OPTIMIZING ICU BED ALLOCATION FOR IMPROVED PATIENT OUTCOMES AND RESOURCE UTILIZATION

UNC Charlotte School of Data Science

HCIP 6396: Business Intelligence in Healthcare

Advisor: George Shaw, PhD

TEAM

MITU BANERJEE | AASHI SETHIYA | JYOTHSNA RAVIPALLI





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BACKGROUND & BUSINESS PROBLEM



Intensive Care Units face challenges in managing bed capacity, leading to extended lengths of stay and increased costs.



Business Problem: Optimize ICU bed allocation for better outcomes and resource utilization.



Research highlights approaches using optimization and simulation to enhance ICU operations.











IDENTIFY

ANALYZE

TRACK

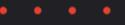
OFFER

patterns in patient flow and potential bottlenecks

length of stay
trends across
different patient
categories and
disease groups

and visualize
resource
utilization and
associated costs

actionable insights
for healthcare
clinicians to make
informed decisions
about bed allocation





AVAILABLE DATA DESCRIPTION

UC IRVINE MACHINE LEARNING REPOSITORY

This dataset includes 9,105 critically ill patients from five medical centers across the United States, with data collected during the periods 1989-1991 and 1992-1994.

Each row represents a hospitalized patient who met specific inclusion and exclusion criteria across <u>nine disease categories</u>: acute respiratory failure, chronic obstructive pulmonary disease, congestive heart failure, liver disease, coma, colon cancer, lung cancer, multiple organ system failure with malignancy, and multiple organ system failure with sepsis.



PATIENT DEMOGRAPHICS

Age, Sex, Race

CLINICAL INDICATORS

Mean Whole BP, WBC count, HR, Resp. Rate, Temp., PaO2/FiO2 ratio

DISEASE AND SEVERITY METRICS

Disease Group, Disease Class, No. of Comorbidities

RESOURCE UTILIZATION

LOS, Hospital Charges, Total Cost, Total Medical Cost

PATIENT OUTCOMES

Death Indicator, Days until Death, Hospital Death Indicator

LIMITATIONS OF NON-VISUALIZATION SOLUTIONS

Traditional non-visualization approaches to ICU bed management face several limitations:

- <u>Data Complexity:</u> ICU data is multidimensional and dynamic. Non-visual methods often struggle to represent the interrelationships between various factors affecting bed utilization.
- <u>Lack of Real-Time Insights:</u> Static reports or basic dashboards fail to capture the rapidly changing nature of ICU environments, leading to delayed decision-making.
- <u>Information Overload:</u> Raw data or text-heavy reports can overwhelm busy healthcare professionals, making it difficult to quickly extract actionable insights.
- <u>Limited Pattern Recognition:</u> Non-visual methods make it challenging to identify trends, patterns, and anomalies in patient flow and resource utilization.





