Rancel Hernandez

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SLM2 TASK 1: DATA ANALYSIS

The purpose of the dashboard was to conduct a comparative analysis of two distinct hospital networks. The primary network is referred to as "Medical Clean," which is the name of the original dataset. This chain of hospitals will be compared to the Beth Israel Deaconess Medical Center (BIMC), where the MIMIC IV dataset is derived from. Both datasets include patient demographics, health data, and admissions information. However, they are in two different formats, so they needed to be cleaned and processed to be combined into one data source. The dashboard was created using a common business intelligence tool, Tableau, for informative data visualizations. This comparison aims to gauge the performance of the Medical Clean hospital and assess its standing in relation to competitors, highlighting both strengths and weaknesses to improve patient outcomes. While the analysis faced some data interpretation limitations, the findings provide valuable insights.

The dashboard contains visualizations that compare the performance of the two networks through different perspectives.

Scatter plot - The scatter plot highlights differences in hospital durations across networks and readmission status for various health conditions to enable comparisons. This insight is relevant to the Senior Vice President of Hospital Operations (SVP) and the Vice President of Research (VP). The SVP oversees operations and develops initiatives to improve patient outcomes. Therefore, understanding the differences in hospital durations between the two networks provides a benchmark for how quickly the network should aim to discharge patients and emphasizes the relationship between hospital durations and readmission status. The VP focuses on identifying patterns in patient care to improve outcomes. Thus, the scatter plot highlights which health conditions result in longer hospitalizations, guiding research initiatives aimed at reducing these stays.

Key Performance Indicator Table - The KPI table displays the distribution of patients by gender and health status across networks, categorized by readmission status. This visualization highlights population trends, helping to identify whether certain genders are at a higher risk for readmission or specific health conditions. The SVP and the Panel of Regional Vice Presidents (Regional VPs) can use this table to better understand patient demographics and consider gender-focused treatments for health conditions that are more prevalent among specific genders.

Pie Charts - The pie charts consolidate the data to provide an overall readmission rate based on the current set of filter options for each network. These charts serve as a performance metric, reflecting how effectively each network delivers patient care. A higher readmission rate could indicate that patients are receiving ineffective care, resulting in their readmission. The SVP can use the performance metrics to evaluate the quality of care provided by the network, compare it to the competitor, and identify areas needing improvement by adjusting the filter options.

Heatmap - The heat map is used to identify the density of the patient population by age groups and health conditions. Spreading out the populations by these demographics allows stakeholders to identify if certain health conditions become more prominent with age. The SVP and VP can collaborate to lead a team of analysts in researching preventative measures for health conditions that become greater risks for older patients. Since everyone will eventually be at risk for these conditions, addressing them could help lower admissions and reduce the strain on healthcare resources.

Filter - The dashboard contained the following filters:

> Filter Condition - This filter limits the Condition filter to the top or bottom 5 health conditions ranked by the percentage of readmitted patients with each condition in the Medical Clean dataset. This allows stakeholders to compare readmission rates across health conditions based on their prevalence. Additionally, restricting the visualization to 5 health conditions enhances interpretability by reducing clutter and maintaining focus.

> Condition - The condition filter includes two sets of health conditions: the top 5 and the bottom 5 ranked by the percentage of readmissions associated with each condition. The top 5 health conditions and their corresponding readmission percentages are: Overweight (69.99%), High Blood Pressure (48.16%), Reflux Esophagitis (40.72%), Back Pain (40.53%), and Allergic Rhinitis (39.22%). The bottom 5 health conditions and their readmission percentages are: Arthritis (35.20%), Anxiety (31.10%), Stroke (28.97%), Asthma (28.73%), and Diabetes (26.87%).

Network - This filter allows stakeholders to focus the visualizations on one of the two networks being compared in the analysis: BIMC and Medical Clean.

Health Status - Filters patients based on whether they had a specific condition.

