🏥 ReadmitGuard: Healthcare Patient Readmission Analysis Guide

🧩 Section 1. 📊 Data Exploration in Google Sheets

a. Descriptive Stats

- Load dataset into Google Sheets
- Use:

  `=AVERAGE(), =MEDIAN(), =MIN(), =MAX(), =STDEVP()`

- Apply to each numerical column

🧾 Summary Metrics

Metric	Lab Procedures	Procedures	Medications	Outpatient	Emergency	Inpa
Average	43.10	1.34	16.02	0.37	0.20	0.64
Min	1	0	1	0	0	0
Max	132	6	81	42	76	21
Median	44	1	15	0	0	0
Std. Dev.	19.67	1.71	8.13	1.27	0.93	1.26

b. Re-admissions by Gender and Age (Pivot Table)

- Create a Pivot Table:
  - **Rows:** `gender, age`
  - **Columns:** `readmitted`
  - **Values:** `COUNTA(encounter_id)`

gender	age	<30	>30	NO	Grand Total
Female	[0-10)	1	13	69	83
	[10-20)	24	147	231	402
	[20-30)	177	346	591	1114
	[30-40)	242	647	1273	2162
	[40-50)	511	1685	2615	4811
	[50-60)	851	3105	4616	8572
	[60-70)	1206	4012	5843	11061
	[70-80)	1635	5108	7242	13985
	[80-90)	1282	3855	5378	10515
	[90-100)	223	600	1180	2003
Female Total		6152	19518	29038	54708
Male	[0-10)	2	13	63	78
	[10-20)	16	77	196	289
	[20-30)	59	164	320	543
	[30-40)	182	540	891	1613
	[40-50)	516	1593	2765	4874
	[50-60)	817	2812	5055	8684
	[60-70)	1296	3885	6240	11421
	[70-80)	1434	4367	6280	12081
	[80-90)	796	2368	3518	6682
	[90-100)	87	208	495	790
Male Total		5205	16027	25823	47055
Unknown/Invalid	[60-70)			1	1
	[70-80)			2	2
Unknown/Invalid Total				3	3
Grand Total		11357	35545	54864	101766

c. Race Distribution Chart

- Steps:
  - Use `=UNIQUE(race_range)` for distinct categories
  - Use `=COUNTIF(race_range, value)` for frequency
  - Replace ? with `"Unknown"`

Race Frequency Table

Race	Frequency
Caucasian	76099
AfricanAmerican	19210
Unknown	2273
Hispanic	2037
Other	1506
Asian	641

d. Re-admission Status Distribution

Status	Count
NO	54,864
>30	35,545
<30	11,357

- Visualize using a bar chart
- Formulas:

  ```
  =COUNTIFS(ReadmittedRange, "*<30*")
  =COUNTIFS(ReadmittedRange, "*>30*")
  ```

🗄️ Section 2. Data Loading & SQL Tasks (MySQL Workbench)

a. Create Database and Table

```
-- Create the database if it doesn't exist
CREATE DATABASE IF NOT EXISTS healthcare;
USE healthcare;

-- Create the main table for diabetic patient records
CREATE TABLE diabetic_data (
  encounter_id BIGINT PRIMARY KEY,
  patient_nbr BIGINT,
  race VARCHAR(50),
  gender VARCHAR(15),
  age VARCHAR(20),
  weight VARCHAR(10),
  admission_type_id INT,
  discharge_disposition_id INT,
  admission_source_id INT,
  time_in_hospital INT,
  payer_code VARCHAR(20),
  medical_specialty VARCHAR(100),
  num_lab_procedures INT,
  num_procedures INT,
  num_medications INT,
  number_outpatient INT,
  number_emergency INT,
  number_inpatient INT,
  diag_1 VARCHAR(10),
  diag_2 VARCHAR(10),
  diag_3 VARCHAR(10),
  number_diagnoses INT,
  max_glu_serum VARCHAR(20),
  A1Cresult VARCHAR(20),
  metformin VARCHAR(20),
  repaglinide VARCHAR(20),
  nateglinide VARCHAR(20),
  chlorpropamide VARCHAR(20),
  glimepiride VARCHAR(20),
  acetohexamide VARCHAR(20),
  glipizide VARCHAR(20),
  glyburide VARCHAR(20),
  tolbutamide VARCHAR(20),
  pioglitazone VARCHAR(20),
```

```
  rosiglitazone VARCHAR(20),
  acarbose VARCHAR(20),
  miglitol VARCHAR(20),
  troglitazone VARCHAR(20),
  tolazamide VARCHAR(20),
  examide VARCHAR(20),
  citoglipton VARCHAR(20),
  insulin VARCHAR(20),
  glyburide_metformin VARCHAR(20),
  glipizide_metformin VARCHAR(20),
  glimepiride_pioglitazone VARCHAR(20),
  metformin_rosiglitazone VARCHAR(20),
  metformin_pioglitazone VARCHAR(20),
  `change` VARCHAR(10),
  diabetesMed VARCHAR(10),
  readmitted VARCHAR(20)
);
```

