

Hospital Patient Analytics Dashboard

OBJECTIVE - This project analyzes hospital patient data using SQL for storing patient and treatment records, Python for data cleaning and analysis, and Power BI for creating interactive dashboards. It helps hospitals track patient admissions, department workload, and recovery trends.

TOOL USED - MySQL for data storage and querying, Python for data cleaning, preprocessing and analysis and Power BI for visualization and dashboard creation.

DATASET INFO - Found the dataset from a GitHub repo:-

https://github.com/mattdejane/PowerBI_Healthcare_Dashboard.git

Every other dataset has a greater number of rows this has 1000 rows exact that will be helpful for importing the data without facing any error in SQL.

There are 2 files Found out that it is in .xlsx format also contain null value so first step I have decided to clean and preprocess the data in python and run EDA on that data. Lately import the data in SQL and run some queries based on the data followed by the final dashboarding in Power BI.

First opened the file in excel adjusted the width of the column add a table format to the columns and then converted the file type to csv and made it a duplicated data so that all cleaning and imputation can be run on this duplicated csv file without altering anything on the original data. Next Step is Data Cleaning and preprocessing in python.

HOSPITAL DATA CLEANING, PREPROCESSING AND EDA

IMPORTING LIBRARIES

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

data1 = pd.read_csv(r"C:\Users\Lenovo\Downloads\HealthCare_Dataset.csv")
print(data1)
```

	PatientID	PatientName	Age	Gender	BloodType	Diagnosis	\
0	1	David Johnson	3	Other	A+	Flu	
1	2	NaN	82	Other	A-	Covid-19	
2	3	William Taylor	56	Other	B+	Hypertension	
3	4	William Davis	36	Other	AB+	Covid-19	

4	5	Robert Davis	78	Male	B+	Flu
..
995	996	Linda Lopez	3	Male	B-	Covid-19
996	997	David Martin	3	Other	A-	Hypertension
997	998	NaN	70	Other	O+	Covid-19
998	999	Joseph Martinez	37	Other	A-	Diabetes
999	1000	John Moore	10	Male	O-	Asthma
0	1	2	3	4	5	6
Treatment	AdmissionDate	DischargeDate	TotalBill	\		
Medication	2021-01-01 00:00:00	2021-01-02 00:00:00	14383.782350			
Medication	2021-01-02 00:00:00	2021-01-03 00:00:00	15512.302210			
Therapy	2021-01-03 00:00:00	2021-01-04 00:00:00	4039.296436			
Therapy	2021-01-04 00:00:00	2021-01-05 00:00:00	4226.498069			
Surgery	2021-01-05 00:00:00	2021-01-06 00:00:00	2562.768983			
..
995	Therapy	2023-09-23 00:00:00	2023-09-24 00:00:00	18796.590760		
996	Surgery	2023-09-24 00:00:00	2023-09-25 00:00:00	7505.551827		
997	Surgery	2023-09-25 00:00:00	2023-09-26 00:00:00	13635.508700		
998	Medication	2023-09-26 00:00:00	2023-09-27 00:00:00	6075.690059		
999	Medication	2023-09-27 00:00:00	2023-09-28 00:00:00	19775.994120		
0	1	2	3	4	5	6
Full Prescription Details						
Eurosemide 40mg, three times a day for 5 days;...						
Losartan 50mg, twice a day for 7 days; Amoxicili...						
Amlodipine 5mg, twice a day for 5 days; Gabape...						
Azithromycin 250mg, three times a day as neede...						
Duloxetine 60mg, three times a day for 5 days;...						
..						
Gabapentin 300mg, once a day for 10 days; Omep...						
Insulin Glargine 100 units/mL, once a day as n...						
Furosemide 40mg, once a day for 5 days; Ibupro...						
Atorvastatin 10mg, three times a day for 5 day...						
Hydrochlorothiazide 25mg, once a day for 7 day...						

[1000 rows x 11 columns]

```
data2 = pd.read_csv(r"C:\Users\Lenovo\Downloads\HealthCare_Dataset2.csv")
print(data2)
```

PatientID	Hospital	DoctorName	RoomNumber	\
0	1 Riverside Hospital	Joseph Lopez	178	
1	2 Green Valley Medical Center	James Moore	368	
2	3 Riverside Hospital	Michael Lopez	260	
3	4 Cedar Sinai Clinic	Linda Rodriguez	228	
4	5 Riverside Hospital	Mary Hernandez	167	
..
995	996 Silver Oak Medical Plaza	Charles Martin	438	
996	997 Green Valley Medical Center	Linda Martin	255	
997	998 Cedar Sinai Clinic	Mary Martin	351	
998	999 Silver Oak Medical Plaza	James Martinez	142	

```

999      1000      Silver Oak Medical Plaza      Barbara Martin      260
          DailyCost      TreatmentType  RecoveryRating
0      359.006021      Surgery           10.0
1      933.915694      Surgery            4.0
2     1272.088112      Counseling         NaN
3     402.609932      Counseling           3.0
4     483.129350      Physical Therapy       NaN
..      ...
995    1625.316045      Surgery           7.0
996    348.339523      Physical Therapy       8.0
997    1485.272908      Physical Therapy       5.0
998    1630.479191      Surgery            3.0
999    1759.963492      Physical Therapy       1.0
[1000 rows x 7 columns]

```

DATA PROFILING

```
data1.columns
```

```
Index(['PatientID', 'PatientName', 'Age', 'Gender', 'BloodType', 'Diagnosis',
       'Treatment', 'AdmissionDate', 'DischargeDate', 'TotalBill',
       'Full Prescription Details'],
      dtype='object')
```

```
data2.columns
```

```
Index(['PatientID', 'Hospital', 'DoctorName', 'RoomNumber', 'DailyCost',
       'TreatmentType', 'RecoveryRating'],
      dtype='object')
```

```
total_columns = data1.shape[1] , data2.shape[1]
total_columns
```

```
(11, 7)
```

```
total_rows = data1.shape[0] , data2.shape[0]
total_rows
```

```
(1000, 1000)
```

AS YOU CAN SEE DATA1 HAS 11 COLUMNS AND DATA2 HAS 7 BUT BOTH OF THEM CONSIST OF 1000 ROWS

```
data1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype  
 ---  -- 
 0   PatientID        1000 non-null   int64  
 1   PatientName      1000 non-null   object 
 2   Age              1000 non-null   float64
 3   Gender           1000 non-null   object 
 4   BloodType        1000 non-null   object 
 5   Diagnosis        1000 non-null   object 
 6   Treatment         1000 non-null   object 
 7   AdmissionDate    1000 non-null   datetime64[ns]
 8   DischargeDate    1000 non-null   datetime64[ns]
 9   TotalBill        1000 non-null   float64
 10  Full Prescription Details  1000 non-null   object 

```

```
0 PatientID           1000 non-null   int64
1 PatientName          940 non-null   object
2 Age                  1000 non-null   int64
3 Gender                1000 non-null   object
4 BloodType             1000 non-null   object
5 Diagnosis              1000 non-null   object
6 Treatment              1000 non-null   object
7 AdmissionDate         1000 non-null   object
8 DischargeDate          1000 non-null   object
9 TotalBill              940 non-null   float64
10 Full Prescription Details 1000 non-null   object
dtypes: float64(1), int64(2), object(8)
memory usage: 86.1+ KB
```

```
data1.isnull().sum()
```

```
PatientID           0
PatientName          60
Age                  0
Gender                0
BloodType             0
Diagnosis              0
Treatment              0
AdmissionDate         0
DischargeDate          0
TotalBill              60
Full Prescription Details 0
dtype: int64
```

```
miss= data1.isnull().sum()
miss
```

```
PatientID           0
PatientName          60
Age                  0
Gender                0
BloodType             0
Diagnosis              0
Treatment              0
AdmissionDate         0
DischargeDate          0
TotalBill              60
Full Prescription Details 0
dtype: int64
```

```
miss_percentage = (data1.isnull().sum()/len(data1))* 100
miss_percentage
```

```
PatientID           0.0
PatientName          6.0
Age                  0.0
```

```
Gender          0.0
BloodType       0.0
Diagnosis       0.0
Treatment        0.0
AdmissionDate   0.0
DischargeDate    0.0
TotalBill        6.0
Full Prescription Details  0.0
dtype: float64
```

PatientName has 6% missing value which can be treated as unknown as name is a critical column we just can't directly remove the blanks as rest of the data are present also TotalBill got 6% null value which will be imputed in the later stage

```
data2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   PatientID        1000 non-null    int64  
 1   Hospital          922 non-null    object  
 2   DoctorName        1000 non-null    object  
 3   RoomNumber        1000 non-null    int64  
 4   DailyCost         1000 non-null    float64
 5   TreatmentType     1000 non-null    object  
 6   RecoveryRating    922 non-null    float64
dtypes: float64(2), int64(2), object(3)
memory usage: 54.8+ KB
```

```
data2.isnull().sum()
```

```
PatientID      0
Hospital        78
DoctorName      0
RoomNumber      0
DailyCost        0
TreatmentType    0
RecoveryRating   78
dtype: int64
```