Readmission Status - Filters by readmission status, where a readmission is defined as a patient being admitted within 30 days of being discharged.

Age Groups - Categorizes patients into common age ranges: 18 - 39, 40 - 59, and 60 - 91. These ranges were inspired by standard age groupings used in the U.S. Census, such as 18 - 35, 36 - 65, and 65+, but were adjusted to provide less granularity and reduce noise [1].

Gender - Filters the visualizations by gender: Female or Male.

Together, these filters allow the stakeholders to adjust the visualizations to analyze differences in initial hospitalization durations, the distribution of the patient populations, and readmission rates between the two networks. With these insights, the strengths and weaknesses of the organization are highlighted so that efforts can be made to improve shortcomings and enhance patient care.

Tableau was the business intelligence tool used to create the dashboard. It is a data visualization program that can be used to plot the data and spot trends and insights. It supports various data source connections, which simplified the workflow by allowing the data to be cleaned and transformed in PGAdmin before easily accessing the tables through Tableau. PGAdmin was used as the database management program for processing the data with PostgreSQL.

Creating the visualizations in Tableau was flexible due to the many graph customization options it offered. These options ranged from selecting the size, color, shape, filters, and aliases of the data to create dynamic and informative data representations. Additionally, these visualizations could be combined into a dashboard and used in a story to present a structured narrative of the data. Tableau was essential for creating the dashboard to discover the key results of the comparative analysis and show stakeholders how well the network was performing.

Before the data could be utilized in the dashboard, it had to be clean and transformed, and this process can be summarized into six steps. The first step was to set up the structure of the database, which involved creating and populating the necessary tables. Three tables were required for the analysis, derived from the MIMIC-IV dataset: mimic_patients, mimic_admissions, and drg_codes.

- The mimic_patients table contains patient demographic information.
- The mimic_admissions table stores details about patient admissions.
- The drg_codes table describes the reasons for these admissions.

These tables were designed with primary keys and foreign keys to establish their relationships. Patients in the mimic_patients table can have multiple admissions in the mimic_admissions table, forming a one-to-many relationship. Each admission is associated with one or more entries in the drg_codes table, providing descriptive information about the diagnoses or treatments related to that admission. Therefore, the drg_codes table forms a one-to-many relationship with both admissions and patients. Once the table structures were established, the next step was to populate them with data. This was done by importing data from the downloaded CSV files, marking the completion of the initial data processing step.

The second step was to determine whether patients were ever readmitted. To achieve this, a readmission_status column was added to the mimic_patients table. The time between visits was calculated for all patient admissions, and the admissions were grouped by patient ID. If a patient had a minimum time between visits of less than 30 days, they were considered to have experienced at least one readmission and were marked as "readmitted." This step was crucial for the analysis because the readmission status was required to calculate the readmission rate for the BIMC, and served as a performance metric for comparing the two networks.

The third step was to calculate the initial days for the patients. This column is present in the Medical Clean dataset and represents the duration of a patient's initial hospitalization. However, this method could not be directly applied to the MIMIC IV dataset because patients can have multiple admissions, and not all their admissions lead to a readmission. For patients who were never readmitted, the average duration of all their admissions was calculated to serve as the "initial days" value. This approach was suitable for the analysis because the focus was on comparing the durations of admissions that did or did not lead to a readmission. For patients who were readmitted, only the durations of admissions prior to the readmission were averaged to determine their initial days. Including the durations of all admissions for readmitted patients would obscure the goal of the analysis because admissions unrelated to readmissions are not relevant in this context.

The fourth step was to identify the descriptions related to the health conditions found in the Medical Clean dataset and convert them to the same format. The health conditions in the Medical Clean dataset are stroke, anxiety, arthritis, diabetes, back pain, reflux esophagitis, overweight, allergic rhinitis, high blood pressure, and asthma. This step was needed to compare how readmission rates differed between health conditions for both networks. To achieve this, a new table named patient_conditions was created to pivot the drg_codes into the specified health conditions. Records from drg_codes were inserted into patient_conditions using pattern matching to map the descriptions to the corresponding health conditions. The records were then aggregated by patients to preserve the health status of each condition. The table below holds the summarized descriptions that were mapped to the health conditions.