b. Data Cleaning

```
UPDATE diabetic_data
SET race = 'Unknown'
WHERE race = '?';

SELECT race, COUNT(*) FROM diabetic_data GROUP BY race;
```

c. Dataset Overview

```
-- Encounters
SELECT COUNT(*) FROM diabetic_data;

-- Age-wise distribution
SELECT age, COUNT(*) FROM diabetic_data GROUP BY age ORDER BY age;
```

d. Readmission Analysis

```
-- Total readmitted
SELECT COUNT(*) FROM diabetic_data WHERE readmitted IN ('<30', '>30');

-- Readmission percentage
SELECT ROUND(
  (SELECT COUNT(*) FROM diabetic_data WHERE readmitted IN ('<30',
'>30')) * 100.0 /
  (SELECT COUNT(*) FROM diabetic_data),
  2
);
```

e. Readmission by Payer Code

```
SELECT payer_code,
       COUNT(*) AS total_cases,
       SUM(CASE WHEN readmitted IN ('<30', '>30') THEN 1 ELSE 0 END)
AS readmitted_cases,
       ROUND(SUM(CASE WHEN readmitted IN ('<30', '>30') THEN 1 ELSE 0
END) * 100.0 / COUNT(*), 2) AS rate_pct
FROM diabetic_data
GROUP BY payer_code
ORDER BY rate_pct DESC;
```

f. Resource Use Metrics

```
-- Hospital stay by admission type
SELECT admission_type_id, AVG(time_in_hospital) FROM diabetic_data
GROUP BY admission_type_id;

-- Drugs vs Age
SELECT age, AVG(num_medications) FROM diabetic_data GROUP BY age;
```

g. Top 10 Diagnoses

```
SELECT diag_1, COUNT(*) FROM diabetic_data GROUP BY diag_1 ORDER BY
COUNT(*) DESC LIMIT 10;
```

🐍 Section 3. Data Analysis in Jupyter (Python)

a. Load Data and Clean

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

df = pd.read_csv("diabetic_data.csv")
df['race'] = df['race'].replace('?', 'Unknown')
df['readmitted'] = df['readmitted'].replace({'&gt;30': '>30',
'&lt;30': '<30'})
```

b. Describe & Summary Stats

```
numeric_cols = [
    'time_in_hospital',
    'num_lab_procedures',
    'num_procedures',
    'num_medications',
    'number_outpatient',
    'number_emergency',
    'number_inpatient'
]

# Get summary statistics
df[numeric_cols].describe()

# Display mean values
display(df[numeric_cols].mean())

# Transpose the result if you prefer vertical view
df[numeric_cols].describe().T
```

[57...

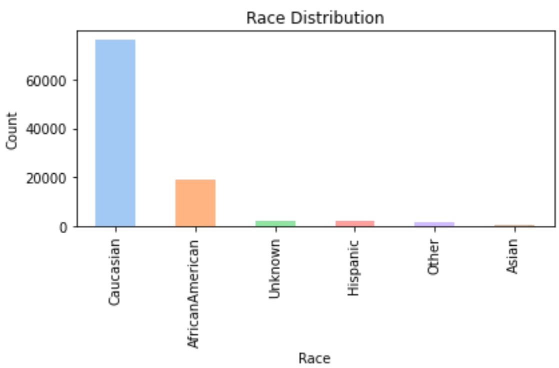
	count	mean	std	min	25%	50%	75%	max
time_in_hospital	101766.0	4.395987	2.985108	1.0	2.0	4.0	6.0	14.0
num_lab_procedures	101766.0	43.095641	19.674362	1.0	31.0	44.0	57.0	132.0
num_procedures	101766.0	1.339730	1.705807	0.0	0.0	1.0	2.0	6.0
num_medications	101766.0	16.021844	8.127566	1.0	10.0	15.0	20.0	81.0
number_outpatient	101766.0	0.369357	1.267265	0.0	0.0	0.0	0.0	42.0
number_emergency	101766.0	0.197836	0.930472	0.0	0.0	0.0	0.0	76.0
number_inpatient	101766.0	0.635566	1.262863	0.0	0.0	0.0	1.0	21.0

Screenshot 2025-07-31 at 10.42.01.png

c. Feature Distribution Plots

i. Race Distribution