```
miss1= data2.isnull().sum()
miss1
```

```
PatientID      0
Hospital        78
DoctorName      0
RoomNumber      0
DailyCost        0
TreatmentType    0
```

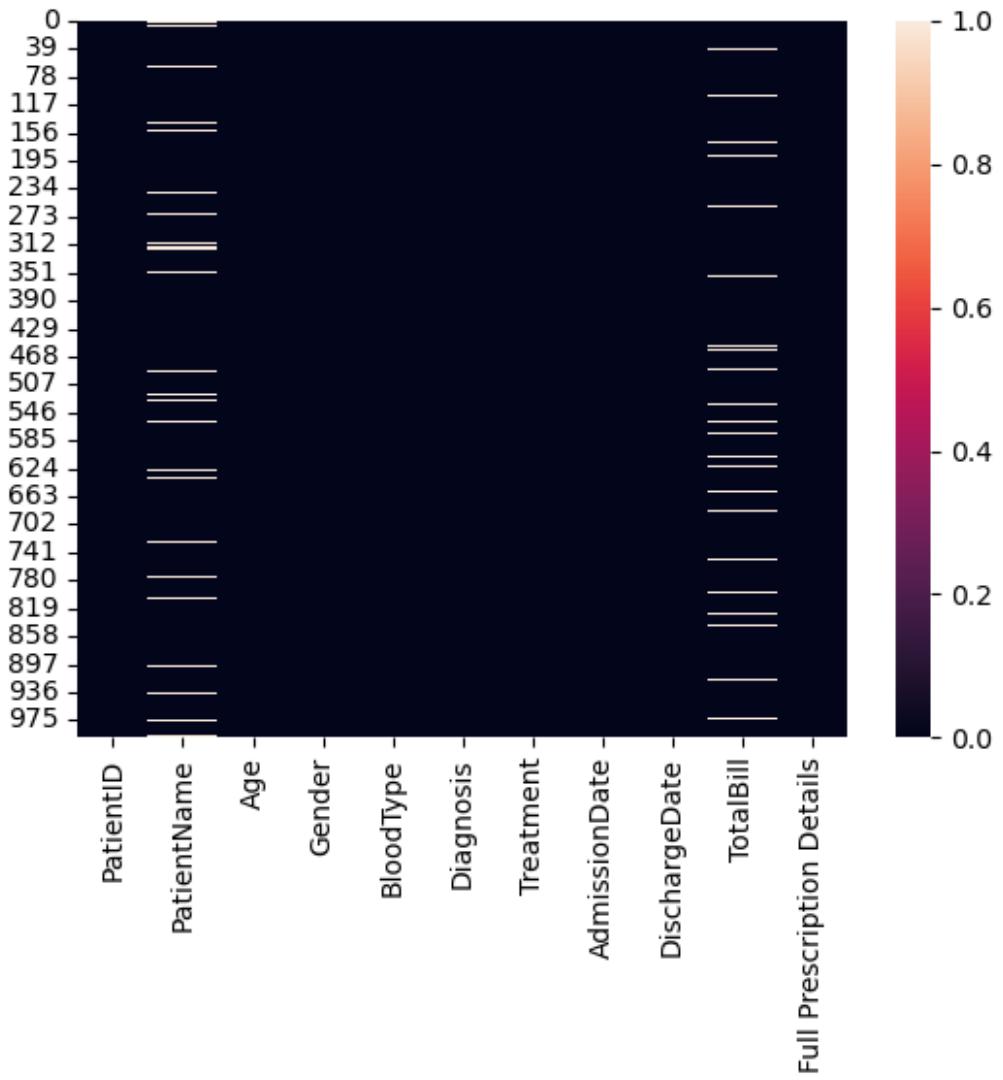
```
RecoveryRating      78
dtype: int64

miss_percentage1 = (data2.isnull().sum()/len(data2))* 100
miss_percentage1

PatientID          0.0
Hospital           7.8
DoctorName         0.0
RoomNumber         0.0
DailyCost          0.0
TreatmentType      0.0
RecoveryRating     7.8
dtype: float64
```

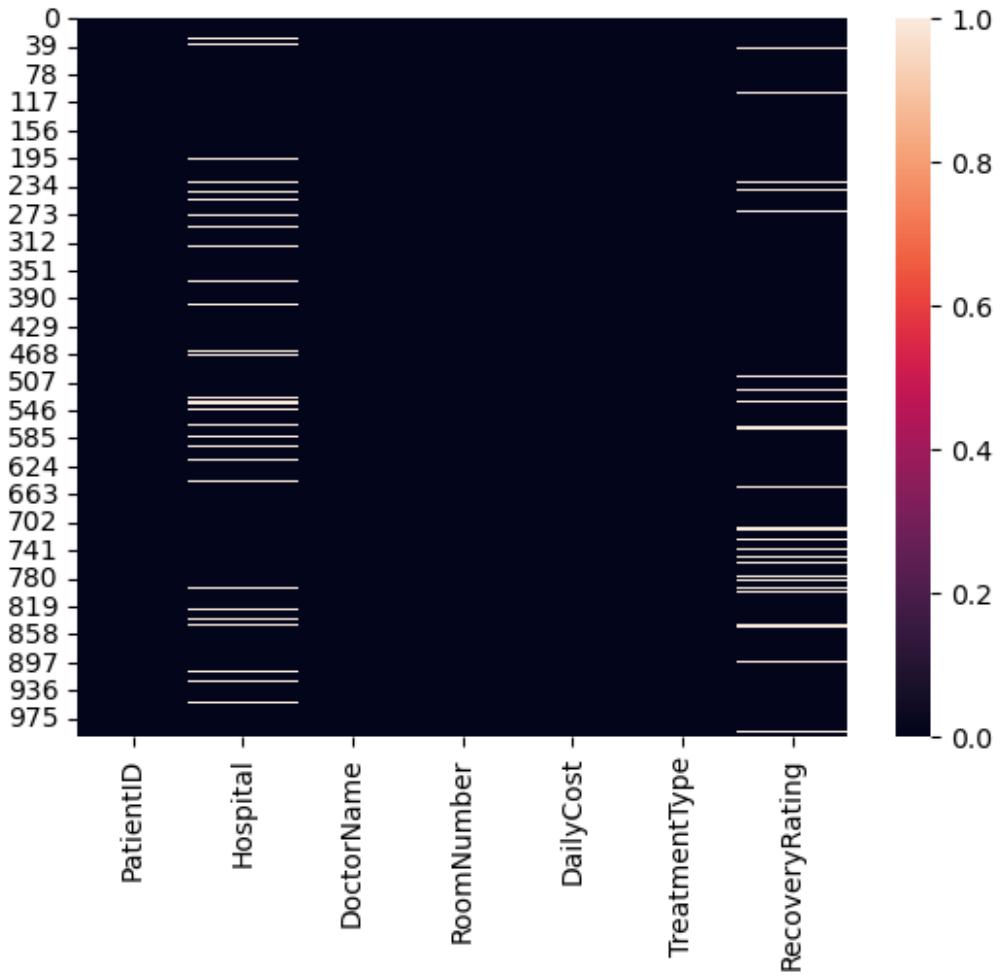
Just Like in data1 data2 also got few null value about 7.8% in columns Hospital and RecoveryRating Hospital column blanks cannot be omitted as it is one of the primary column out there. So unknown will be filled in place of blanks. For RecoveryRating we are going to find the average of it and fill accordingly

```
sns.heatmap(data1.isnull())
<Axes: >
```



```
sns.heatmap(data2.isnull())
```

```
<Axes: >
```



By this it is clearly been seen that the rows that is blank in hospital is not the same blanked rows in recoverrating likewise for patient name and total bill. So we need to deal with both individually and assess different technique for imputations

DATA CLEANING AND PRE PROCESSING

```
data1.drop('Full Prescription Details', axis=1,inplace=True)
data1.columns
Index(['PatientID', 'PatientName', 'Age', 'Gender', 'BloodType', 'Diagnosis',
       'Treatment', 'AdmissionDate', 'DischargeDate', 'TotalBill'],
      dtype='object')
```

DROPPED the Description column to reduce the data redundancy as it was mainly a string column not so useful for analysis

```
data1.shape
```

```
(1000, 10)
```

```
data1['PatientName'] = data1['PatientName'].fillna('unknown')

data1['PatientName'].value_counts()

PatientName
unknown           60
Patricia Hernandez    7
Robert Rodriguez     7
Elizabeth Lopez      7
Jessica Rodriguez     7
..
Sarah Jackson        1
James Thomas         1
Mary Gonzalez        1
Michael Moore        1
Joseph Martinez      1
Name: count, Length: 369, dtype: int64
```

MISSING Patient Name has been treated as per possible. It may not be the best way but still better than having a blank in the selection

```
data2.columns
```

```
Index(['PatientID', 'Hospital', 'DoctorName', 'RoomNumber', 'DailyCost',
       'TreatmentType', 'RecoveryRating'],
      dtype='object')
```

```
data2['Hospital'] = data2['Hospital'].fillna('n/a')
```

```
data2['Hospital'].value_counts()
```

```
Hospital
Green Valley Medical Center    207
Silver Oak Medical Plaza      185
Cedar Sinai Clinic            184
Maple Grove Health Facility   178
Riverside Hospital             168
n/a                            78
Name: count, dtype: int64
```

Dealing with duplicate rows Finding number of duplicate rows in the datasets then Droping the duplicate entries from the dataset.