Bed occupancy tracking

Patient flow visualization

Resource utilization and cost metrics

Length of stay analysis

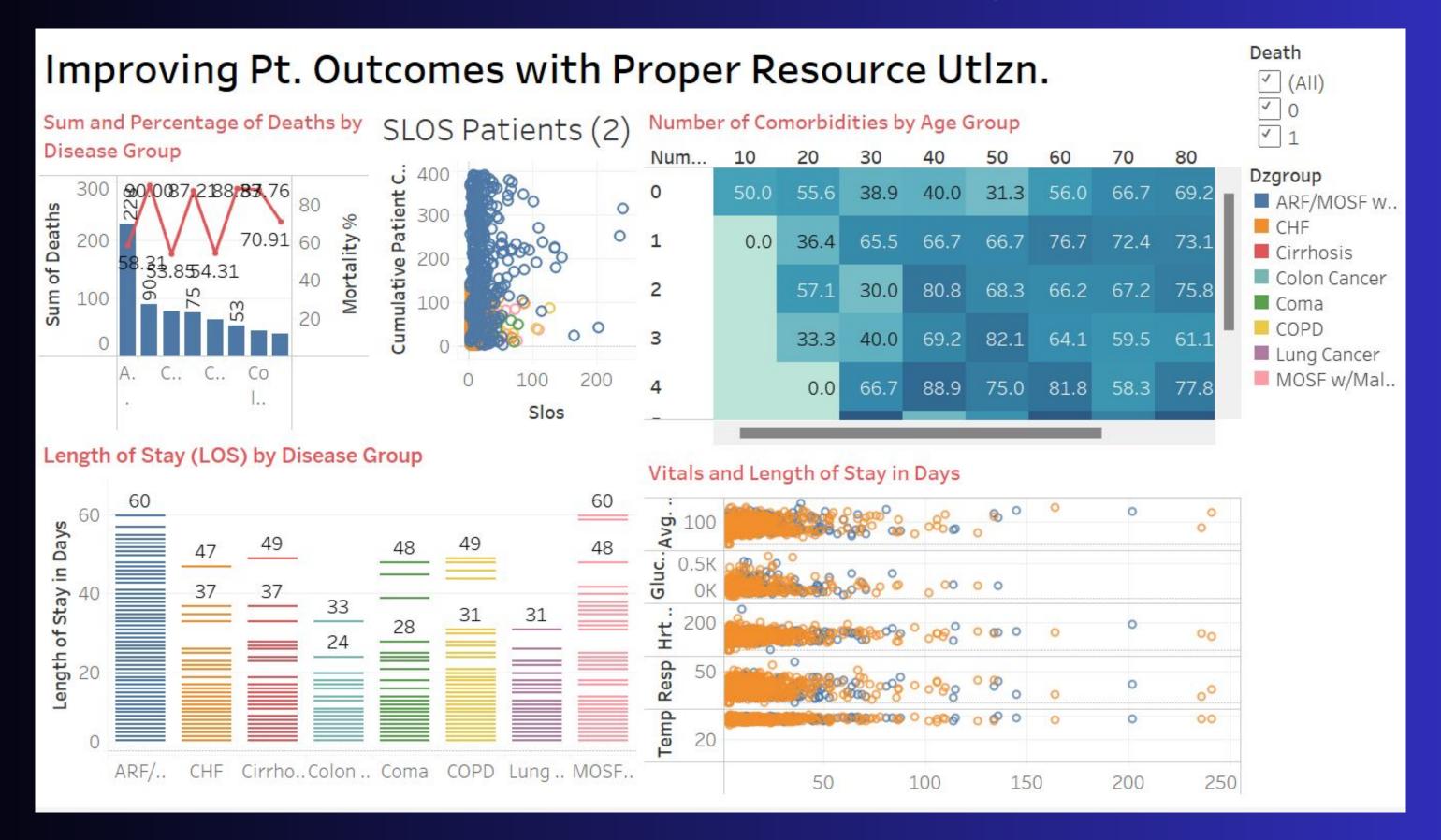
Benefits:
Tailored insights,
dynamic planning,
improved
decision-making