```
df['race'].value_counts().plot(kind='bar', title='Race Distribution',
        color=sns.color_palette('pastel'))
plt.xlabel('Race')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```

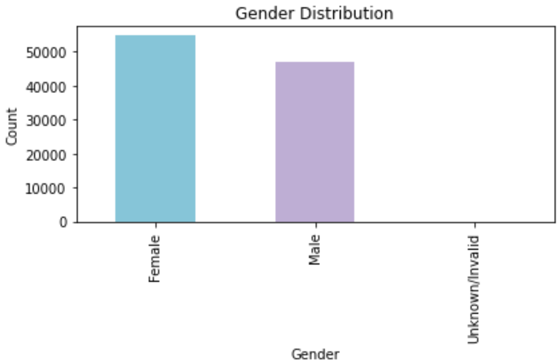


output_8_0.png

> **Findings:**
> The cohort is predominantly Caucasian, with African American as the next largest group. About 2,000 records are “Unknown”, which can affect population health equity analyses.

ii. Gender Distribution

```
df['gender'].value_counts().plot(kind='bar', title='Gender
        Distribution', color=['#86c5d8', '#beaed4', '#fdc086'])
plt.xlabel('Gender')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```

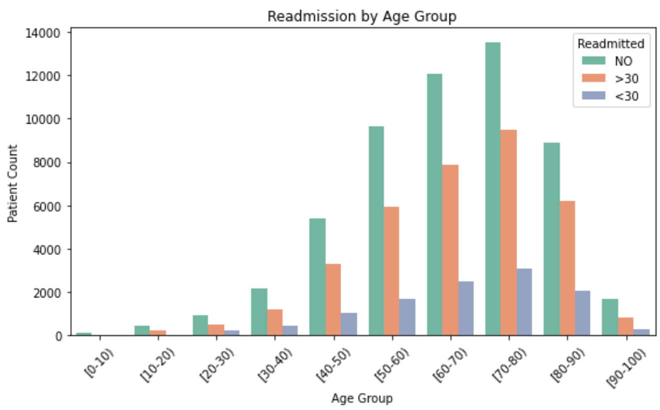


output_10_0.png

> **Interpretation:**
> The gender split is balanced, with a slight female predominance. A very small number of "Unknown/Invalid" entries are present, which were also seen in race.

iii. Readmission by Age Group

```
plt.figure(figsize=(8,5))
sns.countplot(x='age', hue='readmitted', data=df, palette='Set2')
plt.title('Readmission by Age Group')
plt.xlabel('Age Group')
plt.ylabel('Patient Count')
plt.xticks(rotation=45)
plt.legend(title='Readmitted')
plt.tight_layout()
plt.show()
```



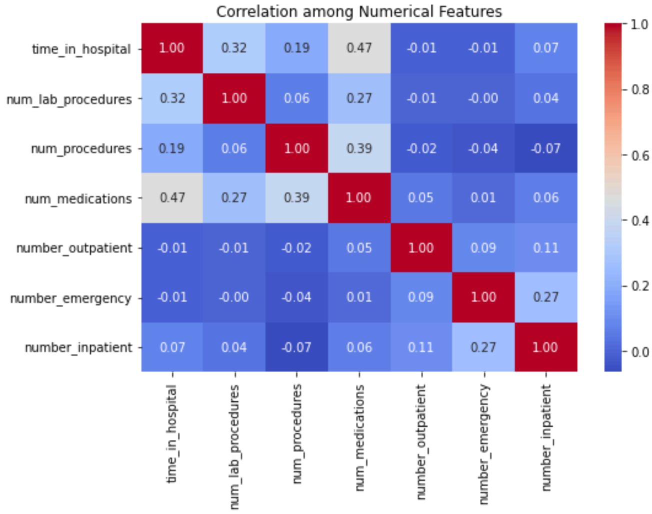
output_12_0.png

> **Insights:**
> - Re-admissions are more frequent in older age groups (≥60). - Both the ">30" and "<30" day re-admissions are highest among elderly patients, highlighting a vulnerable population for targeted intervention.

iv. Correlation among Numerical Features

