healthcare-project-2

June 15, 2024

1 Project: HealthCare Data Analysis and Prediction

2 Domain: Healthcare

3 Organization: Vigor Council

4 Interns Name: Kirti, Nancy, Vishal

[1]:
```
# Import libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
```

[2]:
```
# import data from excel
df=pd.read_excel("healthcare_dataset.xlsx")
df
```

[2]:

	Name	Age	Gender	Blood Type	Medical Condition	Date of Admission	Doctor	Hospital
0	Tiffany Ramirez	81	Female	O-	Diabetes	2022-11-17	Patrick Parker	Wallace-Hamilton
1	Ruben Burns	35	Male	O+	Asthma	2023-06-01	Diane Jackson	Burke, Griffin and Cooper
2	Chad Byrd	61	Male	B-	Obesity	2019-01-09	Paul Baker	Walton LLC
3	Antonio Frederick	49	Male	B-	Asthma	2020-05-02	Brian Chandler	Garcia Ltd
4	Mrs. Brandy Flowers	51	Male	O-	Arthritis	2021-07-09	Dustin Griffin	Jones, Brown and Murray
…	…	…	…	…	…	…	…	…
9995	James Hood	83	Male	A+	Obesity			
9996	Stephanie Evans	47	Female	AB+	Arthritis			
9997	Christopher Martinez	54	Male	B-	Arthritis			
9998	Amanda Duke	84	Male	A+	Arthritis			
9999	Eric King	20	Male	B-	Arthritis			

```
…              …              …                          …
9995        2022-07-29       Samuel Moody   Wood, Martin and Simmons
9996        2022-01-06  Christopher Yates               Nash-Krueger
9997        2022-07-01   Robert Nicholson            Larson and Sons
9998        2020-02-06        Jamie Lewis               Wilson-Lyons
9999        2023-03-22        Tasha Avila  Torres, Young and Stewart

     Insurance Provider  Billing Amount  Room Number Admission Type  \
0             Medicare    37490.983364          146       Elective
1      UnitedHealthcare    47304.064845          404      Emergency
2             Medicare    36874.896997          292      Emergency
3             Medicare    23303.322092          480         Urgent
4      UnitedHealthcare    18086.344184          477         Urgent
…                   …             …          …             …
9995   UnitedHealthcare    39606.840083          110       Elective
9996         Blue Cross     5995.717488          244      Emergency
9997         Blue Cross    49559.202905          312       Elective
9998   UnitedHealthcare    25236.344761          420         Urgent
9999              Aetna    37223.965865          290      Emergency

     Discharge Date   Medication  Test Results
0        2022-12-01      Aspirin  Inconclusive
1        2023-06-15      Lipitor        Normal
2        2019-02-08      Lipitor        Normal
3        2020-05-03   Penicillin      Abnormal
4        2021-08-02  Paracetamol        Normal
…               …           …           …
9995     2022-08-02    Ibuprofen      Abnormal
9996     2022-01-29    Ibuprofen        Normal
9997     2022-07-15    Ibuprofen        Normal
9998     2020-02-26   Penicillin        Normal
9999     2023-04-15   Penicillin      Abnormal

[10000 rows x 15 columns]
```

[3]:
```
# for number of rows and columns
df.shape
```

[3]:
```
(10000, 15)
```

[4]:
```
# checking the top 5 records of data
df.head()
```

[4]:
```
                  Name  Age  Gender Blood Type Medical Condition  \
0      Tiffany Ramirez   81  Female         O-          Diabetes
1          Ruben Burns   35    Male         O+            Asthma
2            Chad Byrd   61    Male         B-           Obesity
```

```
3    Antonio Frederick   49    Male         B-            Asthma
4  Mrs. Brandy Flowers   51    Male         O-         Arthritis

  Date of Admission          Doctor                   Hospital  \
0        2022-11-17  Patrick Parker           Wallace-Hamilton
1        2023-06-01   Diane Jackson  Burke, Griffin and Cooper
2        2019-01-09      Paul Baker                 Walton LLC
3        2020-05-02  Brian Chandler                 Garcia Ltd
4        2021-07-09  Dustin Griffin    Jones, Brown and Murray

  Insurance Provider  Billing Amount  Room Number Admission Type  \
0          Medicare    37490.983364          146       Elective
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3          Medicare    23303.322092          480         Urgent
4   UnitedHealthcare    18086.344184          477         Urgent

  Discharge Date   Medication  Test Results
0     2022-12-01      Aspirin  Inconclusive
1     2023-06-15      Lipitor        Normal
2     2019-02-08      Lipitor        Normal
3     2020-05-03   Penicillin      Abnormal
4     2021-08-02  Paracetamol        Normal
```

[5]:
```
# checking the name of columns
df.columns
```

[5]:
```
Index(['Name', 'Age', 'Gender', 'Blood Type', 'Medical Condition',
       'Date of Admission', 'Doctor', 'Hospital', 'Insurance Provider',
       'Billing Amount', 'Room Number', 'Admission Type', 'Discharge Date',
       'Medication', 'Test Results'],
      dtype='object')
```

[6]:
```
# checking the data type of each column
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 15 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Name                10000 non-null  object
 1   Age                 10000 non-null  int64
 2   Gender              10000 non-null  object
 3   Blood Type          10000 non-null  object
 4   Medical Condition   10000 non-null  object
 5   Date of Admission   10000 non-null  datetime64[ns]
```

```
 6   Doctor              10000 non-null  object
 7   Hospital            10000 non-null  object
 8   Insurance Provider  10000 non-null  object
 9   Billing Amount      10000 non-null  float64
 10  Room Number         10000 non-null  int64
 11  Admission Type      10000 non-null  object
 12  Discharge Date      10000 non-null  datetime64[ns]
 13  Medication          10000 non-null  object
 14  Test Results        10000 non-null  object
dtypes: datetime64[ns](2), float64(1), int64(2), object(10)
memory usage: 1.1+ MB
```

[7]:
```
# checking there is any null value or not
df.isnull().sum()
```

[7]:
```
Name                  0
Age                   0
Gender                0
Blood Type            0
Medical Condition     0
Date of Admission     0
Doctor                0
Hospital              0
Insurance Provider    0
Billing Amount        0
Room Number           0
Admission Type        0
Discharge Date        0
Medication            0
Test Results          0
dtype: int64
```

5 Exploratory Data Analysis

6 1. Age Distribution:

Analyze the age distribution to understand the demographics of patients admitted.

[8]:
```
pd.crosstab(index=df["Age"],columns=df['Age'])
```

[8]:

Age	18	19	20	21	22	23	24	25	26	27	…	76	77	78	79	80
Age											…					
18	164	0	0	0	0	0	0	0	0	0	…	0	0	0	0	0
19	0	132	0	0	0	0	0	0	0	0	…	0	0	0	0	0
20	0	0	169	0	0	0	0	0	0	0	…	0	0	0	0	0
21	0	0	0	153	0	0	0	0	0	0	…	0	0	0	0	0
22	0	0	0	0	123	0	0	0	0	0	…	0	0	0	0	0

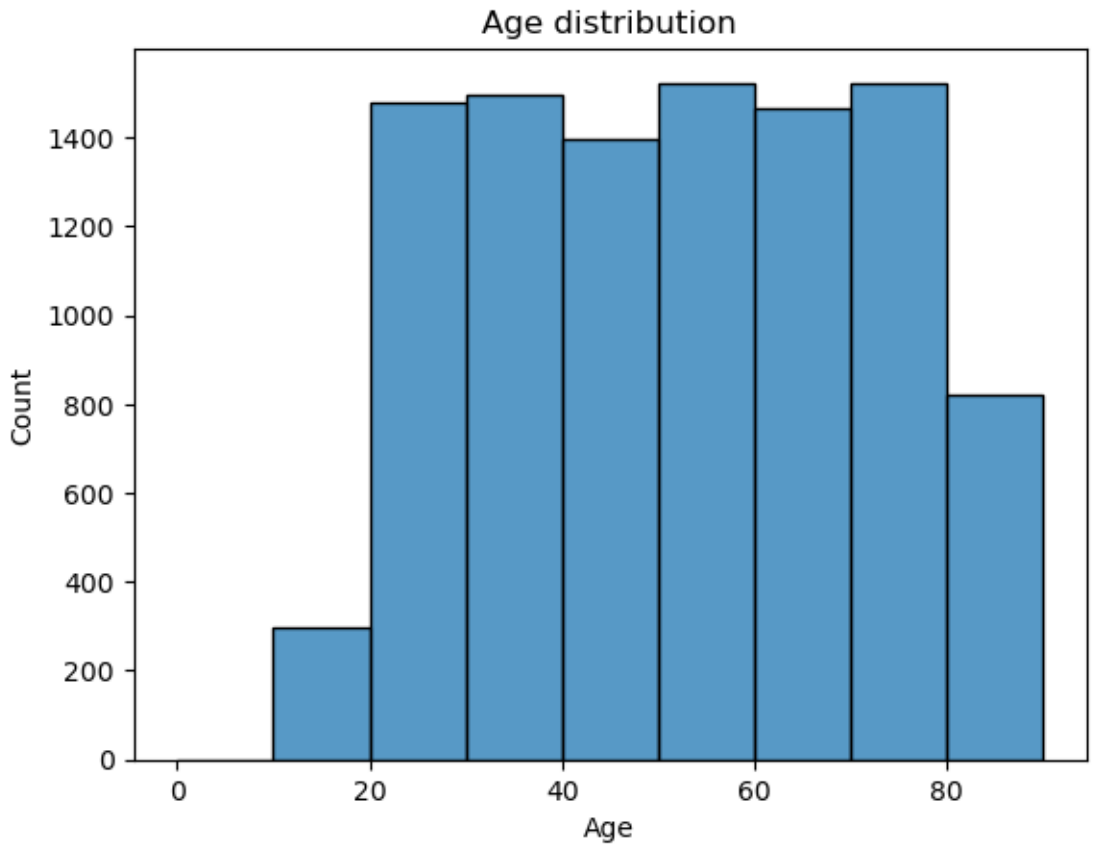
```
..   …  …  …  …  …  ..  ..  ..  ..  ..  …  ..  ..  ..  ..  ..
81     0    0    0    0    0    0    0    0    0    0  …    0    0    0    0    0
82     0    0    0    0    0    0    0    0    0    0  …    0    0    0    0    0
83     0    0    0    0    0    0    0    0    0    0  …    0    0    0    0    0
84     0    0    0    0    0    0    0    0    0    0  …    0    0    0    0    0
85     0    0    0    0    0    0    0    0    0    0  …    0    0    0    0    0

Age   81   82   83   84   85
Age
18     0    0    0    0    0
19     0    0    0    0    0
20     0    0    0    0    0
21     0    0    0    0    0
22     0    0    0    0    0
..   …  …  …  …  …
81   159    0    0    0    0
82     0  147    0    0    0
83     0    0  131    0    0
84     0    0    0  133    0
85     0    0    0    0  123

[68 rows x 68 columns]
```

[9]:
```
df.groupby(pd.cut(df['Age'],bins=[0,10,20,30,40,50,60,70,80,90]))["Age"].count()
```

[9]:
```
Age
(0, 10]         0
(10, 20]      465
(20, 30]     1438
(30, 40]     1504
(40, 50]     1389
(50, 60]     1543
(60, 70]     1448
(70, 80]     1520
(80, 90]      693
Name: Age, dtype: int64
```

[10]:
```
g=sns.histplot(data=df,x=df['Age'],bins=[0,10,20,30,40,50,60,70,80,90])
g.set_title("Age distribution")
```

[10]:
```
Text(0.5, 1.0, 'Age distribution')
```



Research Analysis: From above analysis we conclude that age group of 50-60 people admitted most in the hospital

7 2. Gender Ratio:

Determine the gender ratio of admitted patients to identify any gender-specific healthcare trends.