```
data1[data1.duplicated()]
```

```
Empty DataFrame
Columns: [PatientID, PatientName, Age, Gender, BloodType, Diagnosis,
Treatment, AdmissionDate, DischargeDate, TotalBill]
Index: []
```

```
data1.duplicated().sum()
```

```
0
```

```

data2[data2.duplicated()]

Empty DataFrame
Columns: [PatientID, Hospital, DoctorName, RoomNumber, DailyCost,
TreatmentType, RecoveryRating]
Index: []

data2.duplicated().sum()

0

NO DUPLICATES FOUND

data1.describe()

      PatientID        Age      TotalBill
count  1000.000000  1000.000000  940.000000
mean   500.500000  50.500000  10038.866970
std    288.819436  28.599859  5801.795268
min    1.000000   0.000000  200.928022
25%   250.750000  26.000000  4883.315196
50%   500.500000  51.500000  10152.880440
75%   750.250000  75.000000  14872.452167
max   1000.000000  99.000000  19979.201530

data1.groupby('Diagnosis')[['TotalBill']].mean()

Diagnosis
Asthma          9779.536904
Covid-19         10581.567618
Diabetes         9469.119830
Flu              9771.535403
Hypertension     10615.723800
Name: TotalBill, dtype: float64

data1.groupby('Treatment')[['TotalBill']].mean()

Treatment
Medication       10204.701944
Surgery           9865.776236
Therapy           10026.439343
Name: TotalBill, dtype: float64

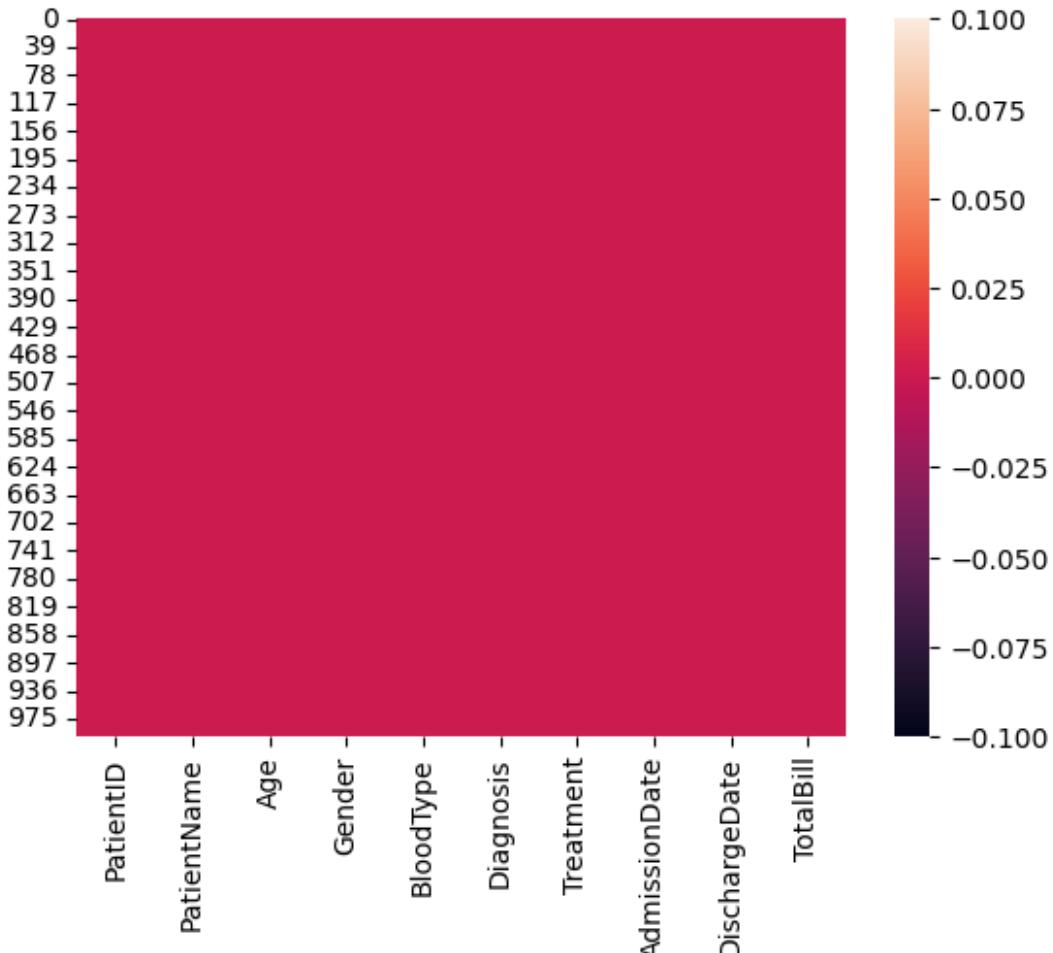
data1['TotalBill'] = data1.groupby('Treatment')[['TotalBill']].transform(lambda
x: x.fillna(x.mean())))

```

Filled the blank value in total bill with their respective treatment mean. It distributed the mean evenly based on their treatment for which they have visited the hospital

```
sns.heatmap(data1.isnull())
```

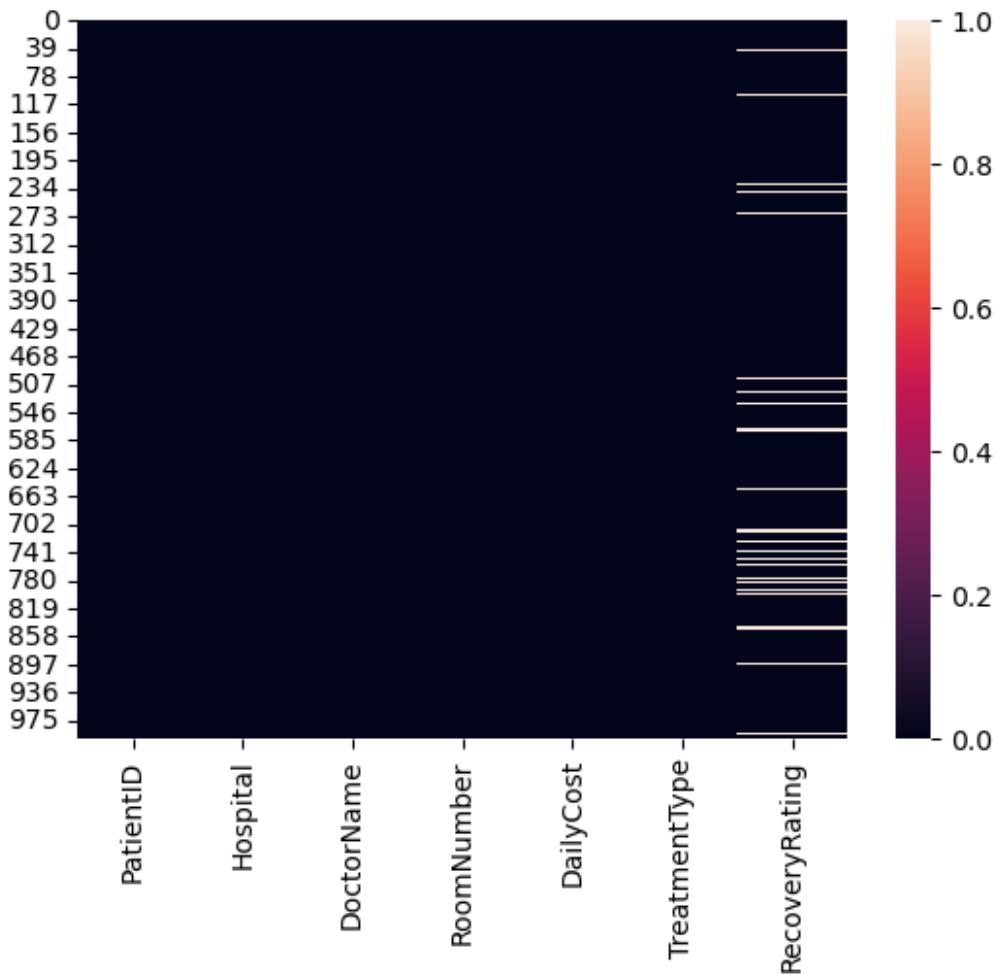
```
<Axes: >
```



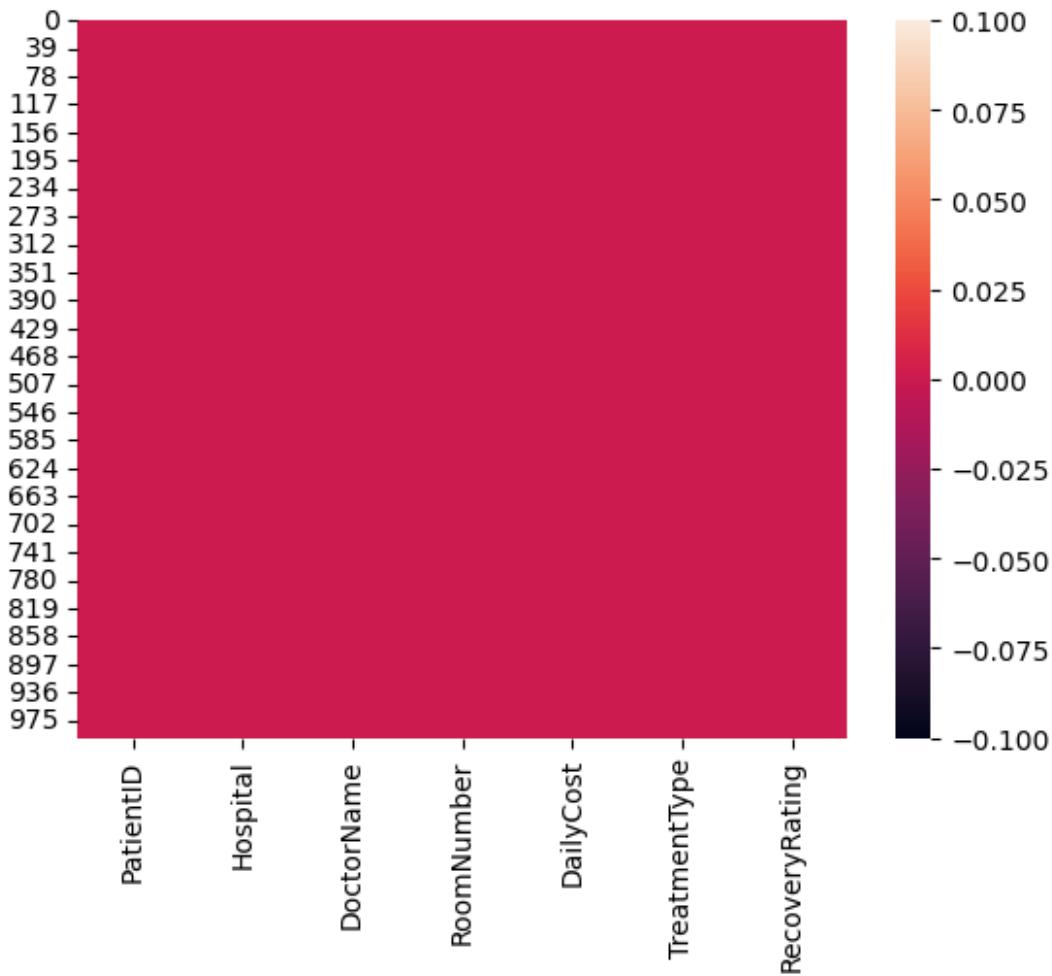
Data1 is cleaned and standardized