Performance indicators

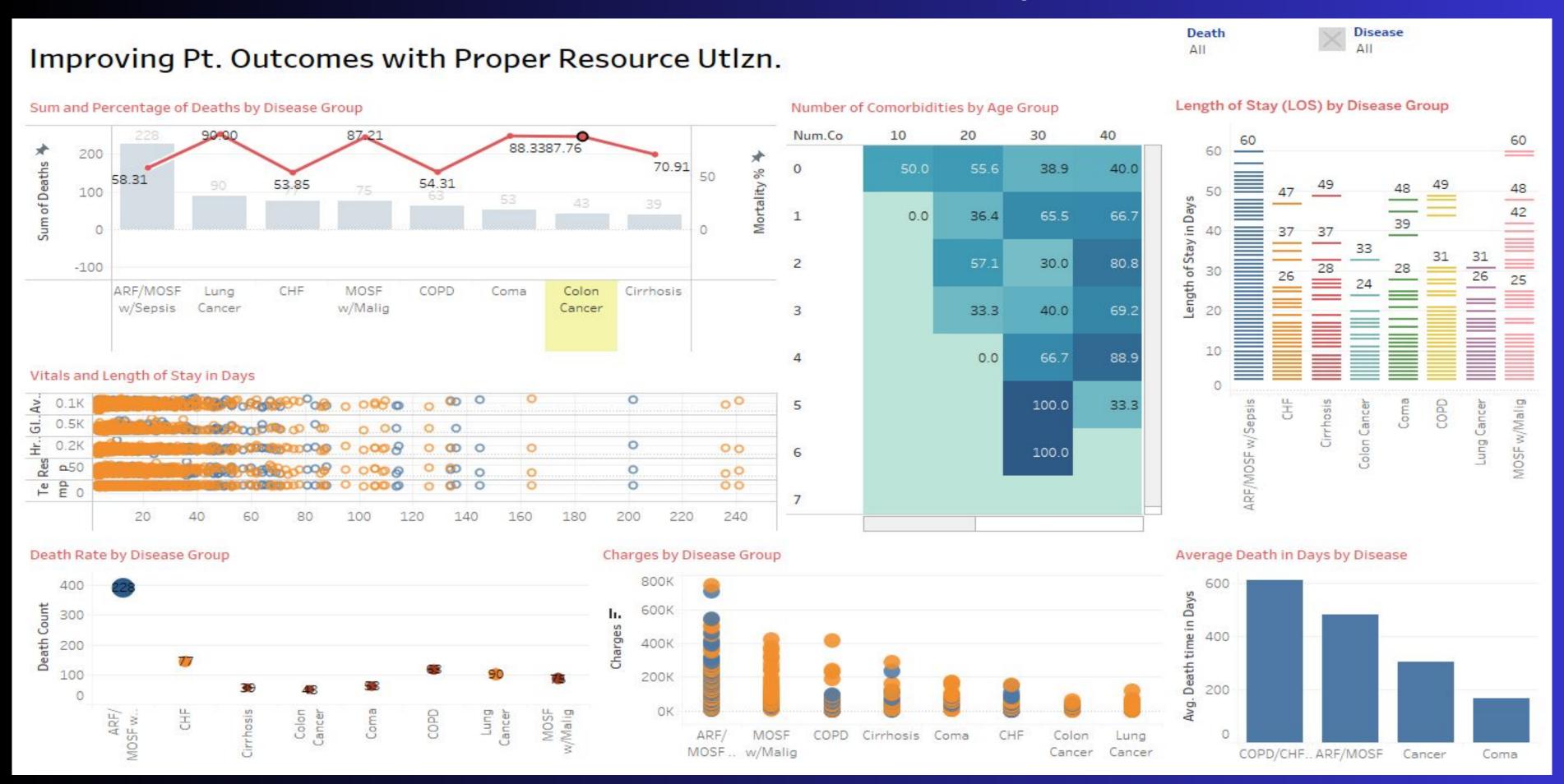
Dashboard Journey



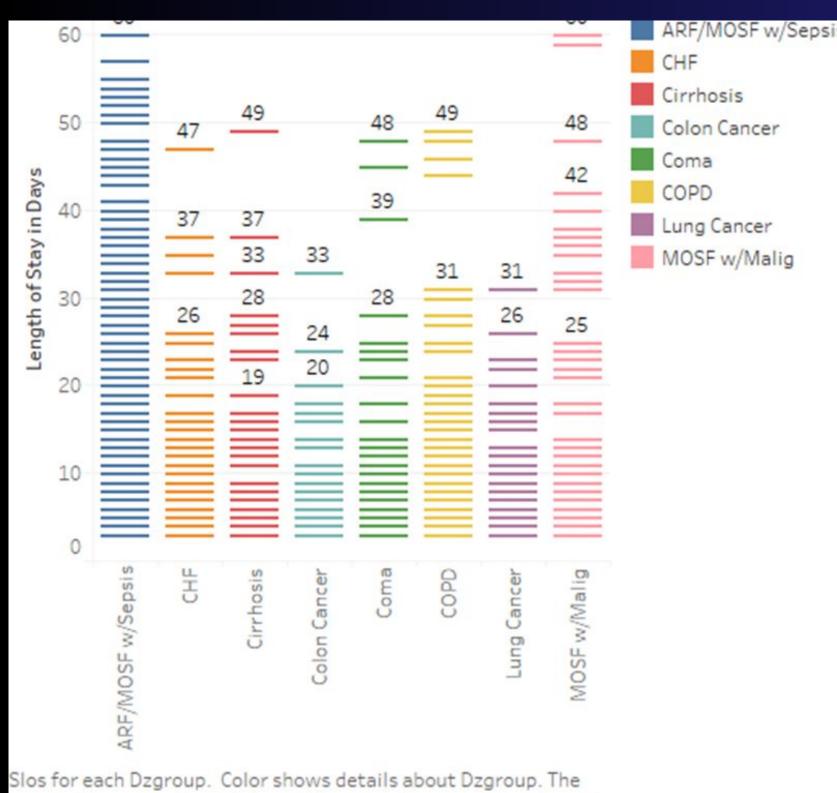
Dashboard Journey



Dashboard Journey



Objective of the Dashboard



Slos for each Dzgroup. Color shows details about Dzgroup. The data is filtered on Death (Sheet1 (data_icu)), which keeps 0 and 1. The view is filtered on Slos and Dzgroup. The Slos filter ranges from 3 to 60. The Dzgroup filter keeps 8 of 8 members.