Mapping MIMIC IV Admission Descriptions to Medical Clean Conditions

Condition	DRG Code Description
Stroke	Acute Ischemic Stroke and Ischemic Stroke (with Thrombolytic Agent).
Anxiety	Acute Anxiety and Delirium states.
Arthritis	Septic Arthritis
Diabetes	Diabetes with or without major complication
Back Pain	Back and Neck Procedures
Reflux Esophagitis	Esophagitis, Gastroent, and Digest Disorders
Overweight	Procedures for Obesity
Allergic Rhinitis	Allergic Reactions
High Blood Pressure	Hypertension

Asthma	Bronchitis and Asthma

The fifth step was to standardize the data, which involved several tasks. The first task was to normalize the gender values in the Medical Clean dataset, converting "Female" to "F" and "Male" to "M." Next, patients were grouped into common age ranges to analyze how readmission rates differ with age across health conditions. The age ranges used were 18 - 39, 40 - 59, and 60 - 91. The third task involved correcting the column name "hignblood" in the Medical Clean dataset to "Highblood." The fourth task was to identify and remove records with negative initial days or negative time between visits. These errors can occur when a patient is recorded as being discharged before being admitted or admitted before being discharged from their last visit. These negative intervals could skew the analysis, so they were deleted to ensure reliable results.

The final step was to combine both datasets into one table. To accomplish this, the patient tables from both datasets were unioned, and then linked to their corresponding health conditions using the patient ID. Only the demographic columns from the MIMIC IV dataset were retained in both tables to ensure a compatible union. Before combining the patients from both datasets, a network_id column was created to distinguish between the two networks. The Medical Clean network was assigned a network_id of 1, while the BIMC network received a network_id of 0.

After combining the patients, the health conditions of the Medical Clean patients were unioned into the patient_conditions table, which already contained the BIMC patient conditions. Once these two sets of data were merged, they were joined with the unioned patient data to create a single table containing all patient records. The table was then unpivoted to consolidate all health conditions into one column, and a new column detailing the health status was added. This final step was included to group the health conditions into a single filter, enabling the comparison of population counts and readmission rates between health conditions in the dashboard visualizations.

To create the dashboard, there was one step for each visualization, as well as a step to set up the filters. The dashboard featured four visualizations: a scatter plot, a Key Performance Indicator (KPI) table, pie charts, and a heatmap. For the scatter plot, Conditions were placed on the Columns shelf, and the average Initial Days were placed on the Rows shelf. To visualize the data points, the "Circle View" was selected from the "Show Me" dropdown. Next, Readmission Status was placed in the Color marks, and the Network was added to the Shape marks. This configuration allowed the scatter plot to display the average initial hospitalization durations for each network, broken down by readmission status and health condition.

For the KPI table, the Gender and Health Status dimensions were placed on the Columns shelf, while the Network and Readmission Status were placed on the Rows shelf. The distinct count of patient IDs was then dragged to the Marks card to display the population breakdown by these categories. Additionally, a row grand total was added from the Analysis dropdown to show the total patient count by readmission status for each network. Finally, the headers and patient counts were formatted to be bold, centered, and in a larger font for improved readability.

For the pie charts, the Network was placed on the Rows shelf to create separate pie charts for each network. A calculated field named "Patient Counts" was created to store the unique count of patient IDs, which represented the size of the pie slices. The Readmission Status was then dragged to the Color marks to distinguish the two groups within the pie charts. To display the percentages of each slice, the Patient Counts field was dragged to the Text marks, and a quick table calculation was applied to calculate the percent of total across. Additionally, the Readmission Status was dragged to the Text marks to further label each slice, and the average Initial Days were added to the tooltips to show the difference in hospitalization durations between readmission statuses.