```
sns.heatmap(data2.isnull())
```

<Axes: >



```
data2[ 'RecoveryRating' ].mean()
5.436008676789588
mean_recovery_rating = round(data2[ 'RecoveryRating' ].mean())
data2[ 'RecoveryRating' ] =
data2[ 'RecoveryRating' ].fillna(mean_recovery_rating)
sns.heatmap(data2.isnull())
<Axes: >
```



Data2 is cleared and standardized

```
data1.to_csv('hospital1_clean.csv')
data2.to_csv('hospital2_clean.csv')
```

EDA

```
data1.dtypes
```

PatientID	int64
PatientName	object
Age	int64
Gender	object
BloodType	object
Diagnosis	object
Treatment	object
AdmissionDate	object
DischargeDate	object
TotalBill	float64
dtype:	object

```
data1['AdmissionDate'] = pd.to_datetime(data1['AdmissionDate'])
data1['DischargeDate'] = pd.to_datetime(data1['DischargeDate'])
```

```
data2.dtypes
```

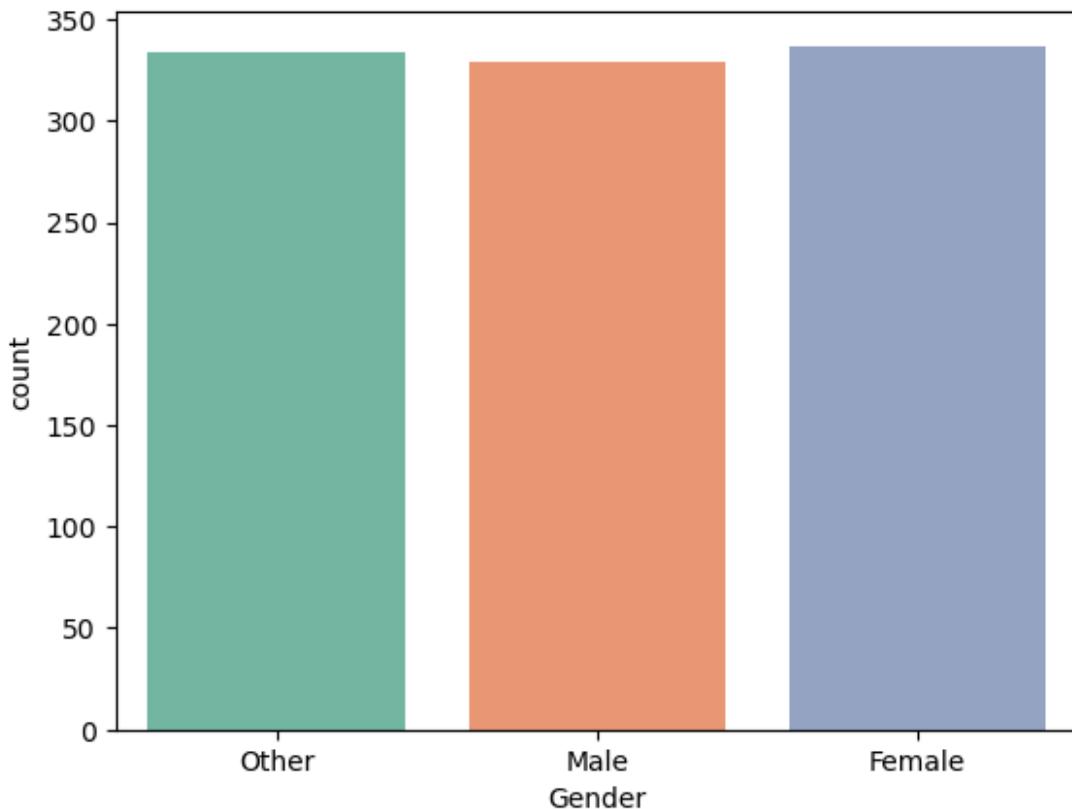
```
PatientID      int64
Hospital       object
DoctorName     object
RoomNumber     int64
DailyCost      float64
TreatmentType  object
RecoveryRating float64
dtype: object
```

```
sns.countplot(x='Gender', data=data1, palette='Set2')
plt.show()
```

```
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_21484\1666141477.py:1:
FutureWarning:
```

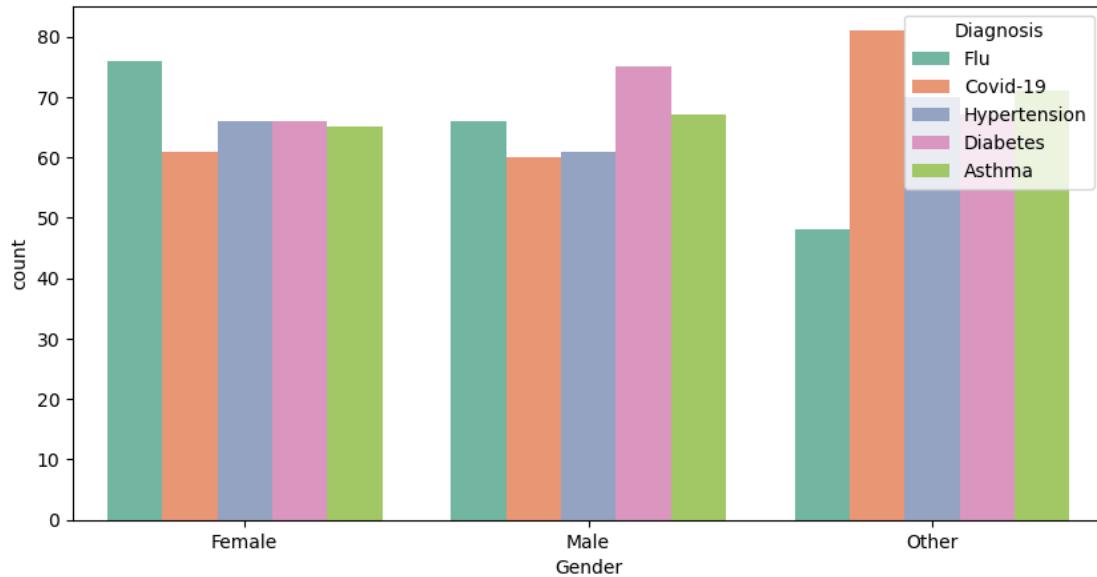
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same effect.

```
sns.countplot(x='Gender', data=data1, palette='Set2')
```



GENDER IS ALMOST SAME FOR ALL TYPE

```
plt.figure(figsize=(10, 5))
sns.countplot(x='Gender',hue='Diagnosis',data=data1,palette='Set2')
plt.xticks([0,1,2],['Female','Male','Other'])
plt.show()
```



INSIGHTS:-FOUND SOME INTERESTING INSIGHTS WHICH WILL BE FURTHER DISCUSSED IN THE LATER PART OF THE PROJECT