Optimizing ICU Bed Allocation for Improved Patient Outcomes and Resource Utilization

- **Goal:** Provide healthcare professionals with actionable insights to optimize ICU bed usage and enhance patient care.
- Key Problems Addressed:
 - Real-time tracking of ICU bed availability.
 - Identifying patterns in patient flow and potential bottlenecks.
 - Analyzing trends in length of stay across patient categories.
 - Monitoring and managing resource utilization and associated costs.

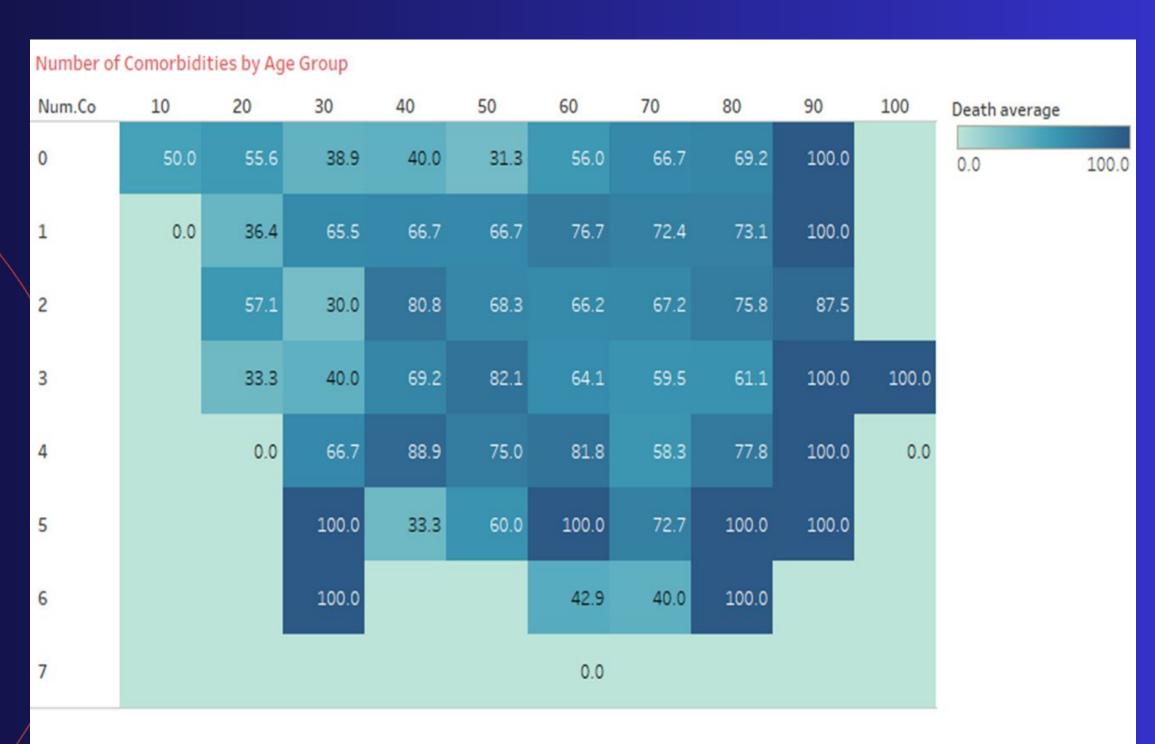
Leveraging Data for Actionable Insights

• Data Insights:

- Patterns of patient flow through the ICU.
- Disease-specific length of stay trends.
- Peak demand periods and associated costs.

Processing Methods:

- Data cleansing to ensure accuracy.
- Aggregation and visualization for clearer insights.