For the heatmap, the Conditions dimension was added to the Columns shelf, Age Groups to the Rows shelf, and Patient Count to the Color marks. The marks type was changed to squares, and the view was resized to fit the entire display. This configuration created a heatmap showing the density of the patient population across age ranges and health conditions. Additionally, the color gradient was adjusted to align with the theme of the other visualizations. A reversed orange-blue gradient was used to indicate density, where warmer colors signaled higher densities, and cooler colors indicated lower densities. Finally, the font of the headers was centered and adjusted to ensure they fit neatly within the borders.

To add filters, the process began by right-clicking on one of the visualizations and selecting the desired fields from the filters option. Since all the visualizations shared the same data source, any visualization could be used to bring in the following filters: Conditions, Network, Health Status, Gender, Age Groups, and Readmission Status. The Condition filter was unique, as it was created using a sheet that displayed the percentage of readmissions associated with each health condition. This filter helped declutter the visualizations by halving the number of conditions displayed at once and grouping them based on their prevalence among readmitted patients in the Medical Clean dataset.

The remaining filters were limited to certain visualizations to restrict filtering in data exploration and comparisons. For instance, the pie charts were not limited by the Network filter since there are only two charts, and removing one would eliminate the ability to compare readmission rates across networks. A filter guide was also added above the filters to provide context and assist users in exploring the dashboard. Finally, all visualizations were enabled as interactive filters to allow users to adjust the dashboard and focus on their desired selections.

The purpose of the analysis was to compare the performance between the Medical Clean and BIMC hospital networks. The evaluation metrics being measured were the readmission rate and average hospitalization durations. The Centers for Medicaid and Medicare Services penalizes hospitals with high readmission rates to encourage better communication and care coordination [2]. This policy is designed to effectively engage caregivers and patients in post-discharge planning. Therefore, the readmission rate serves as a measure of the quality of patient care, reflecting how likely patients are to return to the hospital after being discharged. Average hospitalization durations were associated with higher readmission rates, making them a valuable metric for assessing the efficiency of care delivery [3]. Additionally, admission durations reflect how promptly patients receive treatment and can return home, serving as a measure of efficiency. The analysis yielded four key results, each addressing a distinct aspect of the stakeholders' needs.

The first key result was that BIMC had significantly lower admission durations than Medical Clean, with both networks showing a consistent trend of longer admissions for readmitted patients. The scatter plot highlighted these differences in hospital durations between readmission status. In the Medical Clean dataset, readmitted patients had an average hospital duration of approximately 64 days, compared to approximately 17 days for non-readmitted patients. This trend persisted in the BIMC dataset, where readmitted patients averaged approximately 6 days and non-readmitted patients averaged 4 days. This means readmitted patients at BIMC receive full care in one-tenth of the time compared to Medical Clean, while non-readmitted patients receive care in one-fourth of the time. The drastic difference in admission durations is concerning, as potential patients are likely to avoid Medical Clean when they could expect, at worst, to be admitted for ten times longer than at BIMC. This key result supports the dashboard's purpose by highlighting a crucial network weakness that needs urgent attention.

The second key result revealed that BIMC had a lower overall readmission rate of 20.68% compared to Medical Clean's 36.64%. However, a deeper analysis showed complex patterns in how these rates varied across patient groups. Medical Clean demonstrated consistent readmission rates regardless of health conditions, while BIMC exhibited significant variations. For the top five most prevalent health conditions, BIMC's readmission rate was 39.53%, slightly higher than Medical Clean's 36.75%. However, for the bottom five health conditions, BIMC's rate worsened considerably to 49.17%, while Medical Clean remained stable at 37.09%. A notable exception was observed among overweight patients, where BIMC achieved a notably low readmission rate of 23.35%, in contrast to Medical Clean's consistent 36.94%.