```
sns.distplot(data1['Age'],bins=20)
plt.show()
```

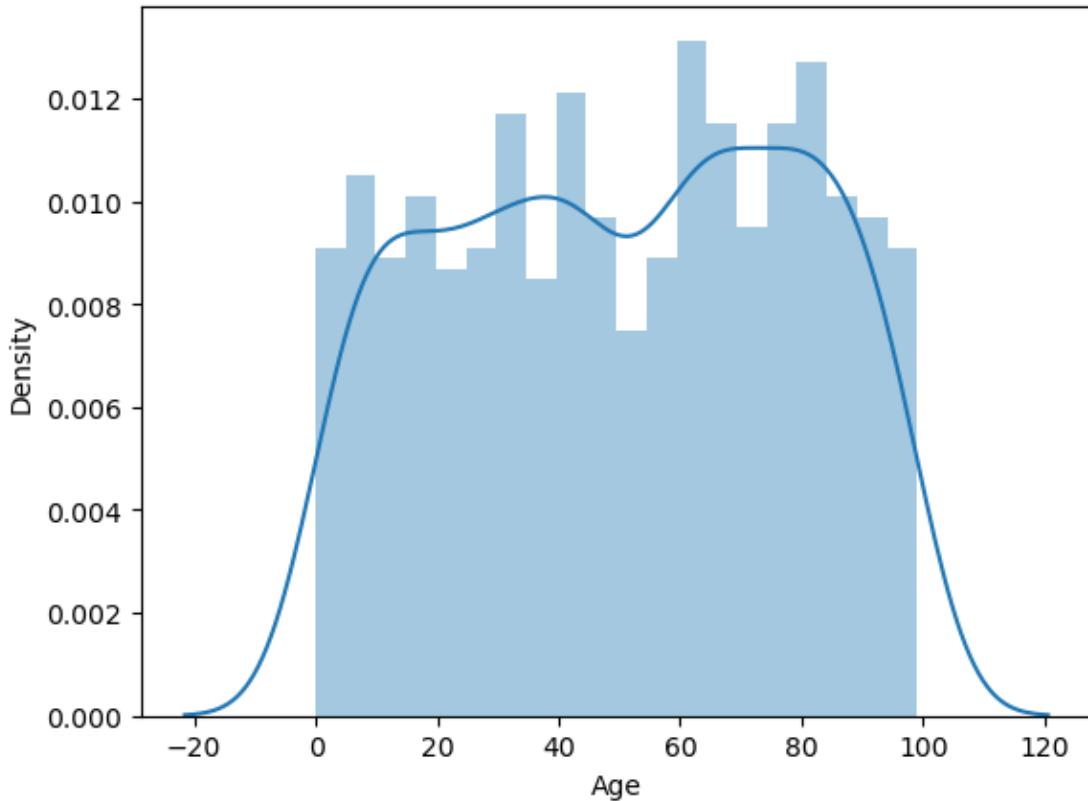
C:\Users\Lenovo\AppData\Local\Temp\ipykernel_21484\1951830225.py:1:
UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

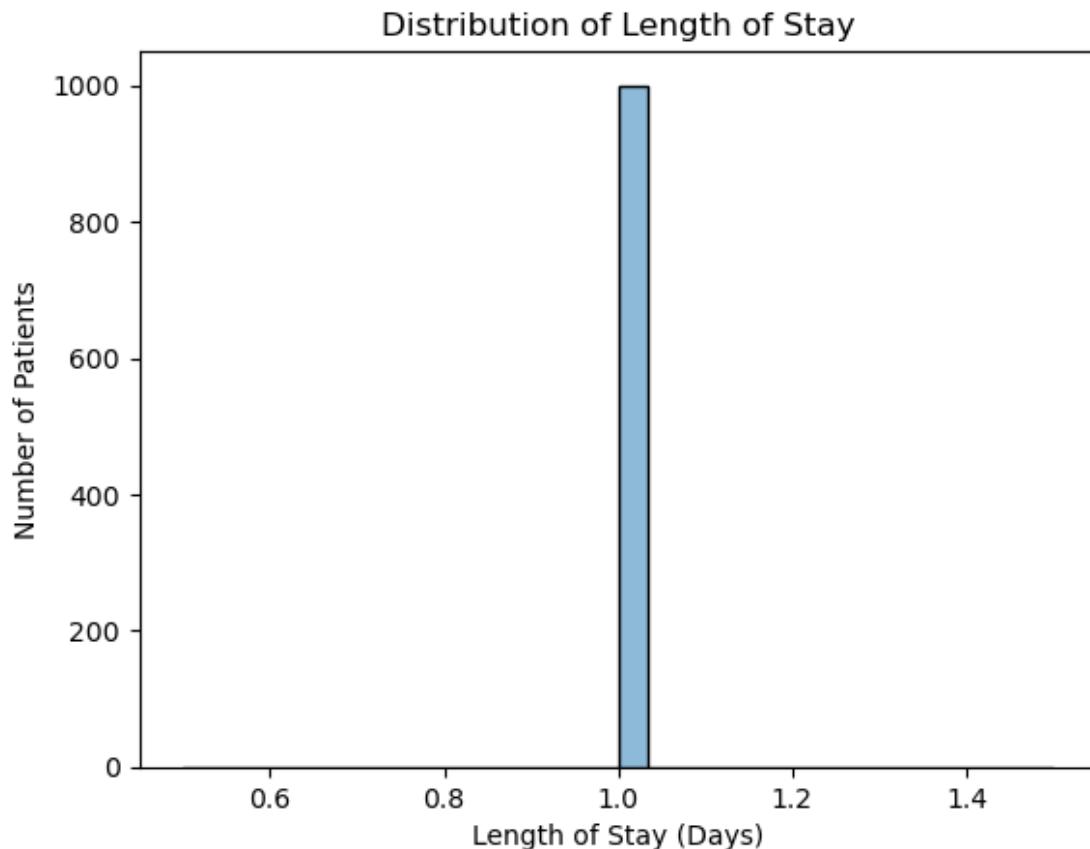
For a guide to updating your code to use the new functions, please see
<https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>

```
sns.distplot(data1['Age'],bins=20)
```



DATA HAS NO OUTLIER IN THE AGE

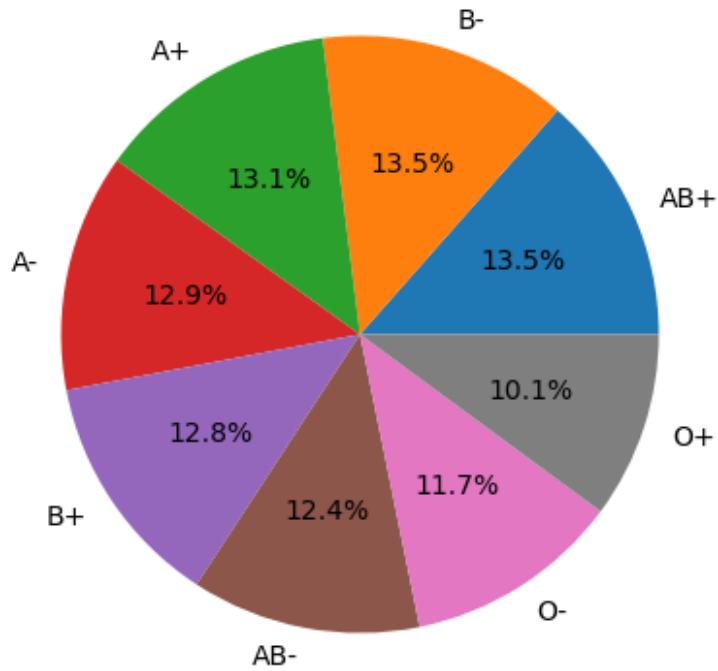
```
data1['LengthOfStay'] = (data1['DischargeDate'] -  
data1['AdmissionDate']).dt.days  
sns.histplot(data1['LengthOfStay'], bins=30, kde=True)  
plt.title('Distribution of Length of Stay')  
plt.xlabel('Length of Stay (Days)')  
plt.ylabel('Number of Patients')  
plt.show()
```



SEEMS THAT THIS DATASET IS A MADEUP DATASET IT IS SHOWING EVERY 1000 PATIENT STAYED ONLY FOR 1 DAY THIS CLARIFIES IT IS FICTIONAL

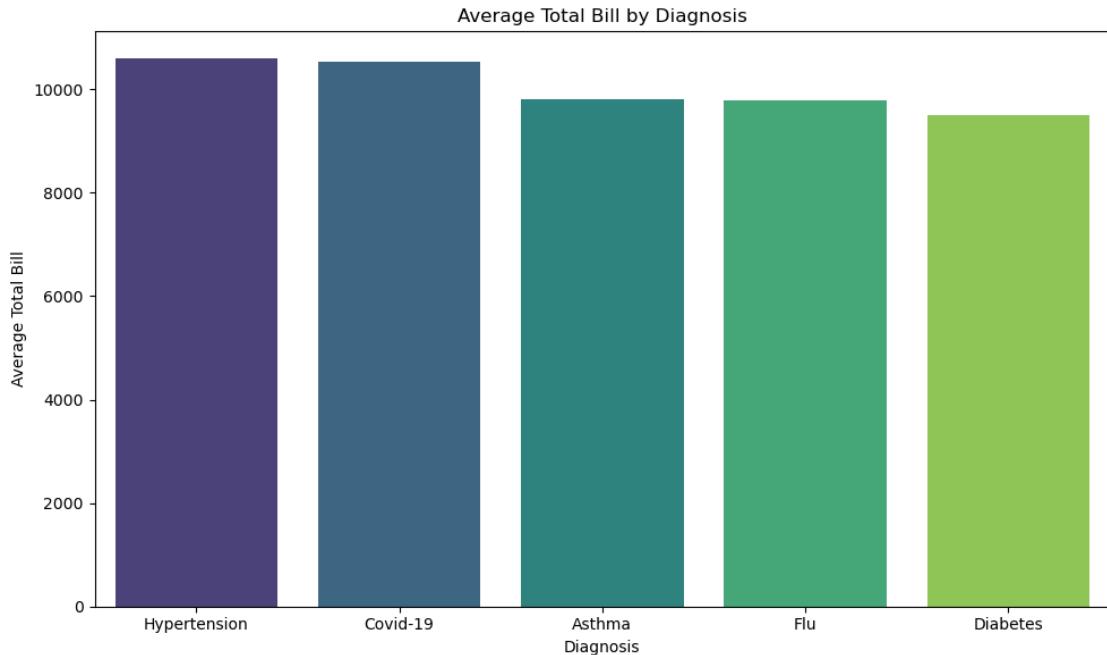
```
blood_type_counts = data1['BloodType'].value_counts()
plt.figure(figsize=(5, 5))
plt.pie(blood_type_counts, labels=blood_type_counts.index, autopct='%.1f%%')
plt.title('Distribution of Blood Types')
plt.show()
```

Distribution of Blood Types



NO SUCH SIGNIFICANT INSIGHTS FOUND

```
avg_bill_by_diagnosis =
data1.groupby('Diagnosis')['TotalBill'].mean().sort_values(ascending=False)
plt.figure(figsize=(10, 6))
sns.barplot(x=avg_bill_by_diagnosis.index, y=avg_bill_by_diagnosis.values,
hue=avg_bill_by_diagnosis.index, palette='viridis', legend=False)
plt.title('Average Total Bill by Diagnosis')
plt.xlabel('Diagnosis')
plt.ylabel('Average Total Bill')
plt.tight_layout()
plt.show()
```



INSIGHTS:- HYPERTENSION AND COVID-19 GENERATE A LOT OF REVENUE

```
data2.dtypes
```

PatientID	int64
Hospital	object
DoctorName	object
RoomNumber	int64
DailyCost	float64
TreatmentType	object
RecoveryRating	float64
dtype:	object

