weighted average scores across EDV categories. The results confirmed that “very high” volume hospitals tend to have wider spreads and higher medians, indicating potential overcrowding or resource constraints. The visualization clearly distinguished performance bands and highlighted systemic stress in busy facilities.



5.Conclusion

This project has made meaningful progress in identifying where and why delays occur within the U.S. healthcare system, particularly in emergency department operations. By analyzing real-world hospital data from CMS and focusing on a range of time-sensitive performance measures including ED throughput (OP_18b), walkout rates (OP_22), admit decision time (ED_2_Strata_1 and ED_2_Strata_2), CT scan turnaround (OP_23), imaging wait times (OP_29, OP_31), sepsis care timing (SEP_1), and stroke intervention delays (STK_05) the project uncovered patterns of inefficiency tied to geography, volume, and quarterly shifts.

Using Python for data preprocessing and Tableau for visualization, a comprehensive dashboard was developed to explore trends by state, hospital, time period, and ED volume (EDV) category. Key insights included longer wait times in high-volume facilities, regional throughput variation, and performance differences across hospital groupings. The use of weighted averages and standardized z-scores enabled fairer benchmarking, especially when accounting for differences in sample size.

6. Future Improvements:

Looking ahead, one of my main goals is to make this project dynamic by setting up a live data pipeline. I plan to integrate Apache Airflow to schedule and automate the data fetching process, allowing the dashboard to update continuously as new information becomes available.

Another exciting enhancement would be incorporating an AI agent that responds to user queries based on ZIP code input. This agent would identify nearby hospitals, check for emergency room availability or inpatient capacity, and provide real-time updates. Since there's no freely available live appointment data, the AI component would simulate that interaction by contacting hospital endpoints (where accessible) or integrating third-party APIs.

Ultimately, the goal is to build a more efficient and user-friendly dashboard that includes interactive filters, real-time updates, and a smart interface to assist patients in locating timely care

7. References

1. **https://data.cms.gov/provider-data/dataset/yv7e-xc69#api**
2. **https://www.geeksforgeeks.org/**
3. **https://docs.python.org/3.14/**