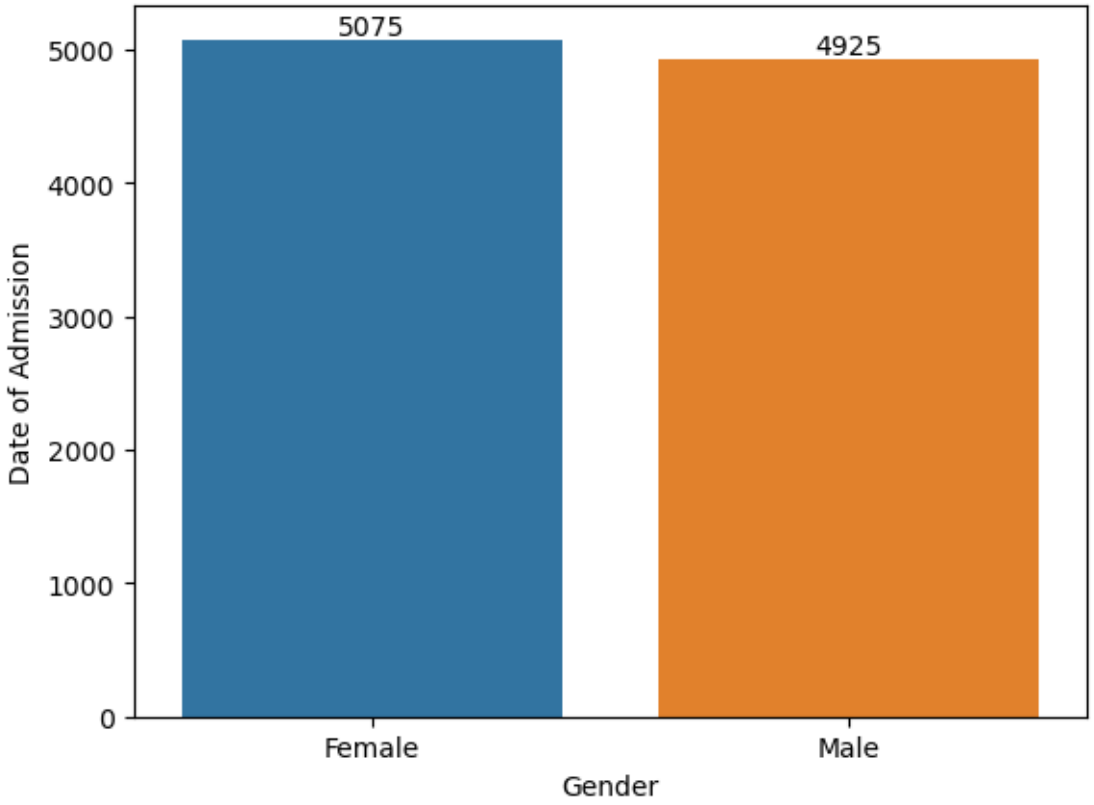
[11]:
```
pd.crosstab(index=df["Medical Condition"],columns=df['Gender'])
```

[11]:

Gender	Female	Male
Medical Condition		
Arthritis	815	835
Asthma	874	834
Cancer	887	816
Diabetes	825	798
Hypertension	836	852
Obesity	838	790

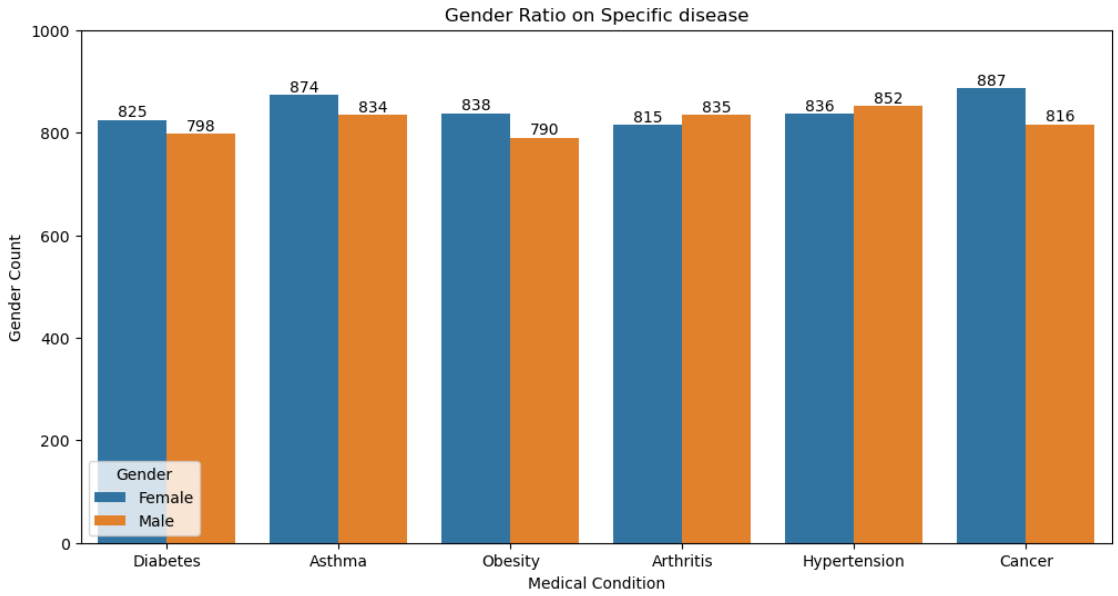
[12]:
```
gen=df.groupby(["Gender"],as_index=False)["Date of Admission"].count().
  ↪sort_values(by='Date of Admission', ascending =False)
print(gen)
ax=sns.barplot(data=gen, x="Gender", y="Date of Admission")
for bar in ax.containers:
    ax.bar_label(bar)
```

```
   Gender  Date of Admission
0  Female               5075
1    Male               4925
```



[13]:
```
plt.figure(figsize=(12,6))
gr=sns.countplot(data=df,x="Medical Condition",hue='Gender')
gr.set_title("Gender Ratio on Specific disease")
gr.set_ylabel("Gender Count")
for bars in gr.containers:
    gr.bar_label(bars)
gr.set_ylim(ymax=1000)
gr.figure.get_axes()[0].legend(title="Gender", loc="lower left")
```

[13]:
```
<matplotlib.legend.Legend at 0x17320a8f2d0>
```



Reseach Analysis: from the above insights we conclude that there is gender specific disease in admitted patients i.e Cancer in Females and Hypertension in Males .
Highest number of admission is taken by Females.

8 3. Blood Type Frequency:

Examine the frequency of different blood types among patients for potential correlation with medical conditions or treatments.

[14]:
```
BT=df.groupby(["Blood Type"],as_index=False)["Date of Admission"].count().
↪sort_values(by="Date of Admission", ascending=False)
BT
```

[14]:

	Blood Type	Date of Admission
3	AB-	1275
2	AB+	1258
5	B-	1252
6	O+	1248
4	B+	1244
7	O-	1244
0	A+	1241
1	A-	1238

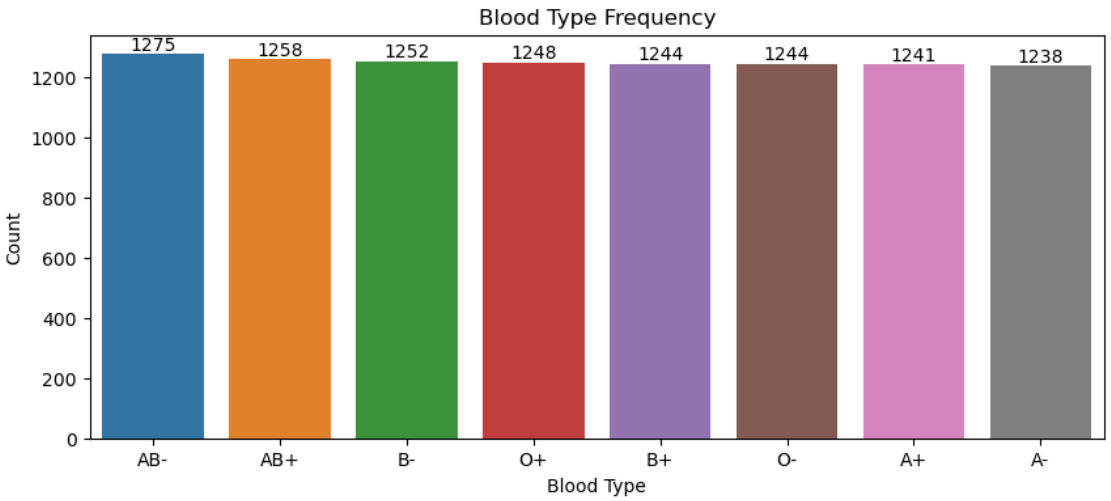
[15]:
```
df.groupby("Blood Type")["Date of Admission"].count()
```

[15]:
```
Blood Type
A+     1241
```

```
A-      1238
AB+     1258
AB-     1275
B+      1244
B-      1252
O+      1248
O-      1244
Name: Date of Admission, dtype: int64
```

[16]:
```
plt.figure(figsize=(10,4))
bf=sns.barplot(data=BT, y="Date of Admission",x="Blood Type")
for bar in bf.containers:
    bf.bar_label(bar)
bf.set_title("Blood Type Frequency")
bf.set_ylabel("Count")
```

[16]:
```
Text(0, 0.5, 'Count')
```



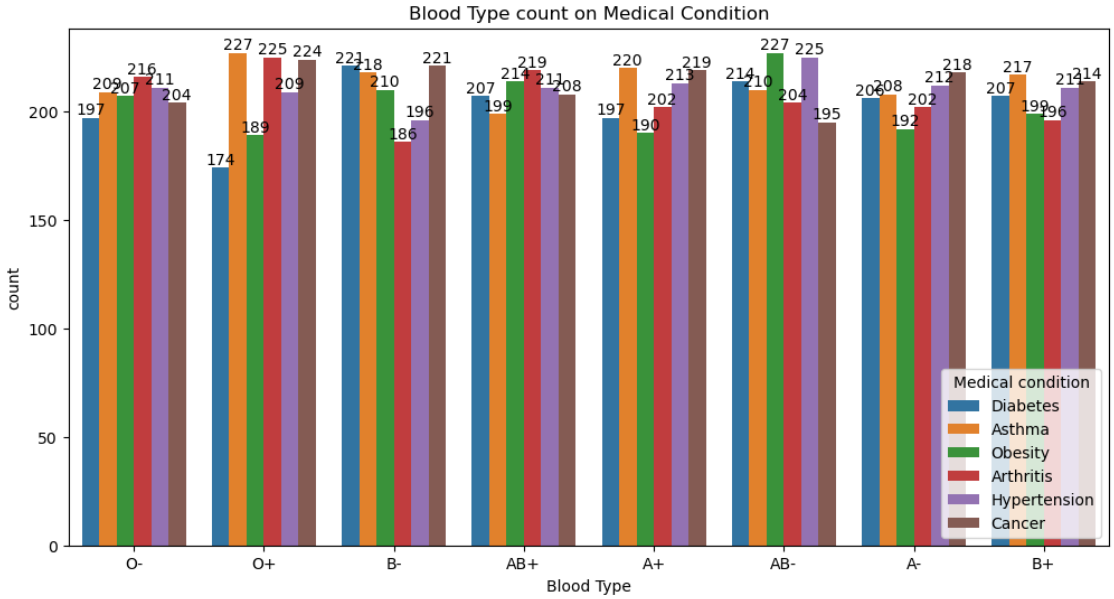
[17]:
```
pd.crosstab(index=df["Blood Type"],columns=df['Medical Condition'])
```

[17]:

Medical Condition	Arthritis	Asthma	Cancer	Diabetes	Hypertension	Obesity
Blood Type						
A+	202	220	219	197	213	190
A-	202	208	218	206	212	192
AB+	219	199	208	207	211	214
AB-	204	210	195	214	225	227
B+	196	217	214	207	211	199
B-	186	218	221	221	196	210
O+	225	227	224	174	209	189
O-	216	209	204	197	211	207

[18]:
```
plt.figure(figsize=(12,6))
bf=sns.countplot(data = df, hue = 'Medical Condition' , x = "Blood Type")
bf.set_title("Blood Type count on Medical Condition")
for bars in bf.containers:
    bf.bar_label(bars)
bf.figure.get_axes()[0].legend(title="Medical condition", loc="lower right")
```

[18]:
```
<matplotlib.legend.Legend at 0x17320b2bc10>
```



Research Analysis: From the above graph we can see that AB- have the highest rate of patients and A- have the lowest rate.