```
num_cols =
        ['time_in_hospital','num_lab_procedures','num_procedures','num_medications','number_outpatien
plt.figure(figsize=(8,6))

# Select these columns from df, then call .corr()
sns.heatmap(df[num_cols].corr(), annot=True, cmap='coolwarm',
        fmt='.2f')
plt.title('Correlation among Numerical Features')
plt.tight_layout()
plt.show()
```

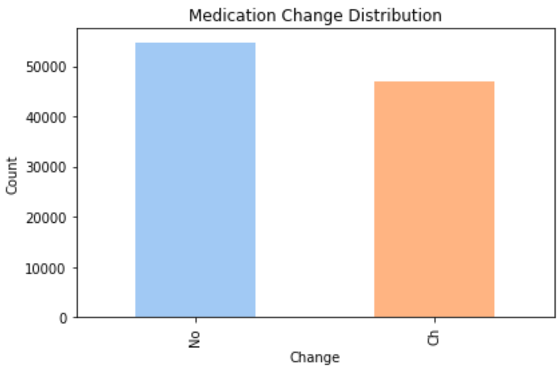


output_14_0.png

> **Key Points:**
> - `time_in_hospital` is most strongly correlated with `num_medications` (r ≈ 0.47) and `num_lab_procedures` (r ≈ 0.32). - Previous encounters (`number_inpatient`, etc.) are not strongly correlated with resource usage, indicating other drivers for hospital resource consumption. - No multi-collinearity concern found.

v. Medication Change Distribution

```
df['change'].value_counts().plot(kind='bar', title='Medication Change
        Distribution', color=sns.color_palette('pastel'))
plt.xlabel('Change')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```

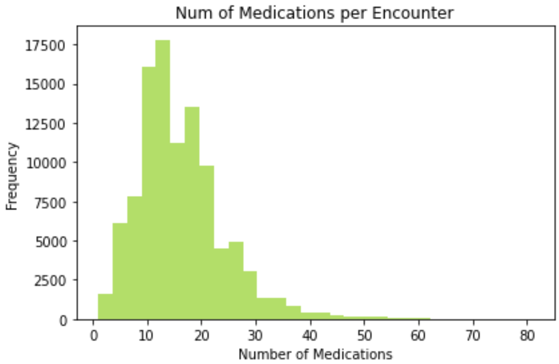


output_16_0.png

> **Observation:**
> About half the patients had their medication regimens changed, supporting CAP_healthcare suggestion to analyze therapy management as a potential influence on readmission.

vi. Number of Medications per Encounter

```
df['num_medications'].plot(kind='hist', bins=30, title='Num of
        Medications per Encounter', color='#b3de69')
plt.xlabel('Number of Medications')
plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```

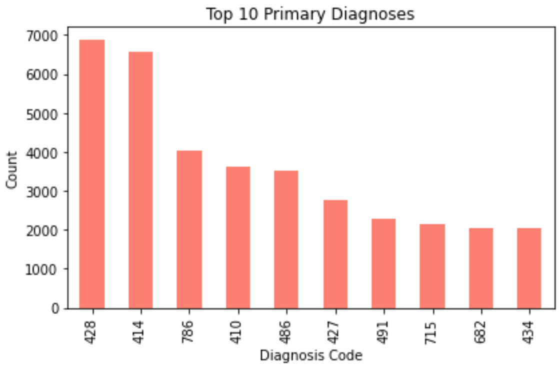


output_18_0.png

> **Insight:**
> Most encounters involved 10-20 medications. High medication count may be a proxy for complex comorbidity or polypharmacy, which deserves attention for risk management.

vi. Top 10 Primary Diagnoses