```
data2.head(3)
```

	PatientID	Hospital	DoctorName	RoomNumber
0	1	Riverside Hospital	Joseph Lopez	178
1	2	Green Valley Medical Center	James Moore	368
2	3	Riverside Hospital	Michael Lopez	260

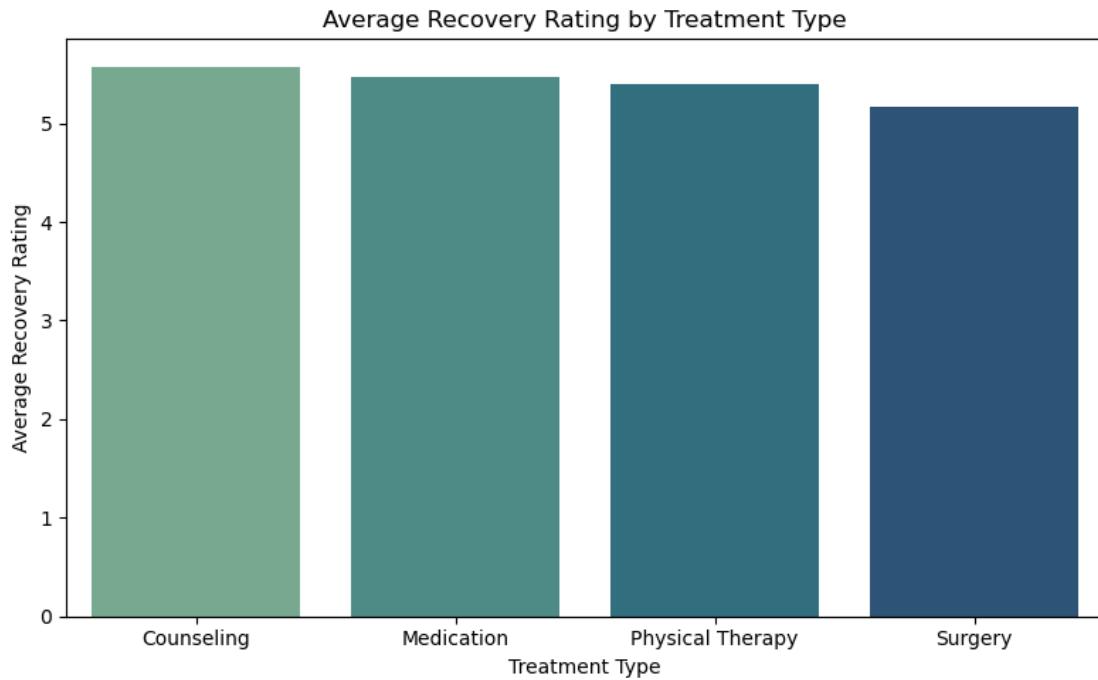
	DailyCost	TreatmentType	RecoveryRating
0	359.006021	Surgery	10.0
1	933.915694	Surgery	4.0
2	1272.088112	Counseling	5.0

```
avg_recovery_by_treatment =
data2.groupby('TreatmentType')[['RecoveryRating']].mean().sort_values(ascending=False)
plt.figure(figsize=(8, 5))
sns.barplot(x=avg_recovery_by_treatment.index,
y=avg_recovery_by_treatment.values, hue=avg_recovery_by_treatment.index,
```

```

palette='crest', legend=False)
plt.title('Average Recovery Rating by Treatment Type')
plt.xlabel('Treatment Type')
plt.ylabel('Average Recovery Rating')
plt.tight_layout()
plt.show()

```

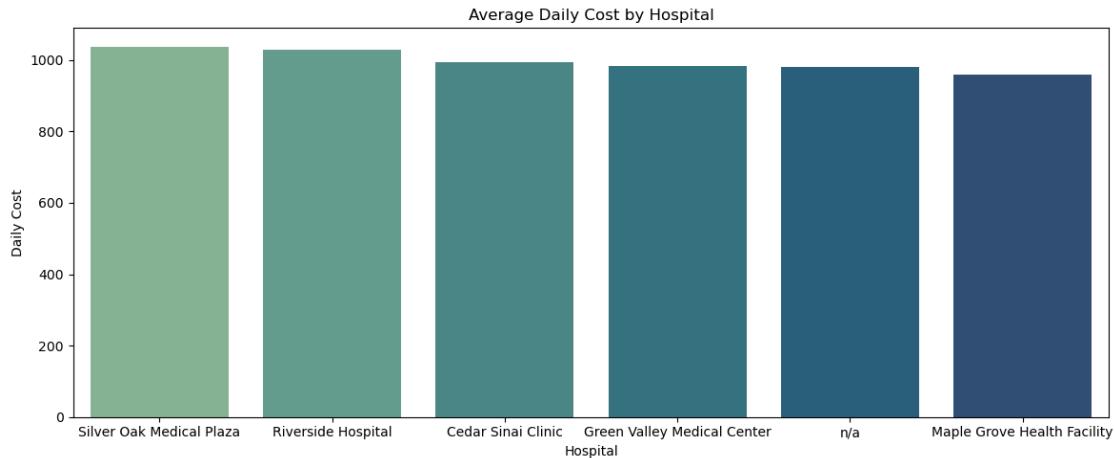


INSIGHTS:- COUNSELING HAS THE BEST AVERAGE RATING COMPARED TO THE REST

```

avg_dailycost_by_hospital =
data2.groupby('Hospital')['DailyCost'].mean().sort_values(ascending=False)
plt.figure(figsize=(12, 5))
sns.barplot(x=avg_dailycost_by_hospital.index,
y=avg_dailycost_by_hospital.values, hue=avg_dailycost_by_hospital.index,
palette='crest', legend=False)
plt.title('Average Daily Cost by Hospital')
plt.xlabel('Hospital')
plt.ylabel('Daily Cost')
plt.tight_layout()
plt.show()

```



INSIGHTS:- SILVER OAK MEDICAL PLAZA IS THE MOST EXPENSIVE WHEN IT COMES TO DAILY BILL

After this next step is in SQL (querying the data)

```
CREATE DATABASE hospital;
```

```
USE hospital;
```

```
SELECT * FROM hospital1;
```

```
ALTER TABLE hospital1
```

```
DROP COLUMN MyUnknownColumn;
```

```
SELECT * FROM hospital2;
```

```
ALTER TABLE hospital2
```

```
DROP COLUMN MyUnknownColumn;
```

```
ALTER TABLE hospital1 ADD PRIMARY KEY (PatientId);
```

```
ALTER TABLE hospital2
```

```
ADD CONSTRAINT fk_hospital2_patientid
```

```
FOREIGN KEY (PatientId) REFERENCES hospital1 (PatientId);
```

-- QUERIES

-- 1. List all patient names, age, gender, diagnosis, and total bill from hospital1

```
SELECT PatientName, Age, Gender, Diagnosis, TotalBill
```

```
FROM hospital1;
```

-- 2. Display patient name, blood type, treatment, and admission date for patients whose total bill > 5000

```
SELECT PatientName, BloodType, Treatment, AdmissionDate
```

```
FROM hospital1
WHERE TotalBill > 5000;
-- INSIGHTS:- 761 PATIENT TOTAL BILL WENT MORE THAN 5000
-- 3. Show patient name, age, and gender for patients diagnosed with 'Covid-19'
SELECT PatientName, Age, Gender
FROM hospital1
WHERE Diagnosis = 'Covid-19';
-- INSIGHTS :- 202 PATIENT HAS BEEN ADMITTED DUE TO BEING AFFECTED BY COVID-19
-- 4. Display patient name, hospital name, doctor name, and room number for every patient
SELECT h1.PatientName, h2.Hospital, h2.DoctorName, h2.RoomNumber
FROM hospital1 h1
INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID;
-- 5. List patient name, diagnosis, treatment type, and recovery rating
SELECT h1.PatientName, h1.Diagnosis, h2.TreatmentType, h2.RecoveryRating
FROM hospital1 h1
INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID;
-- 6. Show patient name, doctor name, treatment, and daily cost
SELECT h1.PatientName, h2.DoctorName, h1.Treatment, h2.DailyCost
FROM hospital1 h1
INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID;
-- 7. Display patient name, room number, admission date, discharge date, and total bill
SELECT h1.PatientName, h2.RoomNumber, h1.AdmissionDate, h1.DischargeDate, h1.TotalBill
FROM hospital1 h1
INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID;
-- 8. Patients treated in 'Riverside Hospital' hospital with doctor name and diagnosis
SELECT h1.PatientName, h2.DoctorName, h1.Diagnosis
FROM hospital1 h1
INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID
WHERE h2.Hospital = 'Riverside Hospital';
-- INSIGHTS:- 168 PATIENTS ARE ADMITTED IN RIVERSIDE HOSPITAL
```

-- 9. Patient name, doctor name, recovery rating > 8

```
SELECT h1.PatientName, h2.DoctorName, h2.RecoveryRating
FROM hospital1 h1
INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID
WHERE h2.RecoveryRating > 8;
```

-- INSIGHTS:- 190 PATIENT GOT RECOVERY RATING MORE THAN 8

-- 10. Patient name, hospital, total bill where DailyCost > 1500

```
SELECT h1.PatientName, h2.Hospital, h2.DailyCost
FROM hospital1 h1
INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID
WHERE h2.DailyCost > 1500;
```

-- INSIGHTS:- 227 PATIENT HAS MORE THAN 1500 DAILYCOST

-- 11. Female patients: name, gender, diagnosis, doctor name

```
SELECT h1.PatientName, h1.Gender, h1.Diagnosis, h2.DoctorName
FROM hospital1 h1
INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID
WHERE h1.Gender = 'Female';
```

-- 12. Total bill per hospital (in descending order)

```
SELECT h2.Hospital, ROUND(SUM(h1.TotalBill),2) AS TotalBillSum
FROM hospital1 h1
INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID
GROUP BY h2.Hospital
ORDER BY TotalBillSum DESC;
```

-- INSIGHTS:- GREEN VALLEY MEDICAL CENTER GENERATES THE MOST MONEY FOLLOWED BY CEDAR SINAI CLINIC AND MAPLE GROVE HEALTH FACILITY

-- 13. Rank doctors by number of patients treated (most patients = rank 1)

```
SELECT h2.DoctorName,
       COUNT(*) AS PatientCount,
       DENSE_RANK() OVER (ORDER BY COUNT(*) DESC) AS DoctorRank
FROM hospital1 h1
```

```

INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID
GROUP BY h2.DoctorName;
-- INSIGHTS:- DR.DAVID MOORE GOT THE MOST PATIENT COUNT FOLLOWED BY MICHAEL THOMAS
-- JENNIFER JOHNSON AND PATRICIA WILSON
-- 14. Average daily cost per hospital (in descending order)
SELECT h2.Hospital, ROUND(AVG(h2.DailyCost),2) AS AvgDailyCost
FROM hospital1 h1
INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID
GROUP BY h2.Hospital
ORDER BY AvgDailyCost DESC;
-- INSIGHTS:- SILVER OAK MEDICAL PLAZA GENERATED THE HIGHEST AVERAGE DAILYCOST
-- 15. Max, min, avg recovery rating per treatment type
SELECT h2.TreatmentType, MAX(h2.RecoveryRating) AS MaxRating,MIN(h2.RecoveryRating) AS MinRating,
ROUND(AVG(h2.RecoveryRating),1) AS AvgRating
FROM hospital1 h1
INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID
GROUP BY h2.TreatmentType;
-- 16. Top 5 highest total bills with hospital
SELECT h1.PatientName, h2.Hospital, h1.TotalBill
FROM hospital1 h1
INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID
ORDER BY h1.TotalBill DESC
LIMIT 5;
-- INSIGHTS:- MAPLE GROVE HEALTH FACILITY TOPS THE LIST
-- 17. Top 3 patients by total bill within each hospital
SELECT PatientName, Hospital, TotalBill, BillRank
FROM (
    SELECT h1.PatientName, h2.Hospital, h1.TotalBill,
    RANK() OVER (PARTITION BY h2.Hospital ORDER BY h1.TotalBill DESC) AS BillRank
)
```

```

FROM hospital1 h1
    INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID
) ranked_patients
WHERE BillRank <= 3
ORDER BY Hospital, BillRank;
-- 18. Categorize patients by age group
SELECT PatientName, Age, Gender,
CASE
    WHEN Age < 18 THEN 'Minor'
    WHEN Age BETWEEN 18 AND 60 THEN 'Adult'
    ELSE 'Senior'
END AS AgeGroup
FROM hospital1;
-- 19. Categorize total bill amounts
SELECT PatientName, TotalBill,
CASE
    WHEN TotalBill < 5000 THEN 'Low Cost'
    WHEN TotalBill BETWEEN 5000 AND 15000 THEN 'Medium Cost'
    ELSE 'High Cost'
END AS BillCategory
FROM hospital1;
-- 20. Recovery rating performance labels per doctor
SELECT h1.PatientName, h2.DoctorName, h2.RecoveryRating,
CASE
    WHEN h2.RecoveryRating >= 9 THEN 'Excellent'
    WHEN h2.RecoveryRating >= 7 THEN 'Good'
    WHEN h2.RecoveryRating >= 5 THEN 'Average'
    ELSE 'Poor'
END AS RecoveryLabel
FROM hospital1 h1

```

```
INNER JOIN hospital2 h2 ON h1.PatientID = h2.PatientID;
```

Last step importing the dataset in Power BI and creating a dashboard to retrieve some insights follow-up by recommendation.

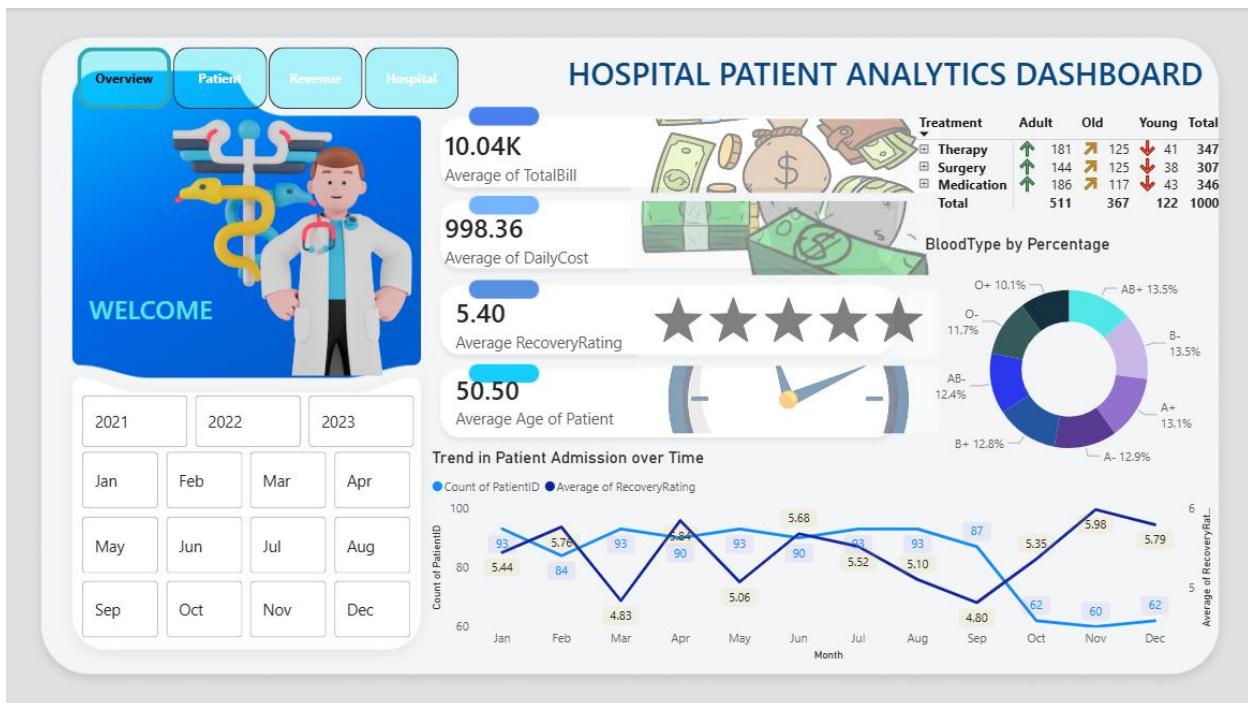
POWER BI DASHBOARD SUMMARY

INTRODUCTION

The Hospital Patient Analytics Dashboard is a multi-page Power BI solution designed to monitor clinical outcomes, patient demographics, and financial performance across hospitals. It provides a unified view of how patients are treated, how resources are utilized, and how these decisions impact revenue and recovery.

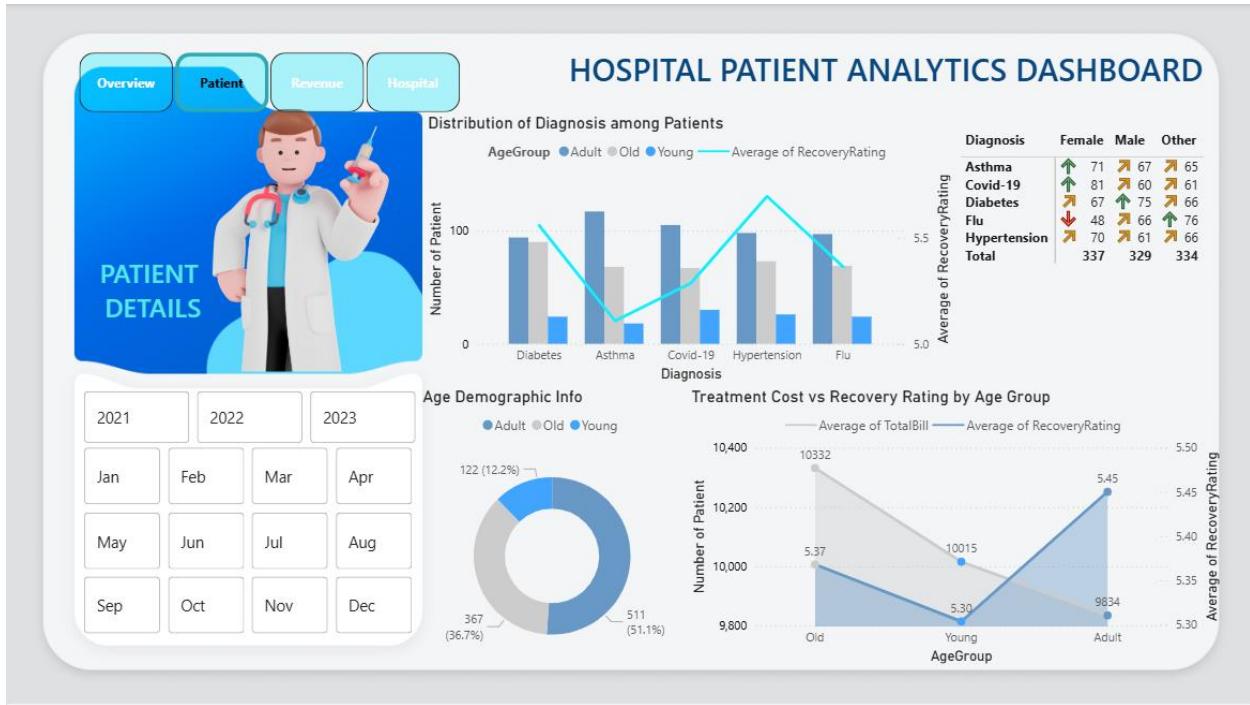
1. Overview Dashboard

The Overview page highlights key KPIs such as average total bill, average daily cost, average recovery rating, and average patient age. It also shows the trend of patient admissions and recovery over time, helping users quickly assess overall performance and seasonality.



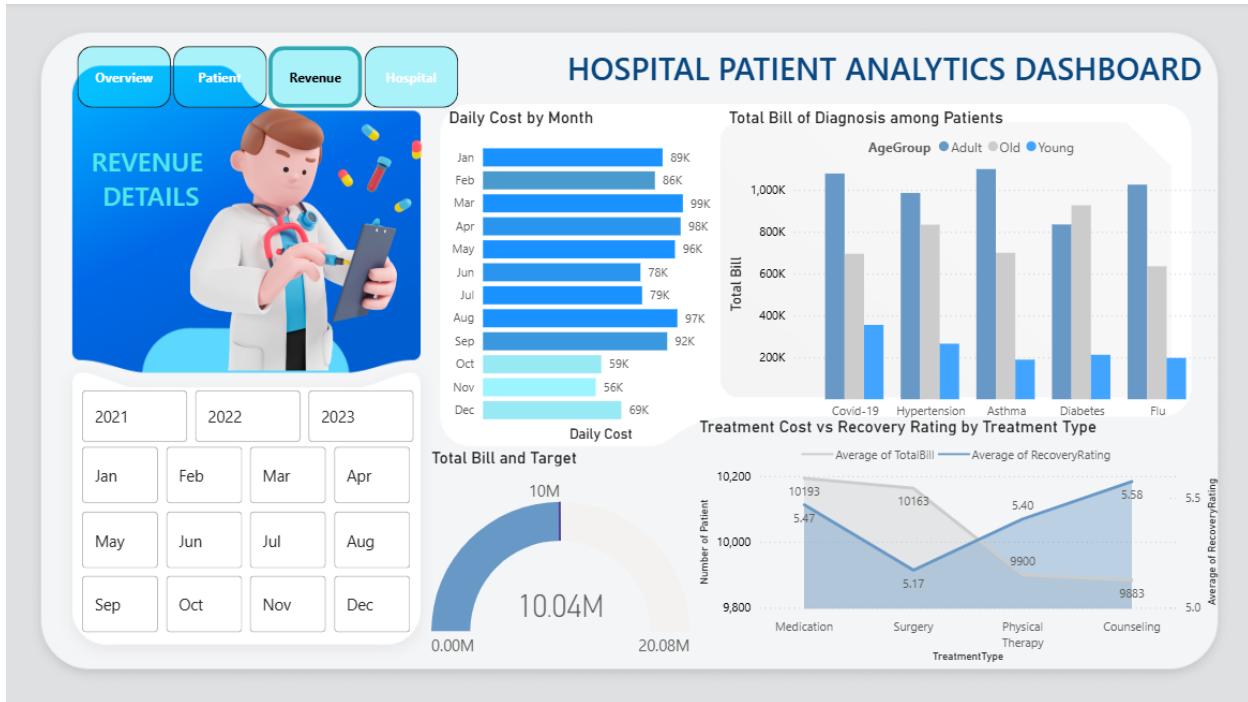
2. Patient Dashboard

The Patient page focuses on clinical patterns and demographics. It analyzes the distribution of diagnoses by age group and gender, age-group proportions, and the relationship between treatment cost and recovery rating by age group. This view supports patient-centric decisions and identification of high-risk segments.



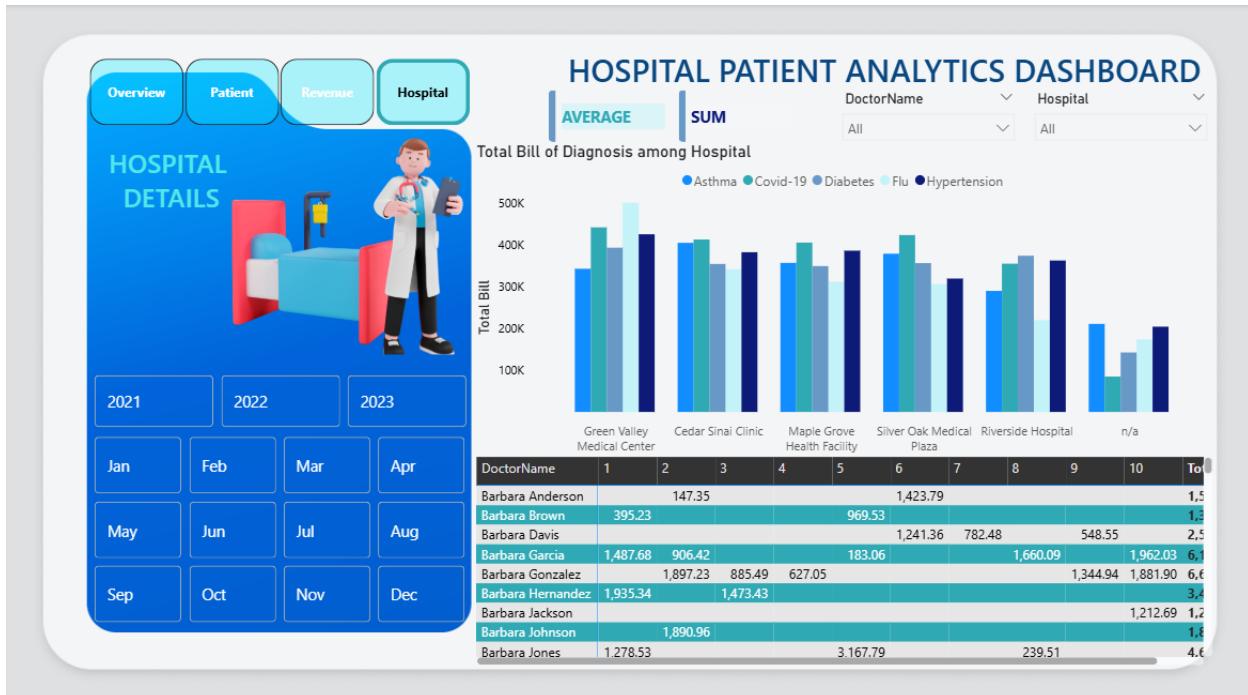
3. Revenue Dashboard

The Revenue page examines financial efficiency, including daily cost by month, total bill by diagnosis, comparison of total bill versus target and total cost vs recovery rating by treatment type. It also shows how different treatment types perform in terms of cost and recovery, enabling management to control expenses while maintaining quality.



4. Hospital Dashboard

The Hospital page compares hospitals and doctors on total bill by diagnosis and summarizes performance at provider level. It helps identify variation in billing and outcomes across facilities and clinicians, guiding standardization efforts and best-practice sharing.



All the dashboards have been supported by slicer: - Month Slicer and Year Slicer which helps in further filtrations in the dashboard.

INSIGHTS

- Revenue and bills

Total bill is about 10.04M against a 10M target, indicating slight over-achievement but also possible overspending or cost creep.

Average daily cost is about 998, so even small reductions per patient day can materially improve margins at current volume levels.

- Recovery and patient profile

Average recovery rating is roughly 5.4, which is good but leaves room to push toward best-in-class by focusing on diagnoses and treatments with lower scores.

Average age is about 50, and age demographics show adults forming roughly half of patients, with smaller but material old and young segments that may need tailored pathways.

- Time trends

Patient admissions are fairly stable but with visible monthly spikes and dips; some months have higher recovery ratings and others show drops, suggesting process or staffing variability.

Daily cost by month peaks around Mar–May and again Aug–Sep, while some later months show lower spend, indicating inconsistent cost control through the year.

- Diagnosis and treatment patterns

Covid-19 and Asthma/Hypertension appear among the highest total-bill diagnoses, while Flu and Diabetes generate moderate bills; some diagnoses show higher bills but not proportionally higher recovery ratings.

Treatment-type view shows differences in cost vs recovery: for example, Surgery is cost-intensive with only slightly better recovery than cheaper options, while Counseling/Physical Therapy show decent recovery at lower or mid-level cost.

- Hospital and doctor variation

Hospitals differ meaningfully in total bill by diagnosis; some centers (e.g., those with the highest bars for Asthma or Covid-19) bill significantly more than others for similar case types.

Doctor-level table shows spread in total bill per doctor, which likely reflects a mix of case complexity and practice style but still indicates opportunities for standardizing protocols.

- Demographics and blood type

Age-group breakdown (Adult, Old, Young) shows that adults dominate volume, but old patients incur higher cost and slightly lower recovery ratings on average.

Blood-type distribution is relatively balanced; it mainly matters for inventory and transfusion planning rather than revenue, but can support better blood-bank stocking.

RECOMMENDATION

Improve cost efficiency without hurting outcomes

Implement clinical pathways for high-bill diagnoses (Covid-19, Asthma, Hypertension) to standardize tests, imaging, and length of stay so that cost per case converges toward the best-performing hospital or doctor.

Introduce monthly cost dashboards at department level that show daily cost by month vs benchmark, with alerts when a department's cost exceeds target bands for more than 2 consecutive months.

Raise recovery ratings where they lag

For treatments where cost is high but recovery rating is only average (e.g., Surgery), conduct case-mix adjusted benchmarking across hospitals and surgeons, and revise pre- and post-operative protocols aiming to lift recovery rating by at least 0.2–0.3 points.

Expand lower-cost treatments that show good recovery (e.g., Counseling, Physical Therapy) through care bundles and early referrals, reducing reliance on medication-only approaches.

Optimize operations by month and capacity

Use the monthly admission and cost trend to reallocate staffing and beds: increase capacity and fast-track teams in the months with peak admissions and cost spikes, and schedule elective surgeries or maintenance in low-volume months.

Set monthly cost and recovery targets per department; review variance in a short operations meeting every month and assign specific actions (e.g., reduce average stay by 0.2 days for selected diagnoses).

Standardize best practices across hospitals and doctors

Identify hospitals with the best combination of lower total bill and higher recovery rating for each major diagnosis, and codify their protocols into standard order sets in the EMR.

For doctors with significantly higher total bills, set up peer review and feedback sessions, combining cost data with quality metrics (readmission, complications) to align practices.

Targeted programs by age group and diagnosis

For older patients with higher cost and slightly lower recovery, design geriatric-focused care pathways (fall-risk checks, medication review, early physiotherapy) to reduce complications and length of stay.

For chronic diagnoses (Diabetes, Hypertension), expand outpatient follow-up and education to reduce readmissions and high inpatient bills, tracking whether total bill per chronic patient falls over time.

--THANK YOU--

PRESENTED BY

- ARIJEET MUKHERJEE