9 4. Common Medical Conditions:

Identify the most prevalent medical conditions among admitted patients to prioritize resources and healthcare services.

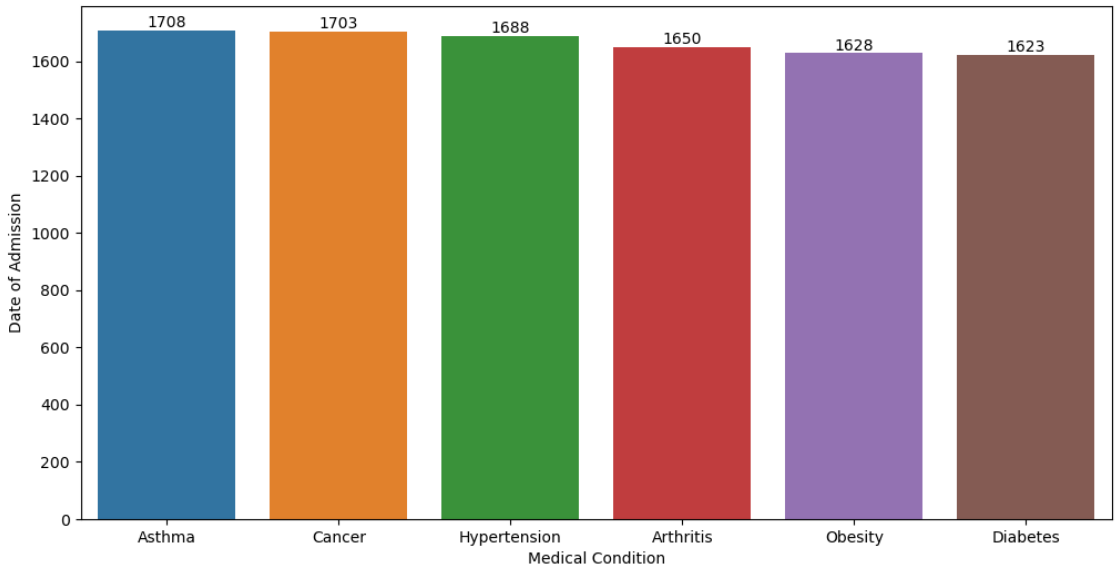
[19]:
```
med_condition=df["Medical Condition"].value_counts()
med_condition
```

[19]:
```
Medical Condition
Asthma          1708
Cancer          1703
Hypertension    1688
Arthritis       1650
Obesity         1628
Diabetes        1623
```

```
Name: count, dtype: int64
```

[20]:
```
plt.figure(figsize=(12,6))
Med = df.groupby(['Medical Condition'], as_index=False)['Date of Admission'].
 ↪count().sort_values(by='Date of Admission', ascending=False).head(10)
print(Med)
ax=sns.barplot(data = Med, x = 'Medical Condition',y= 'Date of Admission')
for bars in ax.containers:
    ax.bar_label(bars)
```

```
  Medical Condition  Date of Admission
1            Asthma               1708
2            Cancer               1703
4      Hypertension               1688
0         Arthritis               1650
5           Obesity               1628
3          Diabetes               1623
```



Research Analysis: from the insights we conclude that the most common medical condition is Asthma

10 5. Admission Trends Over Time:

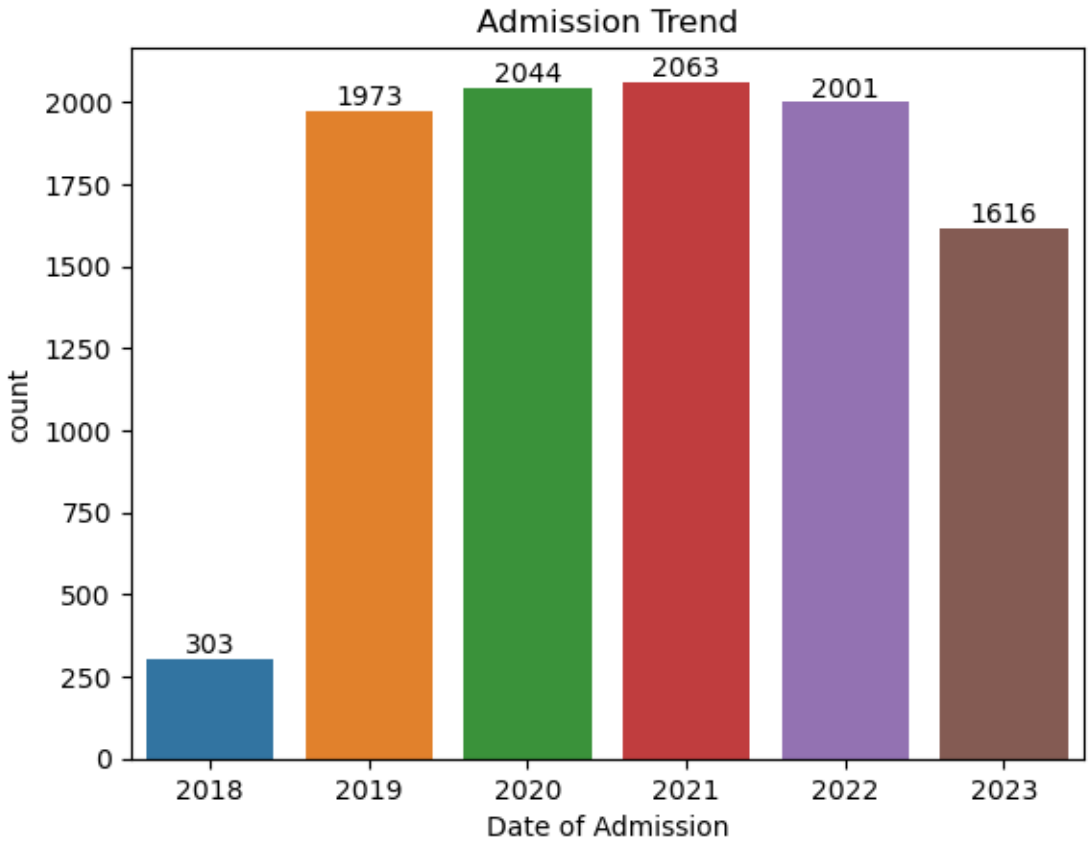
Analyze the dates of admission to identify any seasonal or temporal patterns in hospital admissions.

[21]:
```
df["Date of Admission"]=pd.to_datetime(df['Date of Admission'])
df["Date of Admission"]=df["Date of Admission"].dt.year
```

[22]:
```
admission_per_year=df["Date of Admission"].value_counts()
admission_per_year
```

[22]:
```
Date of Admission
2021    2063
2020    2044
2022    2001
2019    1973
2023    1616
2018     303
Name: count, dtype: int64
```

[23]:
```
DOA=sns.countplot(data= df,  x = df["Date of Admission"])
DOA.set_title('Admission Trend')
plt.figure(figsize=(12,8))
for bar in DOA.containers:
    DOA.bar_label(bar)
```




```
<Figure size 1200x800 with 0 Axes>
```

Research Analysis: from the above graph we can see that in 2021 there is highest number of admission.

11 6. Attending Doctors:

Assess the performance and workload of different doctors based on the number of admissions they handle.

[24]:
```
doc=df.groupby(["Doctor"],as_index=False)['Date of Admission'].count().
↪sort_values(by='Date of Admission', ascending=False).head(20)
doc
```

[24]:

	Doctor	Date of Admission
6460	Michael Johnson	7
6216	Matthew Smith	5
6522	Michael Smith	5
6572	Michelle Anderson	5
7593	Robert Brown	5
4087	Jennifer Smith	5
3724	James Perez	5
3753	James Williams	5
809	Ashley Jackson	4
1753	Christopher Davis	4
1789	Christopher Jones	4
9340	William Rodriguez	4
6400	Michael Brown	4
2302	David Johnson	4
7649	Robert Miller	4
4222	Jessica Wilson	3
2179	Daniel Smith	3
3852	Jason Hall	3
8761	Thomas Brown	3
7847	Ryan Thompson	3

[25]:
```
df["Doctor"].duplicated().any()
```

[25]:
```
True
```

[26]:
```
df["Doctor"].value_counts()
```

[26]:
```
Doctor
Michael Johnson      7
Robert Brown         5
Michelle Anderson    5
Matthew Smith        5
Jennifer Smith       5
                    ..
```

```
Sandra Howard        1
Steven Fuller        1
Benjamin Lawson      1
Allison Woods        1
Tasha Avila          1
Name: count, Length: 9416, dtype: int64
```

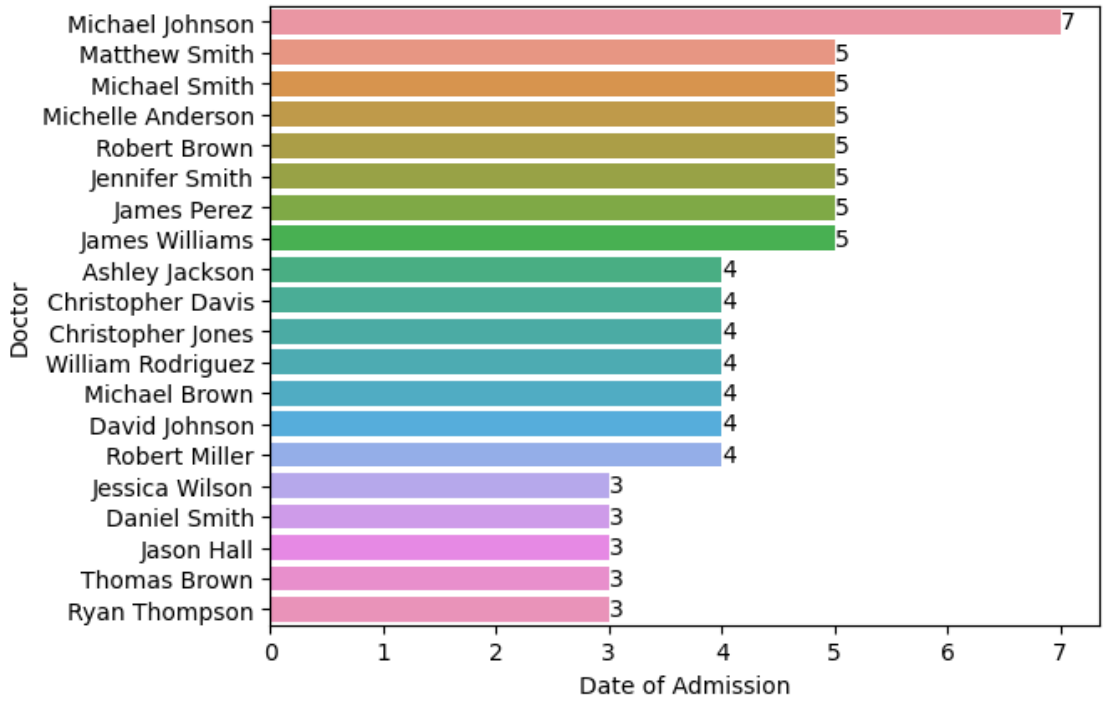
[27]:
```
df[df['Doctor']=='Michael Johnson']
```