```
df['diag_1'].value_counts().head(10).plot(kind='bar', color='#fb8072')
plt.title('Top 10 Primary Diagnoses')
plt.xlabel('Diagnosis Code')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```

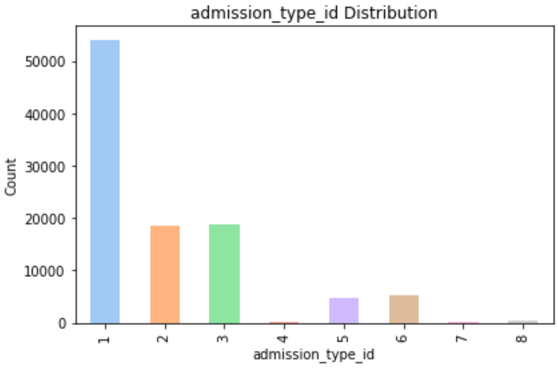


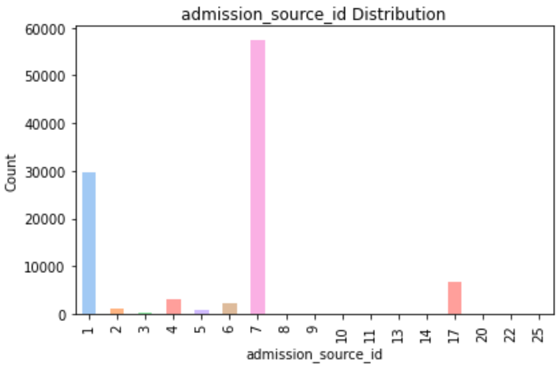
output_20_0.png

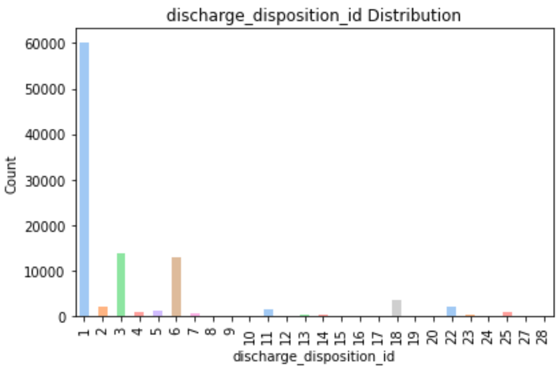
> **Finding:**
> The most frequent diagnoses (e.g., 428, 414) typically correspond to chronic complications of diabetes, such as heart failure and ischemic heart disease, which aligns with the CAP_healthcare clinical recommendations for prioritizing cardiovascular care.

vii. Distribution of Admission/Source/Discharge

```
for col in ['admission_type_id', 'admission_source_id',
        'discharge_disposition_id']:
    df[col].value_counts().sort_index().plot(
        kind='bar',
        title=f'{col} Distribution',
        color=sns.color_palette('pastel')
    )
    plt.xlabel(col)
    plt.ylabel('Count')
    plt.tight_layout()
    plt.show()
```



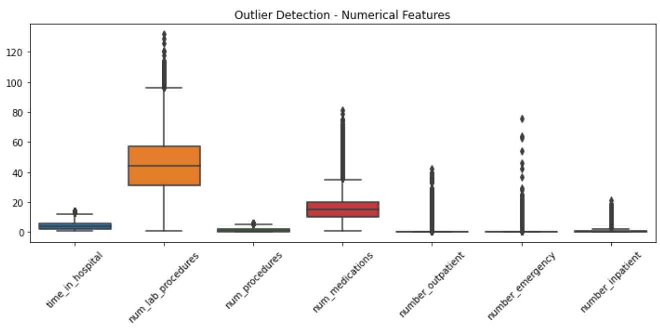




> **Commentary:**
> - Most patients are admitted as emergencies or from outpatient referrals. > - Discharge dispositions show the majority returning home, but non-home discharges could be explored for their relationship to readmission risk.