BIMC's lower overall readmission rate was primarily influenced by patients without health conditions. An analysis of the KPI table revealed that among BIMC's female patients, only about 6% of non-readmitted patients had a health condition, compared to approximately 18% of readmitted patients, indicating that health conditions can be related to an increased risk of readmission at BIMC. In contrast, Medical Clean exhibited an unusual pattern where the proportion of patients with health conditions was similar regardless of their readmission status, and readmission rates remained consistent between patients with and without health conditions.

This anomaly suggests two possible explanations: either there may be no correlation between health status and readmissions within the Medical Clean network, or Medical Clean might be delivering specialized care that ensures consistent readmission rates across all patient groups. Further analysis would be required to fully understand these patterns. This key result aligns with the purpose of the dashboard by revealing that the network has a higher overall readmission rate. This insight highlights that patients at Medical Clean are not only more likely to be readmitted but, as previously noted, also tend to experience longer admission durations. However, it also uncovered that the readmission rate remains consistent across health conditions, indicating consistency in care delivery. The dashboard enables the network to evaluate its ability to care for patients by benchmarking it against a competitor. A detailed breakdown of readmission rates across all health conditions for both networks is provided in the following table.

Readmission Rate Between Networks for All Health Conditions

Condition	BIMC	Medical Clean	Readmission Prevalence
Top 5	39.53%	36.75%	N/A
Bottom 5	49.17%	37.09%	N/A
Overweight	23.35%	36.94%	69.99%
High Blood Pressure	44.62%	37.36%	48.16%

Reflux Esophagitis	54.78%	36.97%	40.72%
Back Pain	31.41%	37.06%	40.53%
Allergic Rhinitis	37.66%	37.41%	39.22%
Arthritis	57.86%	37.13%	35.30%
Anxiety	48.52%	36.22%	31.10%
Stroke	32.51%	36.43%	28.97%
Asthma	50.71%	37.20%	28.73%
Diabetes	50.62%	36.70%	26.87%

The third key result identified is that males in Medical Clean consistently experienced higher readmission rates than females, whereas readmission rates across genders varied by health condition in BIMC. For instance, in Medical Clean, males with high blood pressure had a readmission rate of 38.72%, compared to 36% for females. Conversely, in BIMC, the readmission rate for the same condition was higher overall, with females at 47.97% and males at 39.62%. This highlights a strength for Medical Clean, as patients with high blood pressure are less likely to be readmitted there than at BIMC, with female patients having an 11.97% lower risk.

This trend remained consistent for patients with reflux esophagitis, where males (38.35%) and females (35.70%) in Medical Clean experienced significantly lower readmission rates compared to patients in BIMC, with males at 56.57% and females at 53.64%. These lower rates at Medical Clean reflect greater patient care for these conditions, potentially influencing patients to prefer receiving care at Medical Clean. This key result aligns with the purpose of the dashboard because the pie charts effectively illustrate the differences in readmission rates between these demographics, highlighting a notable strength in the network's quality of care. The difference in readmission rates by gender for the top five prevalent conditions between networks can be seen in the following table.

Readmission Rate by Gender and Network for the Top 5 Health Conditions

Condition	BIMC F	Medical Clean F	BIMC M	Medical Clean M
Overweight	23.18%	36.18%	23.86%	37.73%
High Blood Pressure	47.97%	36.08%	39.62%	38.72%
Reflux Esophagitis	53%.64%	35.70%	56.57%	38.35%
Back Pain	31.99%	36.89%	30.79%	37.24%
Allergic Rhinitis	39.51%	37.40%	35.62%	37.41%

The fourth key result identified a consistent trend across both networks: readmission rates increase with patient age. However, the gaps between age groups were more pronounced in BIMC compared to Medical Clean, with BIMC achieving a notably lower readmission rate of 13.96% for patients aged 18 - 39. This increase in readmission rates with age can likely be attributed to the growing prevalence of health conditions among older age groups, often due to the cumulative effects of cellular damage in the aging process [4].