[27]:

	Name	Age	Gender	Blood Type	Medical Condition	Date of Admission	Doctor	Hospital	Insurance Provider	Billing Amount	Room Number	Admission Type	Discharge Date	Medication	Test Results
1862	Sherri Mckinney	67	Male	O+	Asthma	2022	Michael Johnson	Harris-Cowan	Aetna	49559.841901	288	Urgent	2022-03-05	Lipitor	Inconclusive
5908	Brittany Glover	57	Male	A+	Asthma	2021	Michael Johnson	Harrison LLC	Medicare	33099.519497	192	Elective	2021-12-20	Ibuprofen	Abnormal
6397	Maria Carter	59	Female	AB-	Diabetes	2022	Michael Johnson	Jackson, Thompson and Thomas	Blue Cross	1428.619493	461	Urgent	2022-02-14	Aspirin	Abnormal
6411	Joshua Bailey	78	Female	A+	Obesity	2019	Michael Johnson	Thomas-Franklin	Aetna	38310.284764	386	Emergency	2019-12-04	Ibuprofen	Abnormal
6875	Rebecca King	45	Female	O+	Cancer	2021	Michael Johnson	Farrell Inc	UnitedHealthcare	3678.787754	457	Elective	2021-10-10	Paracetamol	Inconclusive
9085	Peter Matthews	30	Male	B-	Asthma	2019	Michael Johnson	Fletcher Group	UnitedHealthcare	27108.266411	241	Elective	2019-06-21	Aspirin	Abnormal
9909	Jonathan Perry	24	Male	A-	Arthritis	2022	Michael Johnson	Watkins and Sons	Medicare	28391.155073	198	Emergency	2022-01-20	Lipitor	Abnormal

[28]:
```
d=sns.barplot(data=doc, y="Doctor", x="Date of Admission")
plt.figure(figsize=(15,8))
```

```
for bar in d.containers:
    d.bar_label(bar)
```




```
<Figure size 1500x800 with 0 Axes>
```

Research Analysis from the above graph we can see that the doctor Michael Johnson have the more workload .

12 7. Hospital Utilization:

Determine which hospitals have the highest admission rates and assess their capacity to handle patient influx.

[29]:
```
hospital=df["Hospital"].value_counts().head(120)
hospital
```

[29]:
```
Hospital
Smith PLC          19
Smith and Sons     17
Smith Ltd          14
Smith Inc          14
Johnson PLC        13
                   ..
Alvarez Inc         4
```

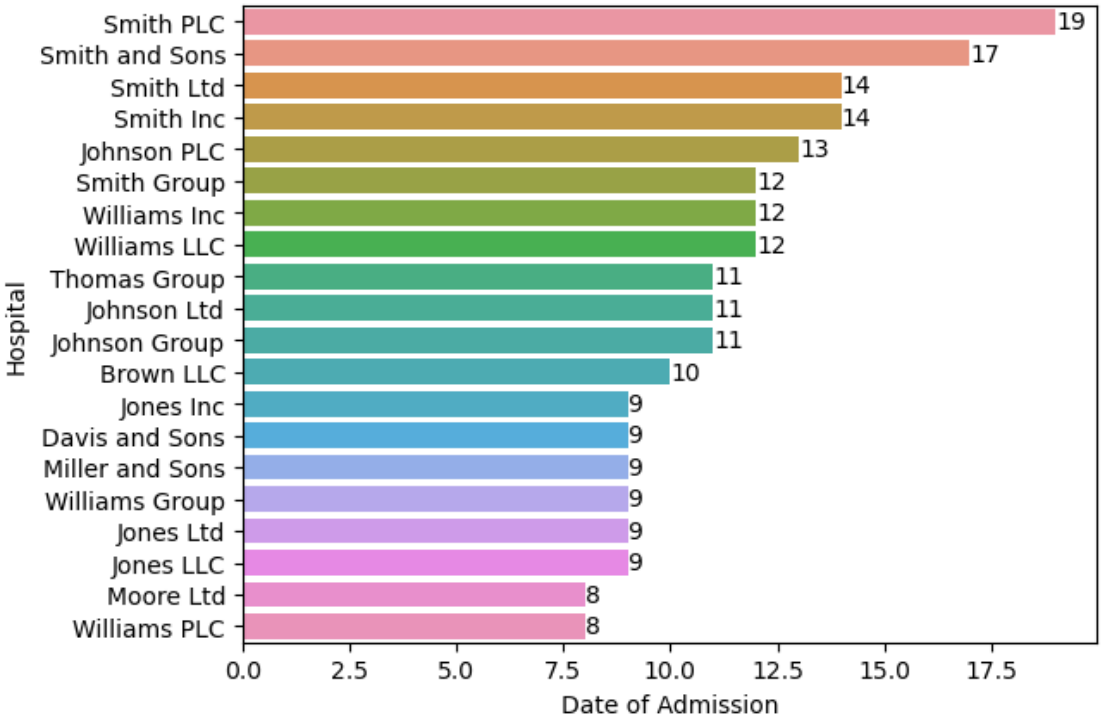
```
Bell LLC           4
Morgan Ltd         4
Allen Group        4
West PLC           4
Name: count, Length: 120, dtype: int64
```

[30]:
```
hos=df.groupby(["Hospital"],as_index=False)["Date of Admission"].count().
 ↪sort_values(by='Date of Admission', ascending=False).head(20)
hos
```

[30]:

	Hospital	Date of Admission
7114	Smith PLC	19
7115	Smith and Sons	17
7113	Smith Ltd	14
7111	Smith Inc	14
3769	Johnson PLC	13
7110	Smith Group	12
8282	Williams Inc	12
8283	Williams LLC	12
7561	Thomas Group	11
3768	Johnson Ltd	11
3765	Johnson Group	11
835	Brown LLC	10
3899	Jones Inc	9
1797	Davis and Sons	9
5002	Miller and Sons	9
8281	Williams Group	9
3901	Jones Ltd	9
3900	Jones LLC	9
5151	Moore Ltd	8
8285	Williams PLC	8

[31]:
```
h=sns.barplot(data=hos, y='Hospital', x='Date of Admission')
for bar in h.containers:
    h.bar_label(bar)
```



Research Analysis: from the above graph we can see that the SMITH PLC hospital have the highest rate of admissions.

13 8.Insurance Coverage:

Analyze the distribution of insurance providers among admitted patients to understand coverage gaps or preferences.

[32]:
```
pd.crosstab(index=df["Insurance Provider"],columns=df["Date of Admission"])
```

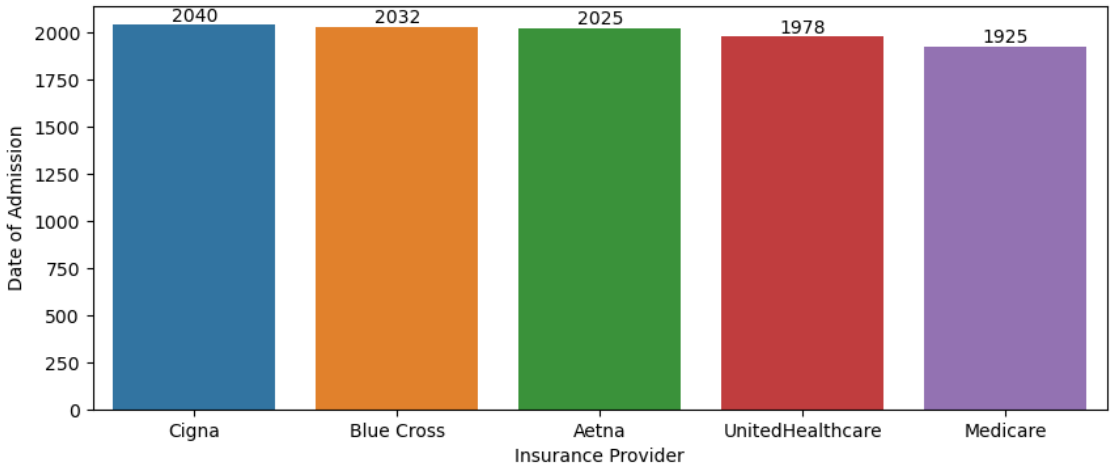
[32]:

Date of Admission	2018	2019	2020	2021	2022	2023
Insurance Provider						
Aetna	63	401	421	406	401	333
Blue Cross	56	403	429	420	407	317
Cigna	65	385	427	438	401	324
Medicare	59	374	390	385	396	321
UnitedHealthcare	60	410	377	414	396	321

[33]:
```
plt.figure(figsize=(10,4))
IP=df.groupby(["Insurance Provider"], as_index=False)["Date of Admission"].
  ↪count().sort_values(by='Date of Admission', ascending=False)
print(IP)
ins=sns.barplot(data=IP, x="Insurance Provider", y="Date of Admission")
```

```
for bar in ins.containers:
    ins.bar_label(bar)
```

	Insurance Provider	Date of Admission
2	Cigna	2040
1	Blue Cross	2032
0	Aetna	2025
4	UnitedHealthcare	1978
3	Medicare	1925