viii. Outlier Detection – Numerical Features

```
plt.figure(figsize=(10,5))
sns.boxplot(data=df[num_cols])
plt.title('Outlier Detection - Numerical Features')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



output_24_0.png

> **Interpretation:**
> The box plot highlights outliers in procedures and previous visits. These may represent super-utilizers or possible data entry anomalies, and should be carefully checked before predictive modeling.

ix. Enhancement: Additional Visualizations

A. Readmission Counts

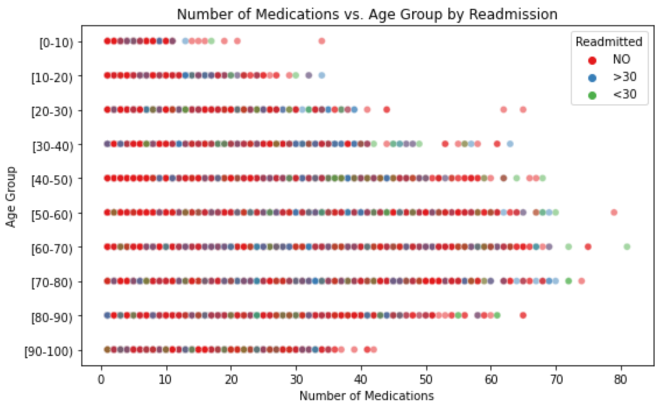
```
sns.countplot(x= 'readmitted', data=df, palette='Set1')
plt.title('Overall Readmission Status Counts')
plt.xlabel('Readmission Status')
plt.ylabel('Count')
plt.tight_layout()
plt.show()
```

output_26_0.png

> **Takeaway:**
> The majority of patients are not readmitted, but nearly half experience some form of readmission, highlighting the clinical and operational importance of this issue.

B. Age vs. Number of Medications (Scatter for Complexity)