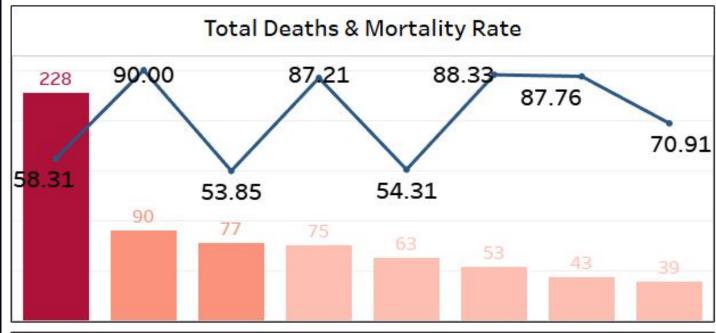


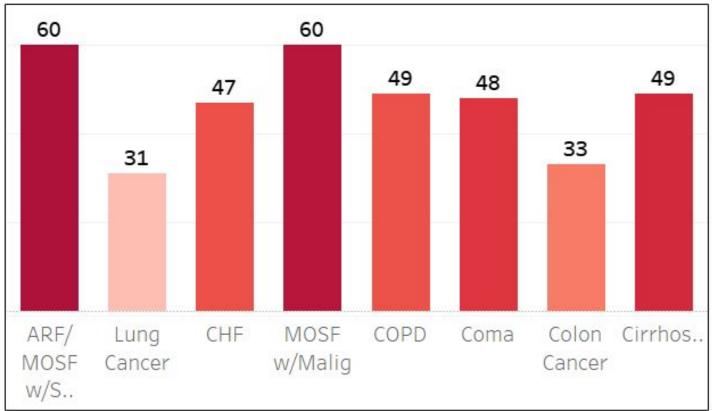
Death average broken down by age (bin) vs. Num.Co. Color shows Death average. The marks are labeled by Death average. The data is filtered on Death, Action (Dzgroup, Slos) and Dzgroup (Sheet1 (data_icu) (3)). The Death filter keeps 0 and 1. The Action (Dzgroup, Slos) filter keeps 257 members. The Dzgroup (Sheet1 (data_icu) (3)) filter keeps 8 of 8 members.