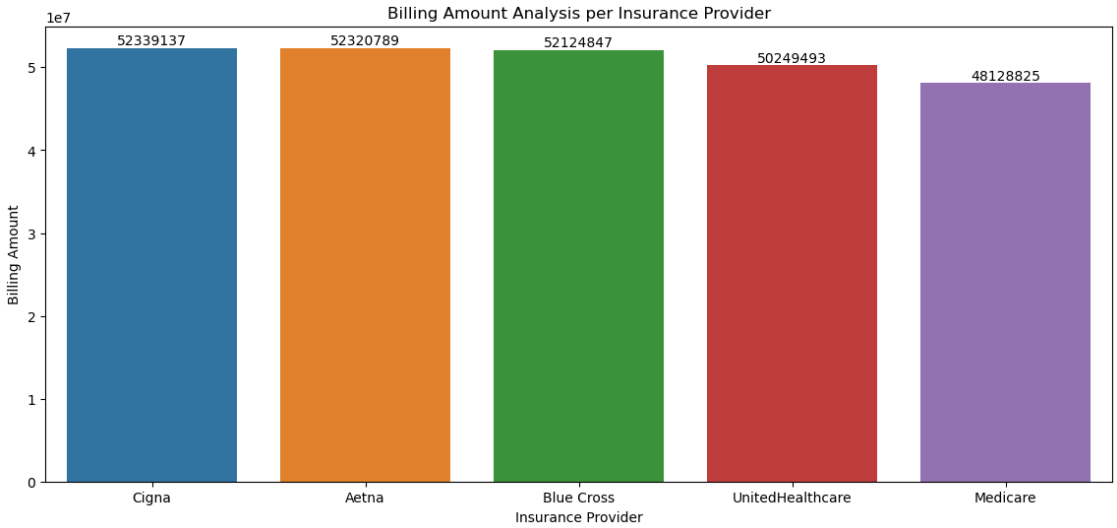


[34]:
```
df['Billing Amount']=df['Billing Amount'].astype('int64')
```

[35]:
```
plt.figure(figsize=(14,6))
BA = df.groupby(['Insurance Provider'], as_index=False)['Billing Amount'].sum().
  ↪sort_values(by='Billing Amount', ascending=False)
print(BA)
ax=sns.barplot(x = 'Insurance Provider',y= 'Billing Amount',data = BA)
ax.bar_label(container=ax.containers[0], labels=BA['Billing Amount'])
ax.set_title("Billing Amount Analysis per Insurance Provider")
```

	Insurance Provider	Billing Amount
2	Cigna	52339137
0	Aetna	52320789
1	Blue Cross	52124847
4	UnitedHealthcare	50249493
3	Medicare	48128825

[35]: Text(0.5, 1.0, 'Billing Amount Analysis per Insurance Provider')



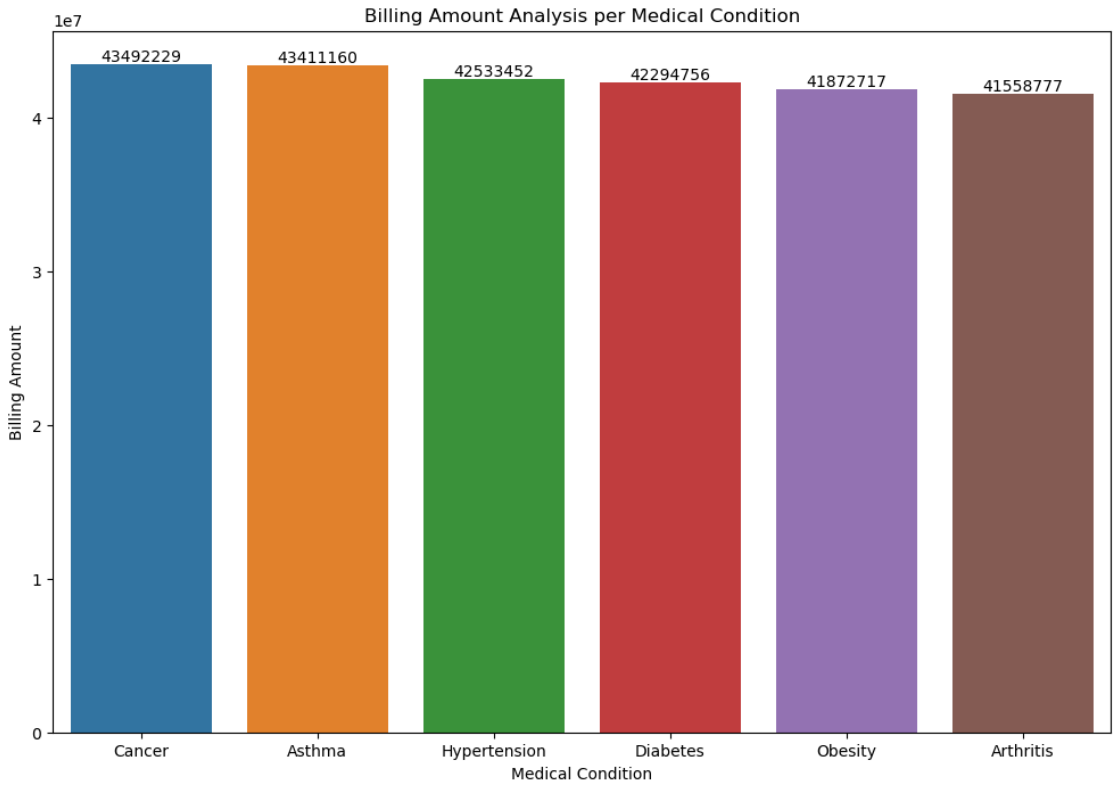
Research analysis: from the above graph we can see that the Cigna is the most prefered insurance provider chosen by the patients and generating highest amount of billing.

9. Billing Amount Analysis: Investigate the billing amounts to identify any outliers or trends in healthcare costs.

[36]:
```
plt.figure(figsize=(12,8))
BA = df.groupby(['Medical Condition'], as_index=False)['Billing Amount'].sum().
 ↪sort_values(by="Billing Amount", ascending=False)
print(BA)
ax=sns.barplot(x = 'Medical Condition',y= 'Billing Amount',data = BA)
ax.bar_label(container=ax.containers[0], labels=BA['Billing Amount'])
ax.set_title("Billing Amount Analysis per Medical Condition")
```

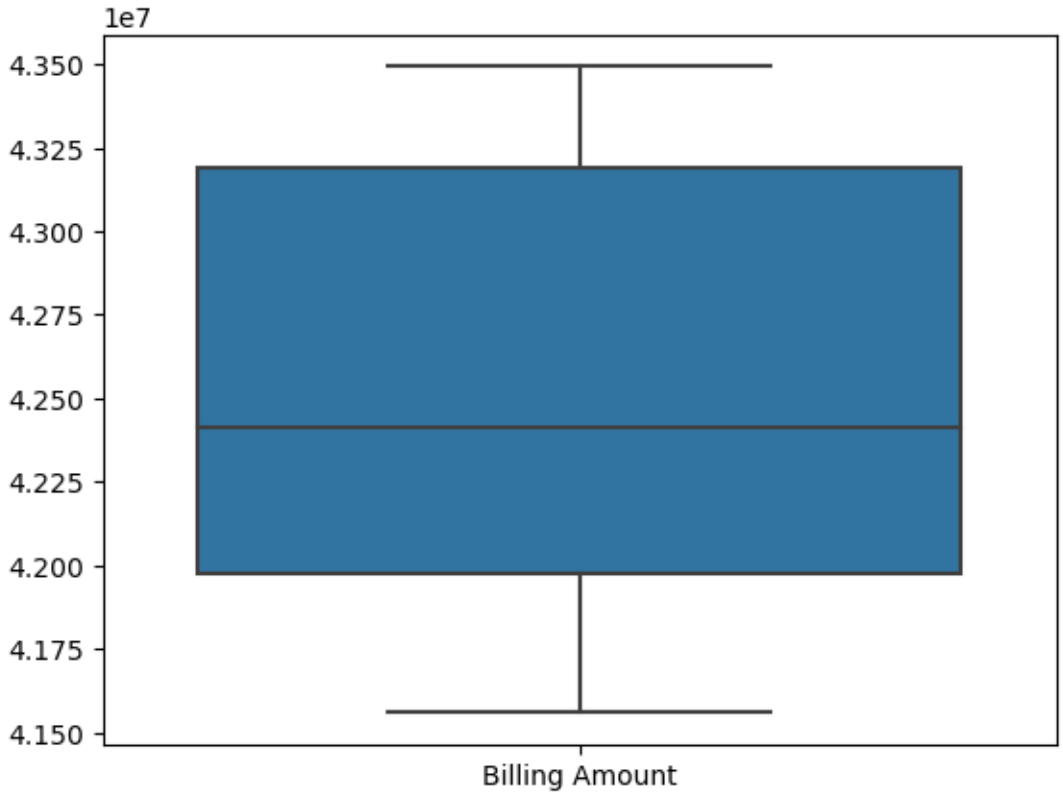
```
  Medical Condition  Billing Amount
2            Cancer        43492229
1            Asthma        43411160
4      Hypertension        42533452
3          Diabetes        42294756
5           Obesity        41872717
0         Arthritis        41558777
```

[36]: `Text(0.5, 1.0, 'Billing Amount Analysis per Medical Condition')`



[37]:
```
sns.boxplot(data=BA)
```

[37]: <Axes: >



[38]:
```
df['Billing Amount'].describe()
```

[38]:
```
count    10000.00000
mean     25516.30910
std      14067.29156
min       1000.00000
25%      13506.25000
50%      25257.50000
75%      37733.00000
max      49995.00000
Name: Billing Amount, dtype: float64
```

Research analysis: from the above graph we see that Cancer has the highest Billing Amount and no outlier is the billing amount.

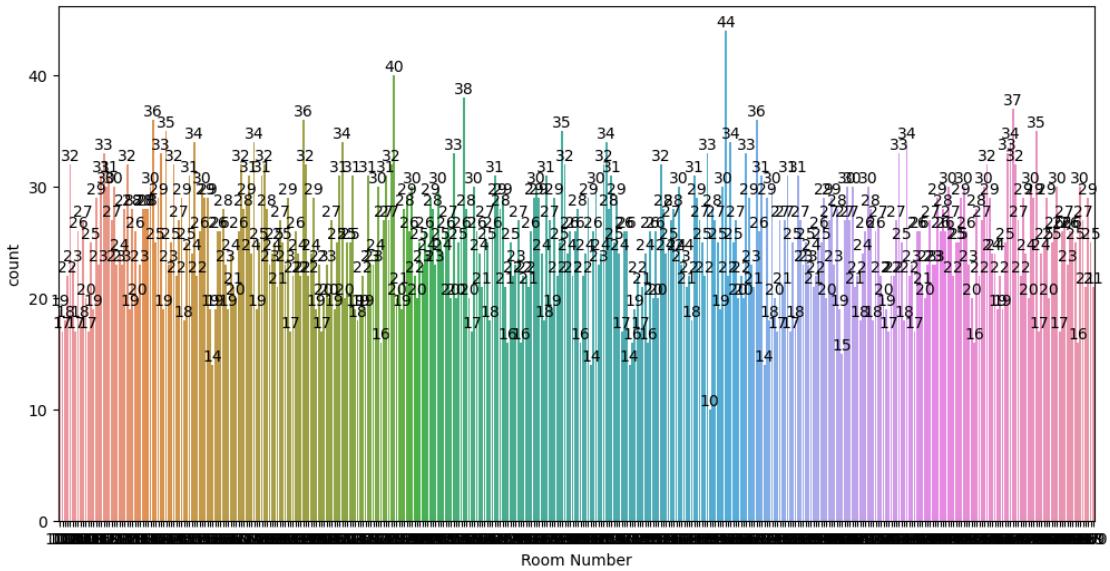
14 10.Room Occupancy:

Examine the distribution of room numbers to optimize room allocation and utilization

[39]:
```
df['Room Number'].value_counts()
```

[39]:
```
Room Number
358    44
230    40
257    38
469    37
195    36
       ..
160    14
306    14
321    14
373    14
352    10
Name: count, Length: 400, dtype: int64
```

[40]:
```
plt.figure(figsize=(12,6))
ax = sns.countplot(data=df, x=df['Room Number'])
for data in ax.containers:
    ax.bar_label(data)
```



Research Analysis: From the above graph we see that the 358 room number is more utilize according to other rooms.