```
plt.figure(figsize=(8,5))
sns.scatterplot(data=df,x='num_medications',y='age',hue='readmitted',alpha=0.5,palette='Set1')
plt.title('Number of Medications vs. Age Group by Readmission')
plt.xlabel('Number of Medications')
plt.ylabel('Age Group')
plt.legend(title='Readmitted')
plt.tight_layout()
plt.show()
```



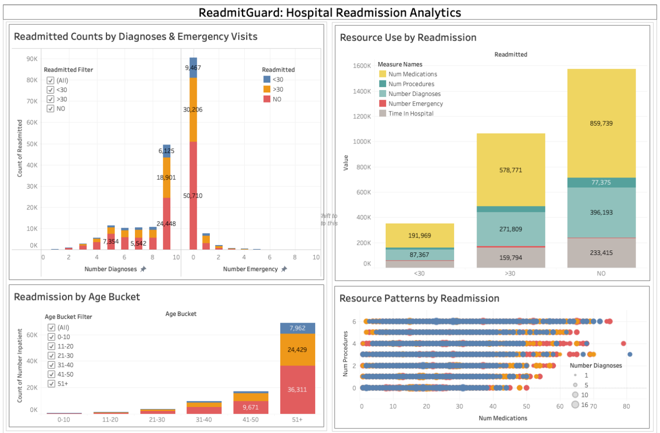
output_28_0.png

> **Note:**
> This plot reveals patterns between age, poly-pharmacy, and readmission. Considered alongside earlier findings, multi-morbidity in older patients is visually evident.

📊 Section 4. Tableau Public Dashboard (Interactive)

a. Layout Design

- **Fixed size:** `1366 x 900 px`
- **Containers:**
  - 1 Vertical → 1 Horizontal → 2 Vertical (Left & Right)
- Charts:
  - Readmitted Counts (Diagnosis/Emergency)
  - Age vs Readmitted
  - Resource Usage by Readmitted
  - Bubble Chart: Medications vs Diagnoses



Screenshot 2025-08-03 at 11.15.04.png

b. Fields & Calculated Columns

- `Age Bucket` (calculated from age string)
- **Calculated Fields:**
  - `Age Numeric`:

    ```
    INT(LEFT(REPLACE(REPLACE([age], "[", ""), ")", ""), 2))
    ```

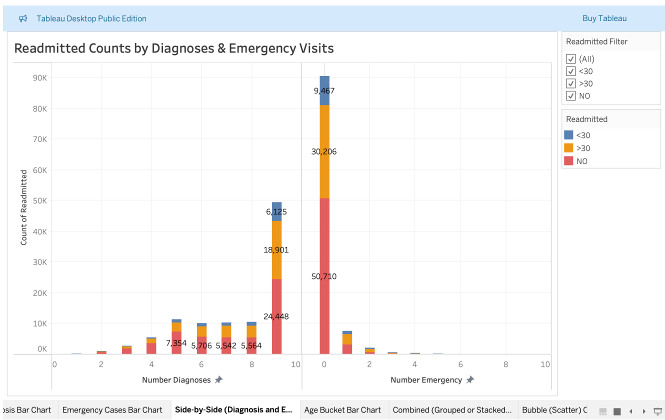
  - `Age Bucket`:

    ```
    IF [Age Numeric] <= 10 THEN "0–10"
    ELSEIF [Age Numeric] <= 20 THEN "11–20"
    ELSEIF [Age Numeric] <= 30 THEN "21–30"
    ELSEIF [Age Numeric] <= 40 THEN "31–40"
    ELSEIF [Age Numeric] <= 50 THEN "41–50"
    ELSE "51+"
    END
    ```

- Custom filters: `readmitted`, `Age Bucket`

i. Readmitted Counts by Diagnoses and Emergencies

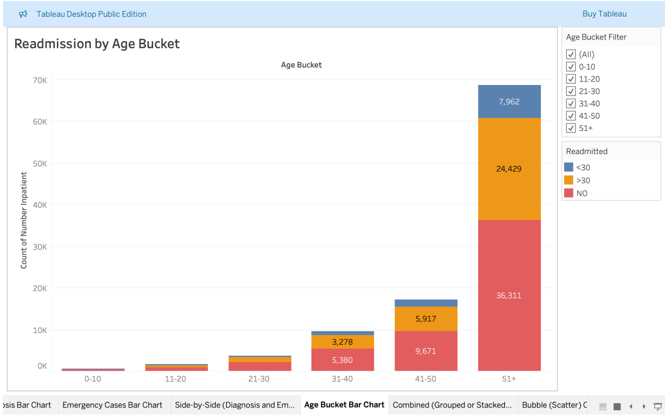
- **Type:** Stacked/side-by-side bar chart
- **X-Axis:** `number_diagnoses` (or `number_emergency`)
- **Y-Axis:** Count (by `readmitted`)
- **Color:** `readmitted` status (NO, <30, >30)
- **Worksheet Name:** `Readmitted Counts by Diagnoses & Emergencies`
- **Purpose:** Bar: Diagnoses/Emergencies by Readmission



Screenshot 2025-08-03 at 11.28.02.png

ii. Readmission by Age Bucket

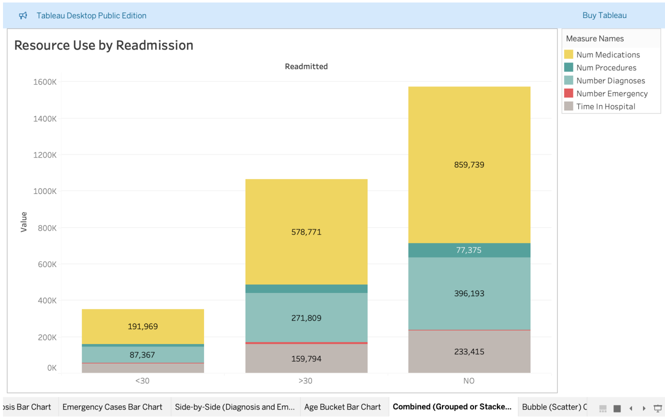
- **Type:** Stacked/clustered bar chart
- **X-Axis:** `Age Bucket`
- **Y-Axis:** Count of `number_inpatient`
- **Color:** `readmitted`
- **Labels:** Show mark labels
- **Worksheet Name:** `Readmission by Age Bucket`
- **Purpose:** Bar: Age group distribution across readmission