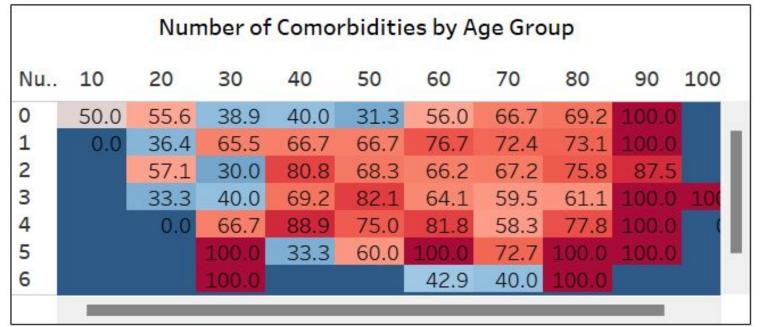
Final Dashboard

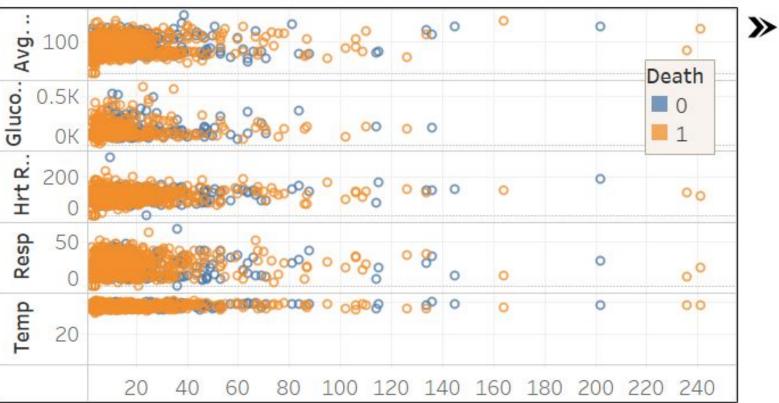










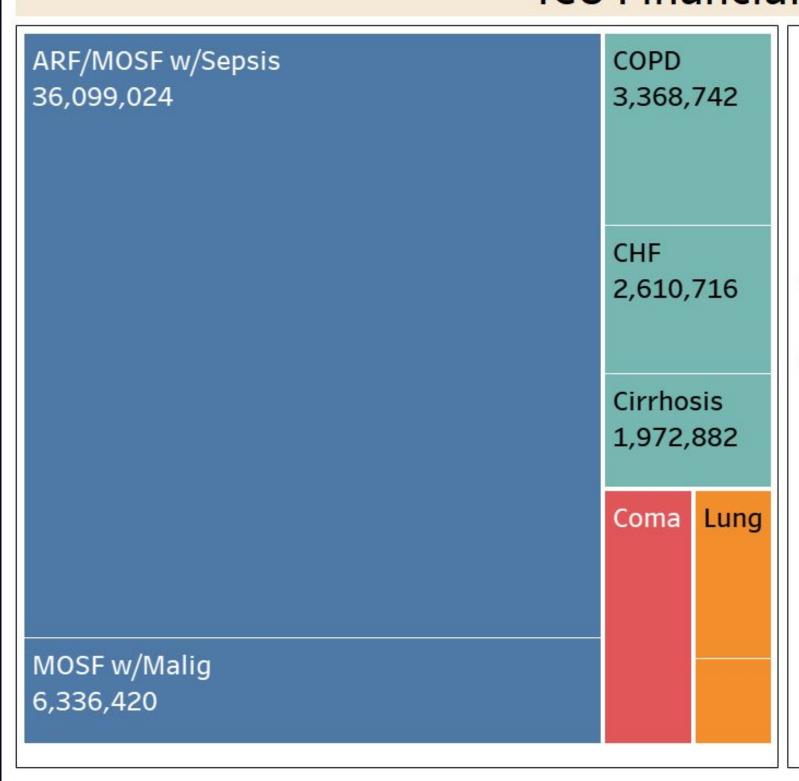


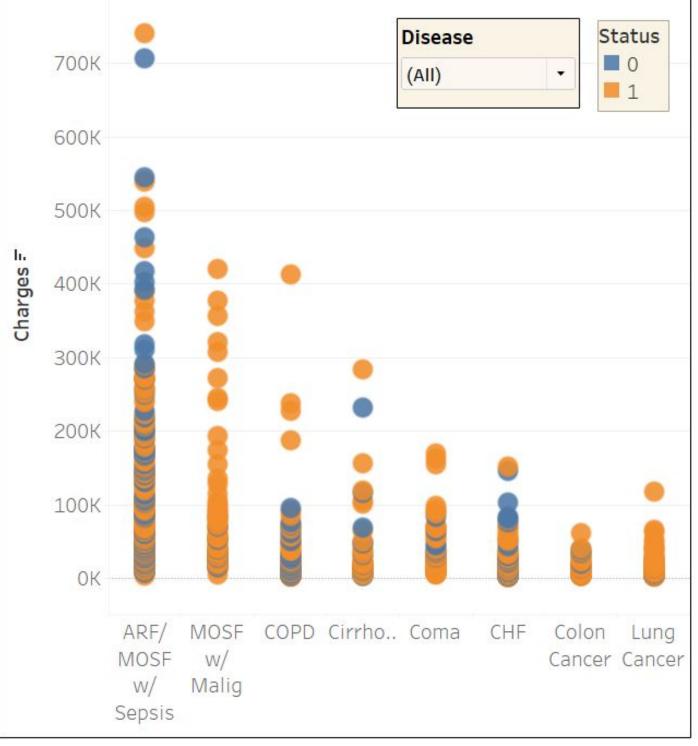
Length of Stay

Vitals and Length of Stay in Days

Final Dashboard

ICU Financial Burden





Final dashboard Key Insights

Purpose:

Optimize ICU operations by addressing mortality, length of stay, and resource allocation for better patient outcomes.

Sum and Percentage of Deaths by Disease Group

- Highest deaths: ARF/MOSF w/Sepsis (228 deaths, 58.31% mortality).
- Colon Cancer shows the lowest mortality.

Number of Comorbidities by Age Group

Younger age groups have **0 comorbidities**,
 while older groups show higher numbers
 (2-6).

Length of Stay (LOS) by Disease Group

- Longest stays: COPD, CHF (~60 days).
- Shortest stays: Colon Cancer, Coma (~25 days).

Vitals vs. Length of Stay

 Scatterplot links vitals (e.g., heart rate, glucose) to LOS.

Death Rate by Disease Group

- Top cause: ARF/MOSF w/Sepsis (228 deaths).
- Low death counts in Coma, Cirrhosis.

Charges by Disease Group

High charges for ARF/MOSF w/Sepsis and MOSF w/Malignancy

Average Death Time by Disease

- Longest: Cancer, ARF/MOSF (~500+ days).
- Shorter for COPD and others...

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