15 11. Admission Type:

Differentiate between planned admissions (e.g., elective surgeries) and emergency admissions to understand healthcare demands

[41]:
```
pd.crosstab(index=df["Admission Type"], columns=df["Medical Condition"])
```

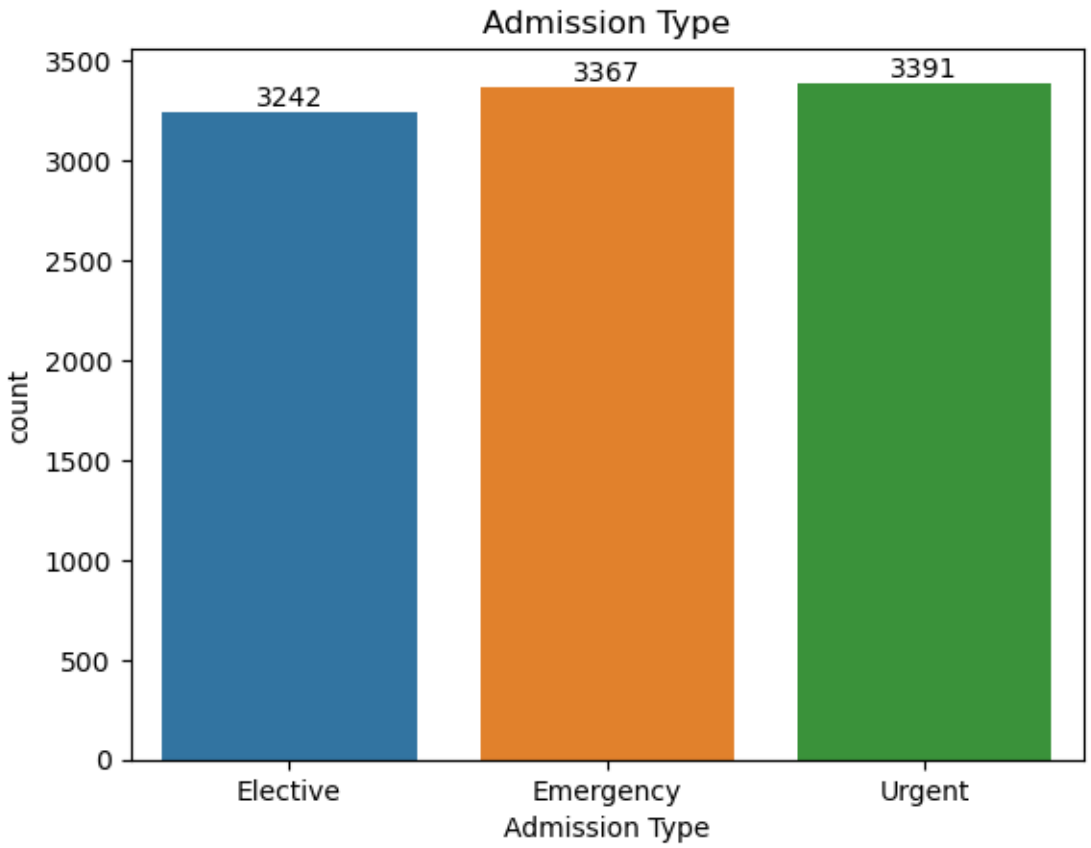
[41]:
```
Medical Condition  Arthritis  Asthma  Cancer  Diabetes  Hypertension  Obesity
Admission Type
Elective                 569     570     555       528           515      505
Emergency                529     556     578       557           578      569
Urgent                   552     582     570       538           595      554
```

[42]:
```
df["Admission Type"].value_counts()
```

[42]:
```
Admission Type
Urgent       3391
Emergency    3367
Elective     3242
Name: count, dtype: int64
```

[43]:
```
AT= sns.countplot(data=df, x="Admission Type")
for bar in AT.containers:
    AT.bar_label(bar)
plt.figure(figsize=(12,4))
AT.set_title("Admission Type")
```

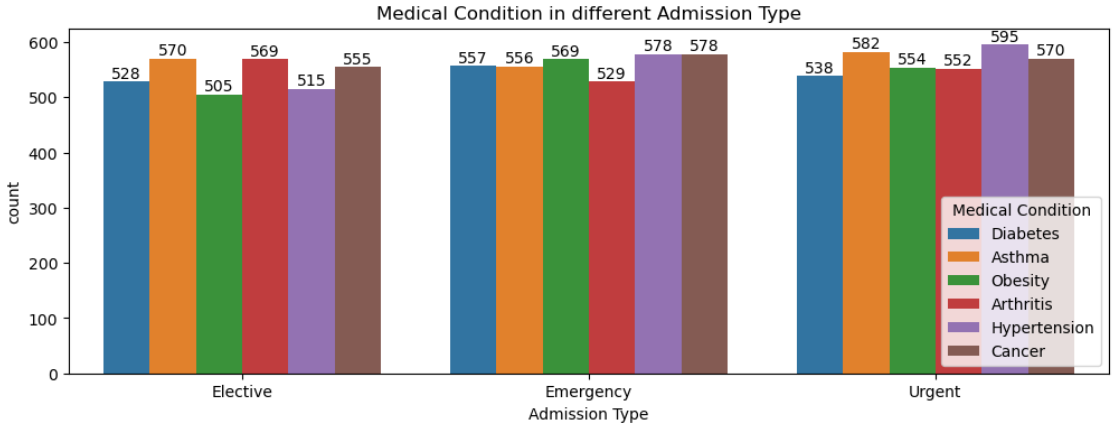
[43]:
```
Text(0.5, 1.0, 'Admission Type')
```




```
<Figure size 1200x400 with 0 Axes>
```

[44]:
```
plt.figure(figsize=(12,4))
ax = sns.countplot(data = df, x = 'Admission Type', hue = 'Medical Condition')

for bars in ax.containers:
    ax.bar_label(bars)
ax.set_title('Medical Condition in different Admission Type')
ax.figure.get_axes()[0].legend(title="Medical Condition", loc="lower right")
```

[44]:
```
<matplotlib.legend.Legend at 0x17324933850>
```



Research Analysis: from the above graph we can see that in EMERGENCY , cancer and hypertension has the highest rate of admission

16 12.Length of Stay:

Calculate the duration of hospital stays to identify any prolonged admissions or trends in discharge times.

[45]:
```
from datetime import date
```

[46]:
```
df["Date of Admission"]=pd.to_datetime(df['Date of Admission'])
df["Date of Admission"]=df["Date of Admission"].dt.day
```

[47]:
```
df["Discharge Date"]=pd.to_datetime(df['Discharge Date'])
df["Discharge Date"]=df["Discharge Date"].dt.day
```

[48]:
```
df["stay_length"]=(df["Discharge Date"]-df["Date of Admission"])
```

[49]:
```
df['stay_length'].describe()
```

[49]:
```
count    10000.000000
mean        14.591200
std          8.809827
min          0.000000
25%          7.000000
50%         14.000000
75%         22.000000
max         30.000000
Name: stay_length, dtype: float64
```

Research Analysis From the insight we can see that length of stays vary greatly, from 0 to 30 days.

17 13.Medication Usage:

Analyze the types and frequencies of medications prescribed to patients to monitor treatment patterns and effectiveness.

[50]:
```
pd.crosstab(index=df["Medication"], columns=df["Medical Condition"])
```

[50]:

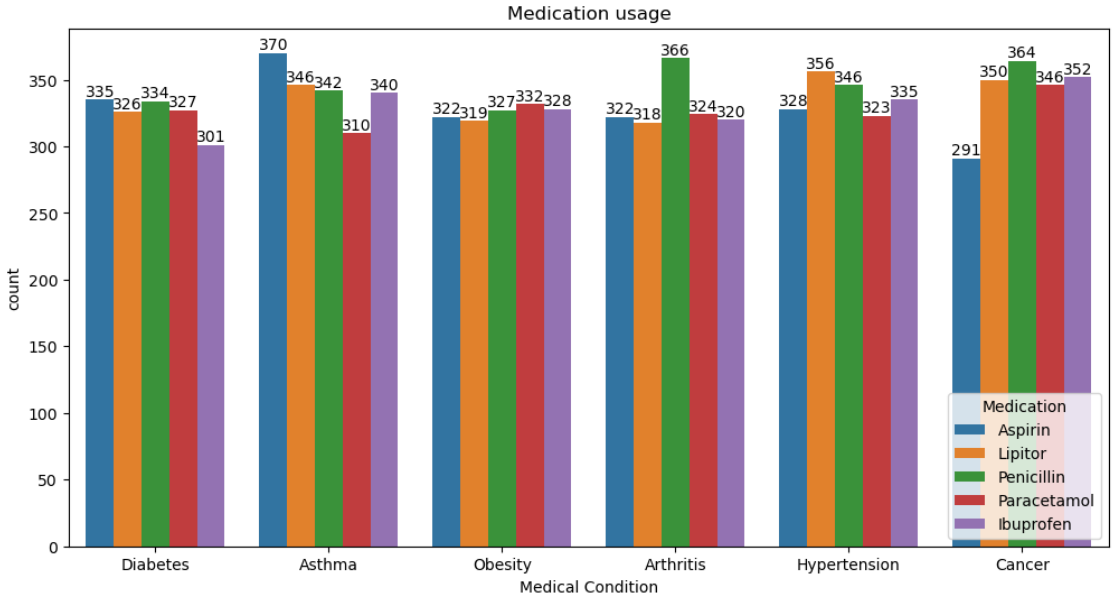
Medical Condition	Arthritis	Asthma	Cancer	Diabetes	Hypertension	Obesity
Medication						
Aspirin	322	370	291	335	328	322
Ibuprofen	320	340	352	301	335	328
Lipitor	318	346	350	326	356	319
Paracetamol	324	310	346	327	323	332
Penicillin	366	342	364	334	346	327

[51]:
```
df["Medication"].value_counts()
```

[51]:
```
Medication
Penicillin     2079
Lipitor        2015
Ibuprofen      1976
Aspirin        1968
Paracetamol    1962
Name: count, dtype: int64
```

[52]:
```
plt.figure(figsize=(12,6))
ax=sns.countplot(data=df,  x="Medical Condition", hue="Medication")
for bar in ax.containers:
    ax.bar_label(bar)
ax.figure.get_axes()[0].legend(title="Medication", loc="lower right")
ax.set_title("Medication usage")
```

[52]:
```
Text(0.5, 1.0, 'Medication usage')
```



Research Analysis: from the above graph we conclude that Penicillin medication is frequently prescribed.