Screenshot 2025-08-03 at 11.28.14.png

iii. Resource Use by Readmission

- **Type:** Grouped or stacked bar chart using “Measure Names and Measure Values.”
- **Measures Visualized:**
  - `num_medications`, `num_procedures`, `number_diagnoses`, `number_emergency`, `time_in_hospital`
- **Worksheet Name:** `Resource Use by Readmission`
- **Interactivity:** Use color or label for `Measure Names`; change aggregation as needed (sum/avg)
- **Purpose:** Bar: Compare clinical metric averages



Screenshot 2025-08-03 at 11.28.21.png

iv. Resource Patterns by Readmission (Bubble Chart)

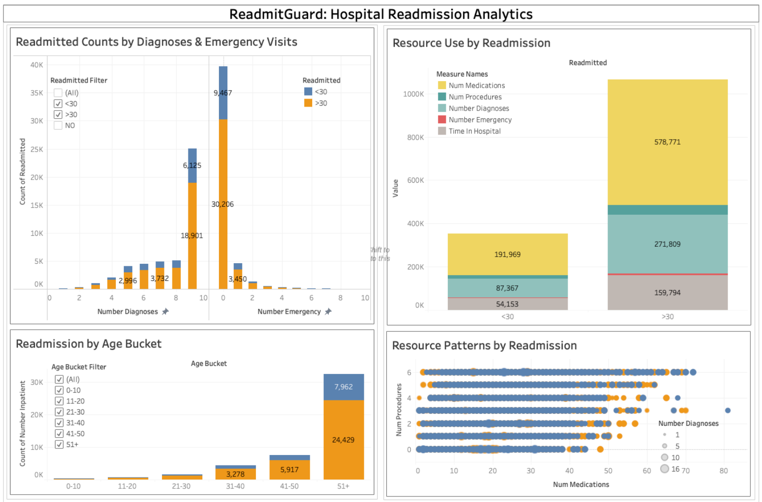
- **Type:** Scatter/Bubble Chart
- **X-Axis:** `num_medications`
- **Y-Axis:** `num_procedures`
- **Size:** `number_diagnoses`
- **Color:** `readmitted`
- **Shape/Filter:** Optionally add `readmitted`
- **Worksheet Name:** `Resource Patterns by Readmission`
- **Purpose:** Bubble: Medications, Labs, Diagnoses pattern

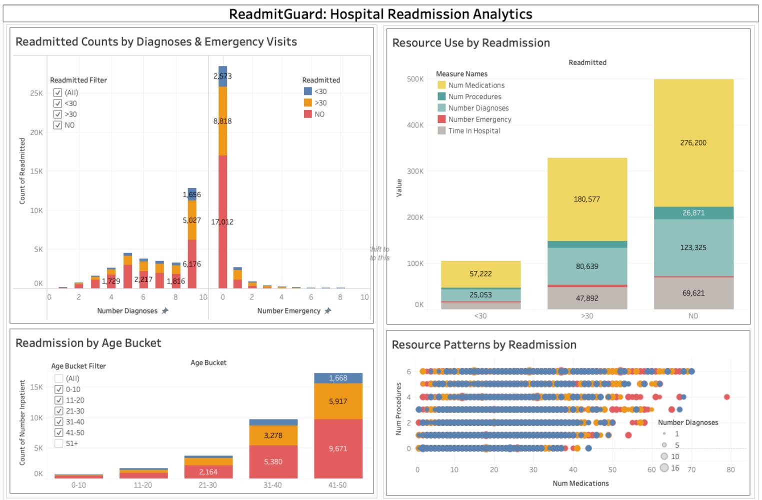
Screenshot 2025-08-03 at 11.28.27.png

C. Interactivity via Filtering

- **Add `readmitted` and `Age Bucket` filters** (as drop-down or list) to the dashboard
- **Make charts “interactive filters”** so clicking a bar or segment filters all other charts

- **Set filters as multi-select for group comparison, or single-select for detailed drill-down**
- **Synchronize filters across all worksheets** by right-clicking filter > “Apply to Worksheets” > “All Using This Data Source”





✅ Summary Conclusion: ReadmitGuard Project

The **ReadmitGuard healthcare analytics guide** provides a streamlined, end-to-end workflow for analyzing diabetic patient re-admissions using:

- **Excel/Sheets** for quick summary statistics and pivot tables.
- **SQL** to structure, cleanse, and summarize healthcare metrics.
- **Python (Pandas + Seaborn)** for deeper exploratory data analysis.
- **Tableau Public** for interactive and presentation-ready dashboards.

This integrated approach:

- Reveals **high-risk patient segments** (e.g., older poly-pharmacy cases).
- Highlights **patterns in diagnoses, procedures, and discharge outcomes.**
- Empowers both **technical and non-technical users** to gain actionable insights.
- Delivers a **reproducible, modular pipeline** that’s easy to adapt for other healthcare datasets.