The heat maps in *Figure 1-2* support this relationship, showing higher patient counts for health conditions as the age increases. This pattern is particularly evident in BIMC patients with back pain and reflux esophagitis. Similarly, in Medical Clean, the 60-91 age group shows the highest concentration of patients across all top 5 health conditions. These patterns in the heat maps support the correlation between higher readmission rates and the prevalence of health conditions. This insight is relevant to the purpose of the dashboard by identifying a crucial pattern that is supported by its presence in both networks, highlighting the need for attention and resources for older demographics to reduce overall readmissions.

Readmission Rate Between Age Ranges

Network	18 - 39	40 - 59	60 - 91
BIMC	13.96%	21.17%%	24.12%%
Medical Clean	35.71%	36.26%	37.59%

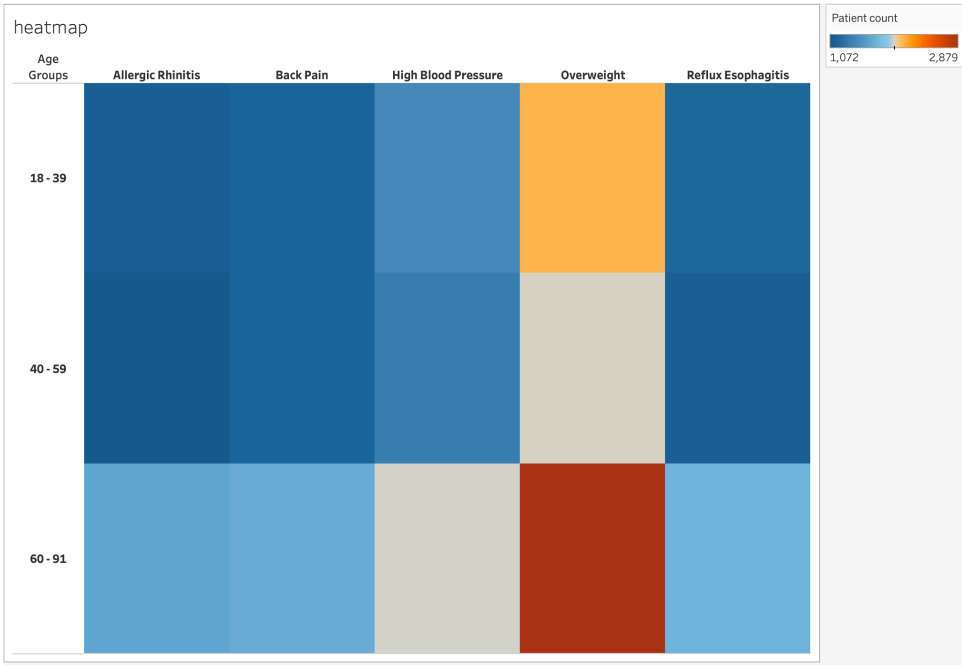

Figure 1: The heat map for Medical Clean patients.

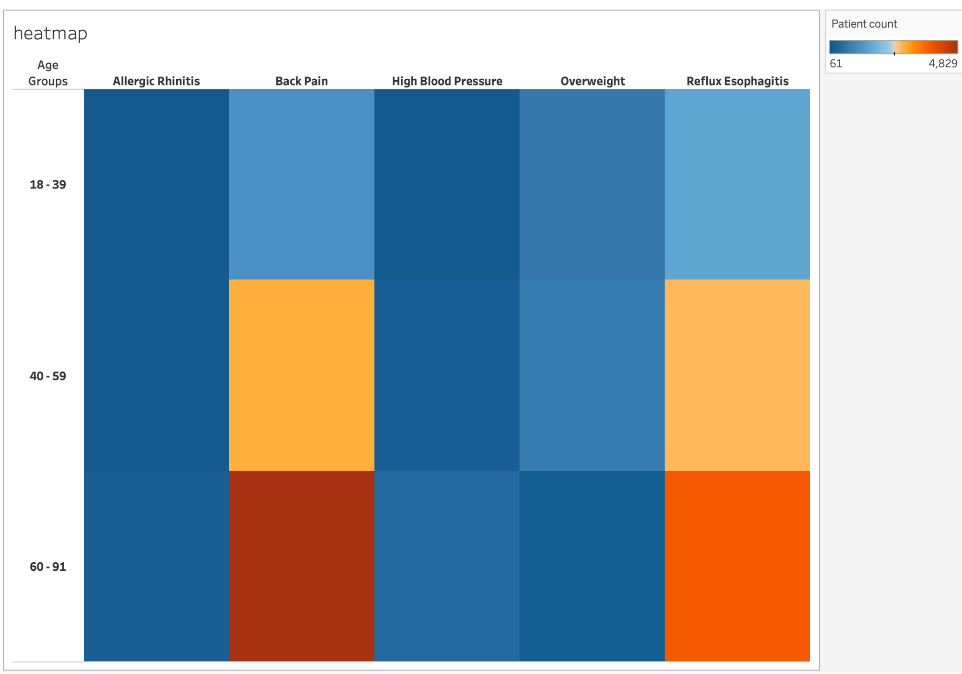

Figure 2: The heat map for BIMC patients.

The comparative analysis of the healthcare networks revealed significant performative differences between BIMC and Medical Clean. BIMC exhibited shorter initial hospitalization durations, with readmitted patients staying 6 days compared to 64 days at Medical Clean. Additionally, BIMC had a lower overall readmission rate of 20.68%, while Medical Clean's rate was 36.64%. However, Medical Clean demonstrated greater consistency in patient care across various health conditions. BIMC's readmission rates varied considerably across patient groups, showing higher rates for patients with the top 5 (39.53%) and bottom 5 (49.17%) health conditions, while Medical Clean maintained stable rates around 37%. The gender analysis showed Medical Clean had consistently higher readmission rates for males, while BIMC's rates varied by condition. Both networks exhibited increasing readmission rates with patient age, though this trend was more pronounced in BIMC, which achieved a notably lower rate of 13.96% for younger patients aged 18 - 39.

The analysis faced three notable limitations, all stemming from challenges in interpreting the data. These complications arose because, while both datasets contained patient information, they were stored in different formats. This required transforming the data, which led to assumptions that might not be accurate, resulting in the following limitations: the interpretation of the MIMIC IV dataset regarding the persistence of health conditions throughout a patient's time with the network, determining an equivalent measure for a patient's initial hospitalization duration, and defining the appropriate method for calculating the readmission rate.

The interpretation of how a patient's health conditions persist over time with BIMC assumes these conditions are chronic and remain active throughout all admissions. In the dataset, patients can have multiple admissions, each with its own set of reasons that can vary through visits. The time between visits ranges from days to years, meaning some conditions might resolve, while others persist. However, for this analysis, conditions were presumed to be active throughout the patient's history, as most are chronic and unlikely to resolve after a single hospitalization. To align with the format of the Medical Clean dataset, conditions were aggregated from the admission level to the patient level. This transformation results in the loss of admission-specific information and relies on the assumption about condition persistence. Nonetheless, this data loss is justifiable because the Medical Clean dataset does not include reasons for admission or condition progression, leaving both datasets with similar limitations.

The second limitation involved calculating readmission rates for the MIMIC IV dataset. In the Medical Clean dataset, each patient has only one recorded admission, so the readmission rate directly reflects the percentage of patients who were readmitted. However, this approach is not suitable for the MIMIC IV dataset, where patients can have multiple admissions and readmissions. Initially, this suggested calculating MIMIC IV's readmission rate as the percentage of total readmissions rather than the percentage of readmitted patients. However, Medical Clean uses patient-level rates, while MIMIC IV reflects admission-level rates. Comparing readmission rates at these different levels would have made interpreting the results more complex. As a result, MIMIC IV admissions were aggregated to the patient level, making both datasets reflect the percentage of readmitted patients. While this standardization enabled direct comparison between networks, it may not fully represent BIMC's true performance since multiple readmissions for patients were excluded.

The third limitation involved calculating the Initial_Days metric for the MIMIC IV dataset. While Medical Clean's Initial_Days simply represents a patient's first hospitalization duration, MIMIC IV's multiple admissions per patient required a different approach. The chosen method was visit-centric, calculating separate averages for readmitted and non-readmitted patients. For non-readmitted patients, all admission durations were averaged since none led to readmissions. For readmitted patients, only durations of admissions that directly led to readmissions were averaged, excluding admissions that didn't result in readmissions. A patient-centric approach would have included all durations based solely on a patient's readmission status, but this would have obscured the distinction between admissions that did and didn't lead to readmissions.

While this approach preserves important admission-level information, it has two key limitations. First, it excludes some duration data for readmitted patients. Second, it creates an inconsistency in data aggregation levels because health conditions and readmission rates are calculated at the patient level, while Initial_Days is calculated at the admission level. Despite these inconsistencies, the method is still reliable because any chosen approach would involve trade-offs and its own set of limitations. Despite these limitations, the analysis provides valuable insights into the performance of both networks and highlights key areas for improvement. The adjustments made to the data were necessary to enable meaningful comparisons, and while some information was lost in the process, the results remain reliable for assessing network performance and identifying trends.

The purpose of this analysis was to conduct a comparative analysis between both hospital networks to evaluate performance, identify strengths and weaknesses, and establish performance benchmarks through a performance comparison. The comparative analysis between Medical Clean and Beth Israel Deaconess Medical Center revealed several significant insights. The most crucial concerns are Medical Clean's substantially longer hospitalization durations and overall higher readmission rate. Readmitted patients stayed an average of 64 days compared to BIMC's 6 days, and this difference in durations is tenfold. The overall readmission rate was higher at

36.64% for Medical Clean than BIMC's 20.68%. The lower readmission rate was greatly influenced by patients with no health conditions in BIMC, but the lower rate does reflect a higher quality of patient care. Regardless of readmission status or health status, the average admission duration and readmission rate was substantially larger at Medical Clean, so this could significantly impact patient satisfaction and potentially deter future patients from seeking their health care needs at Medical Clean. Despite this, Medical Clean demonstrated consistent care delivery across patient populations and conditions, maintaining stable readmission rates around 37%. This suggests a standardized approach to care, in contrast to BIMC, which exhibited greater variation in readmission rates across demographics and health conditions.

The analysis revealed key demographic patterns that highlighted differences between the networks. Medical Clean consistently reported higher readmission rates for male patients, while BIMC's rates varied depending on both gender and condition. Additionally, both networks showed an increase in readmission rates with age, though this trend was more evident in BIMC. These findings emphasized prioritizing older patients, as they tend to have higher concentrations of health conditions across both networks. Although the analysis faced challenges due to data interpretation and differences in standardization between the networks, it still provided meaningful insights into improving patient outcomes and overall performance.

Based on these findings, several key recommendations can be made. First, the network should explore and implement protocols from BIMC to reduce hospital stay durations while improving patient care quality. Additionally, targeted interventions for male patients are needed, as they show consistently higher readmission rates across all health conditions. For older patients, implementing or enhancing preventive care programs aimed at conditions more prevalent in older ages could help reduce admissions and alleviate healthcare strain. Finally, the current standardized approach to care should be maintained, while efforts should focus on reducing overall readmission rates. Moving forward, future analyses would benefit from standardized data collection methods, which would allow for more direct performance comparisons and help uncover additional opportunities for enhancing patient care.

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