18 14.Test Results Trends:

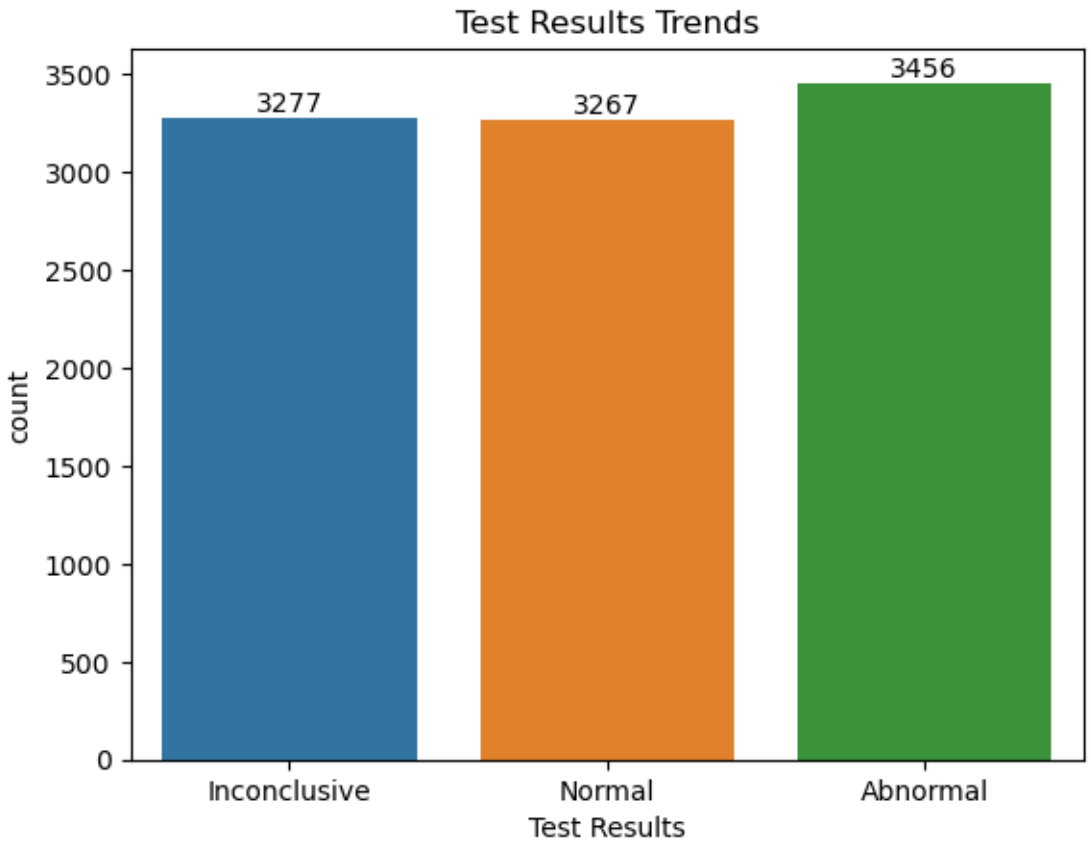
Identify any patterns or abnormalities in test results to improve diagnostic and treatment protocols.

[53]:
```
test=df["Test Results"].value_counts()
test
```

[53]:
```
Test Results
Abnormal        3456
Inconclusive    3277
Normal          3267
Name: count, dtype: int64
```

[54]:
```
ax=sns.countplot( x = df["Test Results"])
for bar in ax.containers:
    ax.bar_label(bar)
ax.set_title("Test Results Trends")
```

[54]:
```
Text(0.5, 1.0, 'Test Results Trends')
```



Research Analysis: From the above we can see that there is highest number of Abnormal test results.

19 15. Readmission Rates:

Track instances of readmission to assess the effectiveness of initial treatments and follow-up care

[55]:
```
df[["Name","Age","Gender","Blood Type"]].value_counts()
```

[55]:
```
Name              Age  Gender  Blood Type
Aaron Burnett     54   Female  A-            1
Melanie Clark     46   Male    AB+           1
Meghan Jordan     52   Male    A-            1
Meghan Lee        56   Male    O+            1
Meghan Robinson   71   Male    B+            1
                                             ..
Gabriella Ware    61   Female  O+            1
Gabrielle Francis 81   Male    A-            1
Gabrielle Mcclain 68   Male    A-            1
```

```
Gabrielle Russell  68   Male    AB+           1
Zoe Moore          74   Male    O-            1
Name: count, Length: 10000, dtype: int64
```

[56]:
```
df.groupby(["Name"], as_index=False)["Date of Admission"].value_counts().
↪sort_values(by="Date of Admission", ascending=False)
```

[56]:
```
                    Name  Date of Admission  count
0           Aaron Burnett                  1      1
6263     Meghan Robinson                   1      1
6247      Megan Phillips                   1      2
6248        Megan Rogers                   1      1
6249         Megan Short                   1      1
…                    …                   …    …
3127   Frederick Sherman                   1      1
3128  Frederick Williams                   1      1
3129      Gabriel Flores                   1      1
3130   Gabriel Henderson                   1      1
9377           Zoe Moore                   1      1

[9378 rows x 3 columns]
```

[57]:
```
df[['Name','Age',"Gender"]].duplicated().any()
```

[57]:
```
True
```

[58]:
```
df[df["Name"]== 'Megan Phillips']
```

[58]:
```
                Name  Age  Gender Blood Type Medical Condition  \
6836  Megan Phillips   29    Male        AB-          Diabetes
9689  Megan Phillips   74  Female         A+      Hypertension

      Date of Admission           Doctor          Hospital Insurance Provider  \
6836                  1  Robert Gonzalez        Martin LLC   UnitedHealthcare
9689                  1    Andrew Cannon  Sanchez and Sons           Medicare

      Billing Amount  Room Number Admission Type  Discharge Date   Medication  \
6836           11639          457         Urgent              25   Penicillin
9689           30105          192       Elective              26  Paracetamol

      Test Results  stay_length
6836        Normal           24
9689  Inconclusive           25
```

Research Analysis: From the above data we can see that there is duplicate data but there Age and Blood Type is different.
So we conclude that there no redamission.

20 16. Age and Medical Condition Correlation:

Investigate if certain medical conditions are more prevalent in specific age groups.

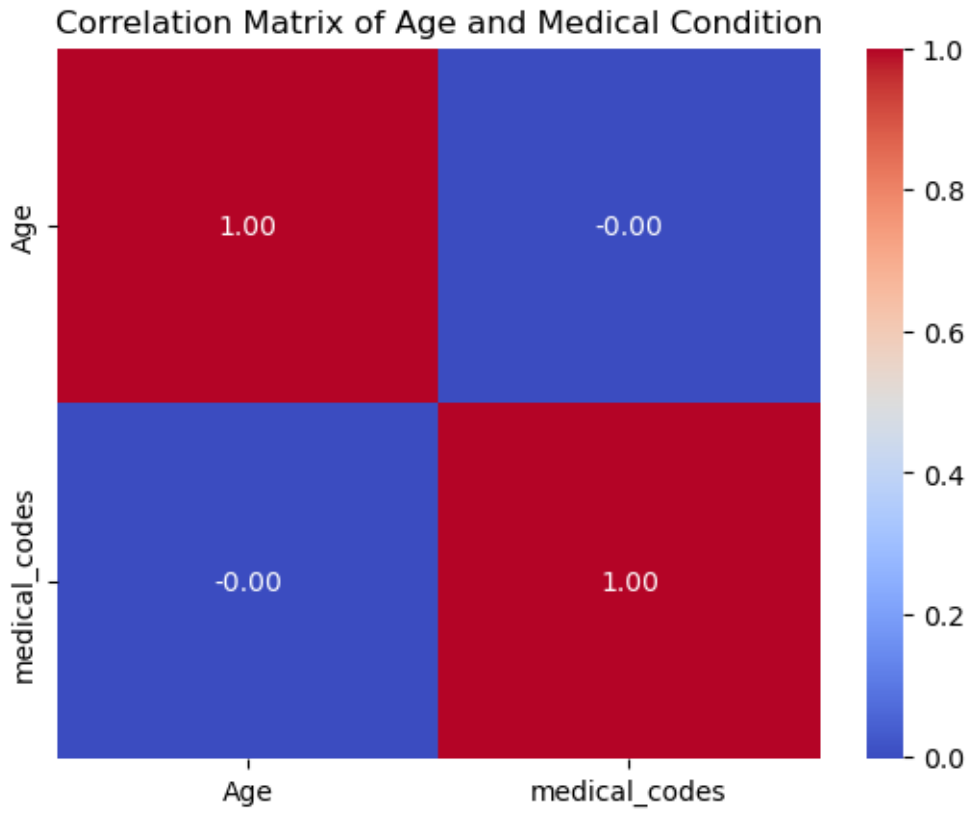
[59]:
```
# Convert to categorical and get codes
df['medical_codes'] = pd.Categorical(df['Medical Condition']).codes
df.head()
```

[59]:

	Name	Age	Gender	Blood Type	Medical Condition	Date of Admission	Doctor	Hospital	Insurance Provider	Billing Amount	Room Number	Admission Type	Discharge Date	Medication	Test Results	stay_length	medical_codes
0	Tiffany Ramirez	81	Female	O-	Diabetes	1	Patrick Parker	Wallace-Hamilton	Medicare	37490	146	Elective	1	Aspirin	Inconclusive	0	3
1	Ruben Burns	35	Male	O+	Asthma	1	Diane Jackson	Burke, Griffin and Cooper	UnitedHealthcare	47304	404	Emergency	15	Lipitor	Normal	14	1
2	Chad Byrd	61	Male	B-	Obesity	1	Paul Baker	Walton LLC	Medicare	36874	292	Emergency	8	Lipitor	Normal	7	5
3	Antonio Frederick	49	Male	B-	Asthma	1	Brian Chandler	Garcia Ltd	Medicare	23303	480	Urgent	3	Penicillin	Abnormal	2	1
4	Mrs. Brandy Flowers	51	Male	O-	Arthritis	1	Dustin Griffin	Jones, Brown and Murray	UnitedHealthcare	18086	477	Urgent	2	Paracetamol	Normal	1	0

[65]:
```
data=df[["Age","medical_codes"]]
corr_matrix=data.corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title("Correlation Matrix of Age and Medical Condition")
```

[65]:
```
Text(0.5, 1.0, 'Correlation Matrix of Age and Medical Condition')
```



Research Analysis The above correlation matrix show that there is no significant correlation between Age and Medical condition.

21 17. Gender and Medical Condition Correlation:

Determine if there are gender-based disparities in the prevalence or treatment outcomes of certain medical conditions.

[61]:
```
df['gender_codes'] = pd.Categorical(df['Gender']).codes
df.head()
```

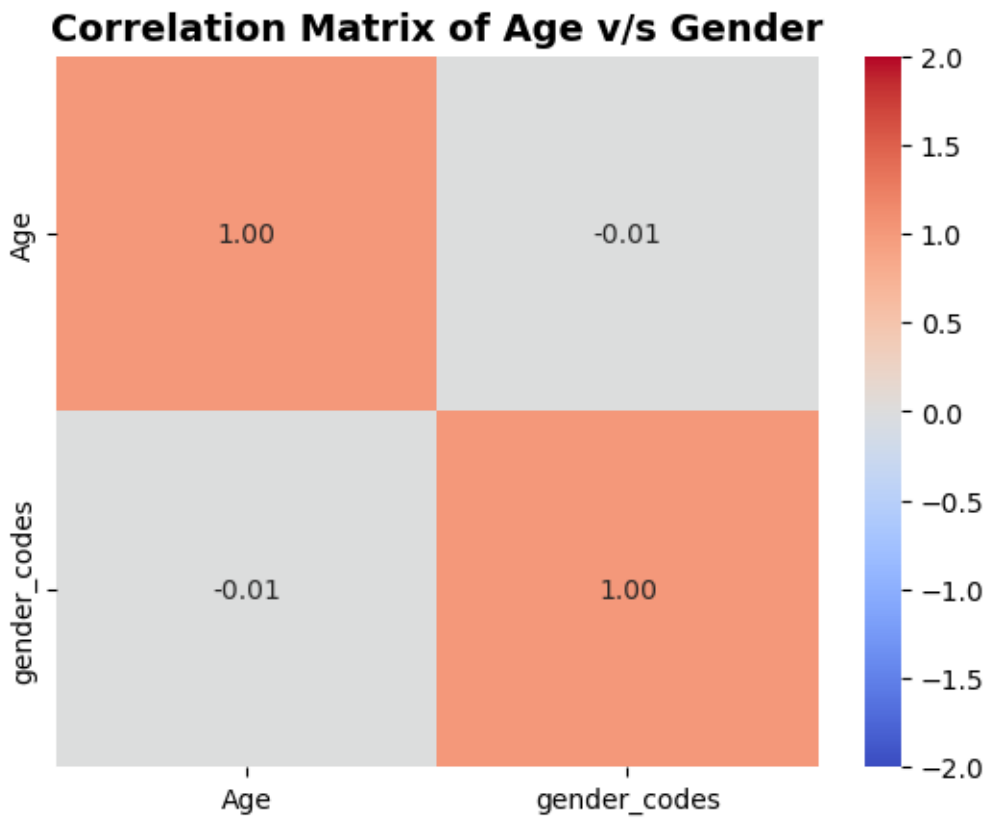
[61]:

	Name	Age	Gender	Blood Type	Medical Condition	Date of Admission	Doctor	Hospital
0	Tiffany Ramirez	81	Female	O-	Diabetes	1	Patrick Parker	Wallace-Hamilton
1	Ruben Burns	35	Male	O+	Asthma	1	Diane Jackson	Burke, Griffin and Cooper
2	Chad Byrd	61	Male	B-	Obesity			
3	Antonio Frederick	49	Male	B-	Asthma			
4	Mrs. Brandy Flowers	51	Male	O-	Arthritis			

```
2                  1      Paul Baker                 Walton LLC
3                  1  Brian Chandler                 Garcia Ltd
4                  1  Dustin Griffin    Jones, Brown and Murray

  Insurance Provider  Billing Amount  Room Number Admission Type  \
0          Medicare           37490          146       Elective
1   UnitedHealthcare           47304          404      Emergency
2          Medicare           36874          292      Emergency
3          Medicare           23303          480         Urgent
4   UnitedHealthcare           18086          477         Urgent

   Discharge Date   Medication  Test Results  stay_length  medical_codes  \
0               1      Aspirin  Inconclusive            0              3
1              15      Lipitor        Normal           14              1
2               8      Lipitor        Normal            7              5
3               3   Penicillin      Abnormal            2              1
4               2  Paracetamol        Normal            1              0

   gender_codes
0             0
1             1
2             1
3             1
4             1
```

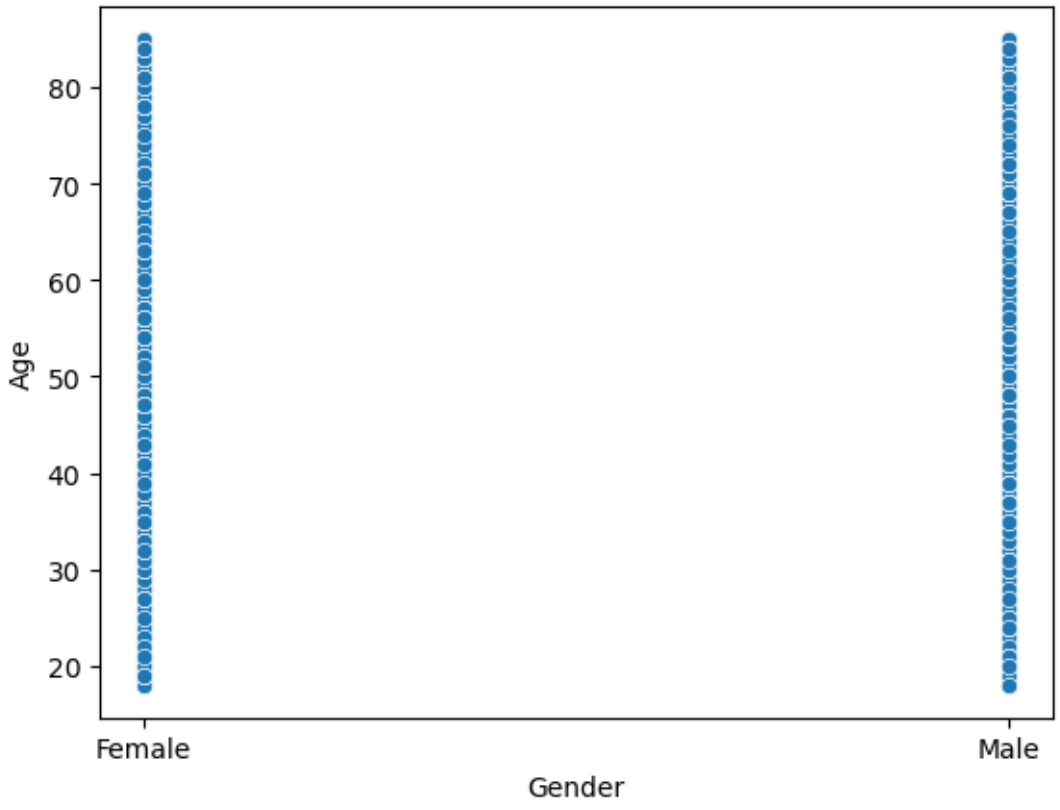
[68]:
```
data=df[["Age","gender_codes"]]
corr_matrix=data.corr()
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f', vmin=-2,␣
 ↪vmax=2)

plt.title("Correlation Matrix of Age v/s Gender", fontsize=14,␣
 ↪fontweight='bold')
```

[68]:
```
Text(0.5, 1.0, 'Correlation Matrix of Age v/s Gender')
```



[79]:
```
sns.scatterplot(y='Age', x="Gender", data=df)
```

[79]: <Axes: xlabel='Gender', ylabel='Age'>



Research Analysis: In correlation matrix -0.01 indicates there is no correlation between Age and Gender.

22 18. Insurance Coverage and Billing Amount:

Analyze if there's any correlation between the patient's insurance provider and the billed amount for services.

[69]:
```
df['Insurance_codes'] = pd.Categorical(df['Insurance Provider']).codes
df.head()
```

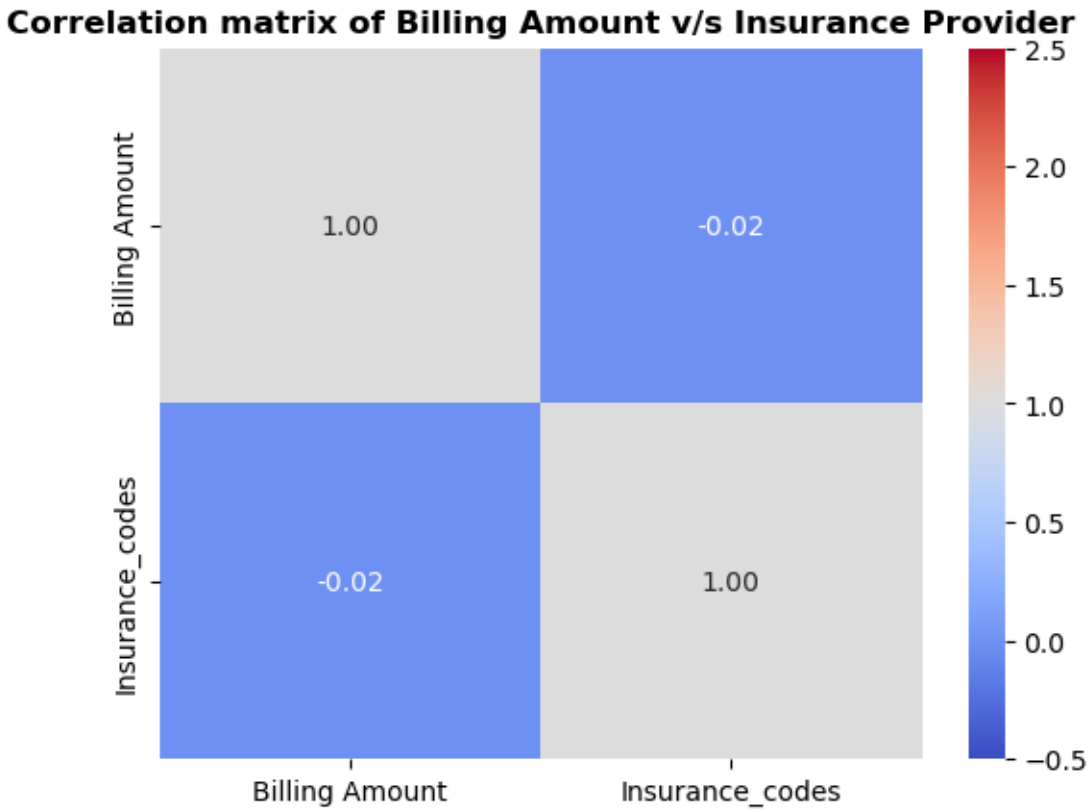
[69]:

	Name	Age	Gender	Blood Type	Medical Condition	Date of Admission	Doctor	Hospital
0	Tiffany Ramirez	81	Female	O-	Diabetes	1	Patrick Parker	Wallace-Hamilton
1	Ruben Burns	35	Male	O+	Asthma	1	Diane Jackson	Burke, Griffin and Cooper
2	Chad Byrd	61	Male	B-	Obesity			
3	Antonio Frederick	49	Male	B-	Asthma			
4	Mrs. Brandy Flowers	51	Male	O-	Arthritis			

```
2                   1      Paul Baker                  Walton LLC
3                   1  Brian Chandler                  Garcia Ltd
4                   1  Dustin Griffin    Jones, Brown and Murray

  Insurance Provider  Billing Amount  Room Number Admission Type  \
0          Medicare           37490          146       Elective
1   UnitedHealthcare           47304          404      Emergency
2          Medicare           36874          292      Emergency
3          Medicare           23303          480         Urgent
4   UnitedHealthcare           18086          477         Urgent

   Discharge Date   Medication  Test Results  stay_length  medical_codes  \
0               1      Aspirin  Inconclusive            0              3
1              15      Lipitor        Normal           14              1
2               8      Lipitor        Normal            7              5
3               3   Penicillin      Abnormal            2              1
4               2  Paracetamol        Normal            1              0

   gender_codes  Insurance_codes
0             0                3
1             1                4
2             1                3
3             1                3
4             1                4
```

[75]:
```
data=df[["Billing Amount", "Insurance_codes"]]
corr_matrix=data.corr()
sns.heatmap(corr_matrix,annot=True, fmt='.2f', cmap="coolwarm", vmin=-0.5,␣
 ↪vmax=2.5)
plt.title("Correlation matrix of Billing Amount v/s Insurance Provider",␣
 ↪fontweight="bold")
```

[75]:
```
Text(0.5, 1.0, 'Correlation matrix of Billing Amount v/s Insurance Provider')
```



Research Analysis: There is weak or almost no linear relationship between Billing amount and Insurance provider

23 Conclusion

A comprehensive analysis of various aspects of healthcare data, including demographics, medical conditions, billing, and insurance. The data suggests that females in the 50-60 age groups are the most admitted patients, with cancer being the predominant diagnosis, while males are often diagnosed with hypertension. Hence, promoting healthcare awareness among this age group, particularly for Cancer and Hypertension, is crucial.

Additionally, individuals with AB negative blood group should be educated about these diseases as they represent a significant portion of admitted patients.

Moreover, raising awareness about Asthma is essential since it's the most prevalent medical condition among all patients.

[ ]: