Comprehensive Analysis of Electronic Health Record Data using Python

In [275]:
```
# Importing the required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import date
from scipy.stats import chi2_contingency
```

Basic Analysis and understanding of the data

In [2]:
```
# Load the datasets
patients = pd.read_csv(r"D:\DSML class\Real world data assignments\Python\EHR Analysis\Data\PATIENTS.csv")
admissions = pd.read_csv(r"D:\DSML class\Real world data assignments\Python\EHR Analysis\Data\ADMISSIONS.csv")
diagnosis = pd.read_csv(r"D:\DSML class\Real world data assignments\Python\EHR Analysis\Data\DIAGNOSES_ICD.csv")
icd = pd.read_csv(r"D:\DSML class\Real world data assignments\Python\EHR Analysis\Data\D_ICD_DIAGNOSES.csv")
```

Observation of the data

In [3]:
```
print('\nFirst five rows of the Patients table')
patients.head(5)
```

```
First five rows of the Patients table
```

Out[3]:

	row_id	subject_id	gender	dob
0	9467	10006	F	2094-03-05 0:00:00
1	9472	10011	F	2090-06-05 0:00:00
2	9474	10013	F	2038-09-03 0:00:00
3	9478	10017	F	2075-09-21 0:00:00
4	9479	10019	M	2114-06-20 0:00:00

In [4]:
```
patients.shape
```

Out[4]: (100, 4)

In [5]:
```
print('\nFirst five rows of the Admissions table')
admissions.head(5)
```

```
First five rows of the Admissions table
```

Out[5]:

	row_id	subject_id	hadm_id	admittime	dischtime	deathtime	admission_type	admission_location	insurance	language	religion	marital_status	ethnicity
0	12258	10006	142345	2164-10-23 21:09:00	2164-11-01 17:15:00	NaN	EMERGENCY	EMERGENCY ROOM ADMIT	Medicare	NaN	CATHOLIC	SEPARATED	BLACK/AFRICAN AMERICAN
1	12263	10011	105331	2126-08-14 22:32:00	2126-08-28 18:59:00	2126-08-28 18:59:00	EMERGENCY	TRANSFER FROM HOSP/EXTRAM	Private	NaN	CATHOLIC	SINGLE	UNKNOWN/NOT SPECIFIED
2	12265	10013	165520	2125-10-04 23:36:00	2125-10-07 15:13:00	2125-10-07 15:13:00	EMERGENCY	TRANSFER FROM HOSP/EXTRAM	Medicare	NaN	CATHOLIC	NaN	UNKNOWN/NOT SPECIFIED
3	12269	10017	199207	2149-05-26 17:19:00	2149-06-03 18:42:00	NaN	EMERGENCY	EMERGENCY ROOM ADMIT	Medicare	NaN	CATHOLIC	DIVORCED	WHITE
4	12270	10019	177759	2163-05-14 20:43:00	2163-05-15 12:00:00	2163-05-15 12:00:00	EMERGENCY	TRANSFER FROM HOSP/EXTRAM	Medicare	NaN	CATHOLIC	DIVORCED	WHITE

In [6]:
```
admissions.shape
```

Out[6]: (129, 17)

In [7]:
```
print('\nFirst five rows of the Diagnosis table')
diagnosis.head(5)
```

```
First five rows of the Diagnosis table
```

Out[7]:

	row_id	subject_id	hadm_id	icd9_code
0	112344	10006	142345	99591
1	112345	10006	142345	99662
2	112346	10006	142345	5672
3	112347	10006	142345	40391
4	112348	10006	142345	42731

In [8]:
```
diagnosis.shape
```

Out[8]: (1761, 4)

In [9]:
```
print('\nFirst five rows of the ICD codes table')
icd.head(5)
```

```
First five rows of the ICD codes table
```

Out[9]:

	row_id	icd9_code	short_title	long_title
0	1	01716	Erythem nod tb-oth test	Erythema nodosum with hypersensitivity reactio...
1	2	01720	TB periph lymph-unspec	Tuberculosis of peripheral lymph nodes, unspec...
2	3	01721	TB periph lymph-no exam	Tuberculosis of peripheral lymph nodes, bacter...
3	4	01722	TB periph lymph-exam unk	Tuberculosis of peripheral lymph nodes, bacter...
4	5	01723	TB periph lymph-micro dx	Tuberculosis of peripheral lymph nodes, tuberc...

In [10]:
```
icd.shape
```

Out[10]: (14567, 4)

In [11]:
```
#Getting the overview of the dataset structure
patients.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   row_id      100 non-null    int64 
 1   subject_id  100 non-null    int64 
 2   gender      100 non-null    object
 3   dob         100 non-null    object
dtypes: int64(2), object(2)
memory usage: 3.2+ KB
```

In [12]:
```
admissions.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 129 entries, 0 to 128
Data columns (total 17 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   row_id                129 non-null    int64 
 1   subject_id            129 non-null    int64 
 2   hadm_id               129 non-null    int64 
 3   admittime             129 non-null    object
 4   dischtime             129 non-null    object
 5   deathtime             40 non-null     object
 6   admission_type        129 non-null    object
 7   admission_location    129 non-null    object
 8   insurance             129 non-null    object
 9   language              81 non-null     object
 10  religion              128 non-null    object
 11  marital_status        113 non-null    object
 12  ethnicity             129 non-null    object
 13  edregtime             92 non-null     object
 14  edouttime             92 non-null     object
 15  diagnosis             129 non-null    object
 16  hospital_expire_flag  129 non-null    int64 
dtypes: int64(4), object(13)
memory usage: 17.3+ KB
```

In [13]:

```
diagnosis.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1761 entries, 0 to 1760
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   row_id      1761 non-null   int64
 1   subject_id  1761 non-null   int64
 2   hadm_id     1761 non-null   int64
 3   icd9_code   1761 non-null   object
dtypes: int64(3), object(1)
memory usage: 55.2+ KB
```

In [14]:

```
icd.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14567 entries, 0 to 14566
Data columns (total 4 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   row_id       14567 non-null  int64
 1   icd9_code    14567 non-null  object
 2   short_title  14567 non-null  object
 3   long_title   14567 non-null  object
dtypes: int64(1), object(3)
memory usage: 455.3+ KB
```

In [15]:

```
#Checking the summary of numerical columns in admissions table
admissions.describe()
```

Out[15]:

	row_id	subject_id	hadm_id	hospital_expire_flag
count	129.000000	129.000000	129.000000	129.000000
mean	28036.441860	28010.410853	152343.441860	0.310078
std	14036.548988	16048.502883	27858.788248	0.464328
min	12258.000000	10006.000000	100375.000000	0.000000
25%	12339.000000	10088.000000	128293.000000	0.000000
50%	39869.000000	40310.000000	157235.000000	0.000000
75%	40463.000000	42135.000000	174739.000000	1.000000
max	41092.000000	44228.000000	199395.000000	1.000000

In [16]:

```
#Unique values and it's count unique of all columns
print('\nUnique values of categorical columns in admissions table')
(admissions.select_dtypes(include='object')).nunique()
```

```
Unique values of categorical columns in admissions table
```

Out[16]:

```
admittime             129
dischtime             129
deathtime              40
admission_type          3
admission_location      5
insurance               4
language                5
religion               10
marital_status          6
ethnicity               9
edregtime              92
edouttime              92
diagnosis              95
dtype: int64
```

In [17]:

```
print('\nUnique values of all columns in patients table')
patients.nunique()
```

```
Unique values of all columns in patients table
```

Out[17]:

```
row_id        100
subject_id    100
gender          2
dob            99
dtype: int64
```

In [18]:
```
print('\nUnique values of categorical columns in diagnosis table')
(diagnosis.select_dtypes(include='object')).nunique()
```

```
Unique values of categorical columns in diagnosis table
```

Out[18]:
```
icd9_code    580
dtype: int64
```

In [19]:
```
print('\nUnique values of categorical columns in icd table')
(icd.select_dtypes(include='object')).nunique()
```

```
Unique values of categorical columns in icd table
```

Out[19]:
```
icd9_code      14567
short_title    14328
long_title     14562
dtype: int64
```

Insights:

- The given dataset contains the data of 100 unique patients.
- The total number of icd9 codes provided is 14567 where as only 580 codes are being used in the data.

Data Processing

In [20]:
```
#Checking for missing values
patients.isna().sum()
```

Out[20]:
```
row_id        0
subject_id    0
gender        0
dob           0
dtype: int64
```

In [21]:
```
admissions.isna().sum()
```

Out[21]:
```
row_id                   0
subject_id               0
hadm_id                  0
admittime                0
dischtime                0
deathtime               89
admission_type           0
admission_location       0
insurance                0
language                48
religion                 1
marital_status          16
ethnicity                0
edregtime               37
edouttime               37
diagnosis                0
hospital_expire_flag     0
dtype: int64
```

In [22]:
```
diagnosis.isna().sum()
```

Out[22]:
```
row_id        0
subject_id    0
hadm_id       0
icd9_code     0
dtype: int64
```

In [23]:
```
icd.isna().sum()
```

Out[23]:
```
row_id         0
icd9_code      0
short_title    0
long_title     0
dtype: int64
```

In [24]:
```
# Duplicate entry check
patients[patients.duplicated()]
```

Out[24]:

row_id	subject_id	gender	dob

In [25]:
```
admissions[admissions.duplicated()]
```

Out[25]:

row_id	subject_id	hadm_id	admittime	dischtime	deathtime	admission_type	admission_location	insurance	language	religion	marital_status	ethnicity	edregtime

In [26]:
```
diagnosis[diagnosis.duplicated()]
```

Out[26]:

row_id	subject_id	hadm_id	icd9_code

In [27]:
```
icd[icd.duplicated()]
```

Out[27]:

row_id	icd9_code	short_title	long_title

In [28]:
```
#Converting date columns type from object to datetime
patients['dob'] = pd.to_datetime(patients['dob'])
admissions['admittime'] = pd.to_datetime(admissions['admittime'])
admissions['dischtime'] = pd.to_datetime(admissions['dischtime'])
admissions['deathtime'] = pd.to_datetime(admissions['deathtime'])
admissions['edregtime'] = pd.to_datetime(admissions['edregtime'])
admissions['edouttime'] = pd.to_datetime(admissions['edouttime'])
```

Demographic Analysis

In [29]:
```
#Joining the Patients table and Admissions table for further analysis
admpt = admissions.merge(patients[['subject_id', 'gender', 'dob']], how='left',on='subject_id')
```

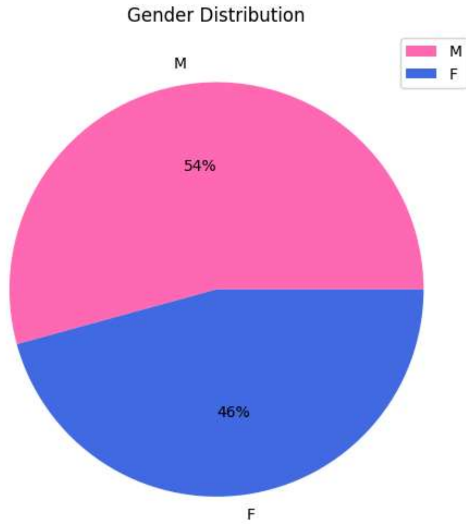
In [30]:
```
#Creating the age column using dob and admittime
admpt['age'] = admpt['admittime'].dt.year - admpt['dob'].dt.year
```

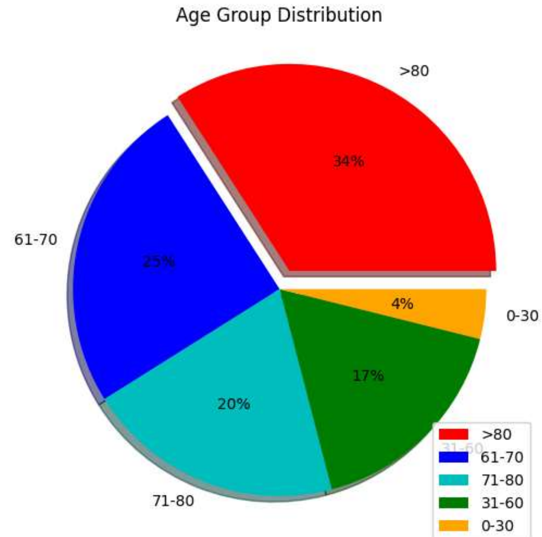
In [31]:
```
#Converting age = 300 to 89
admpt['age'] = admpt['age'].apply(lambda x: 89 if x == 300 else x)
```

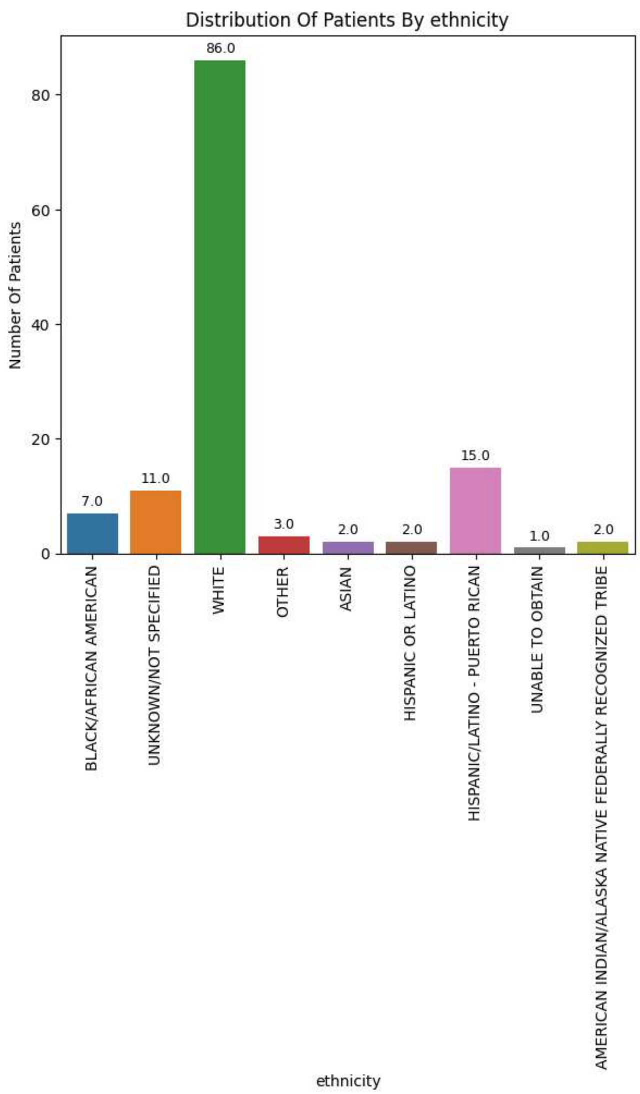
In [32]:
```
admpt['agegroup'] = pd.cut(admpt['age'], bins=[0,30, 60, 70, 80, 100], labels=['0-30', '31-60', '61-70', '71-80', '>80'])
```

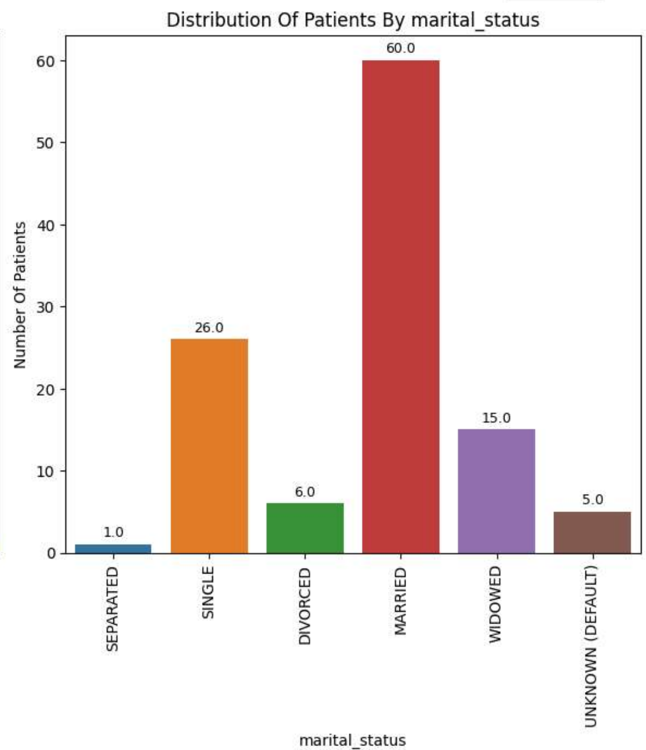
In [33]:

```python
# Plotting the distribution of Gender, Age group, Ethnicity and Marital status
plt.figure(figsize=(12,15))
columns = ['ethnicity', 'marital_status']
plt.subplot(2,2,1)
admpt['gender'].value_counts().plot(kind='pie',
                                        autopct='%1.0f%%',
                                        colors=['hotpink', 'royalblue'],
                                        legend=True,
                                        ylabel='')
plt.title('Gender Distribution')

plt.subplot(2,2,2)
admpt['agegroup'].value_counts().plot(kind='pie',
                                          autopct='%1.0f%%',
                                          legend=True,
                                          explode = (0.1, 0, 0, 0, 0),
                                          colors=['r','b','c','g', 'orange'],
                                          shadow=True,
                                          ylabel='')
plt.title('Age Group Distribution')

for i, column in enumerate(columns, 3):
    plt.subplot(2,2,i)
    ax = sns.countplot(data=admpt, x=column)
    for p in ax.patches:
        ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                    ha='center', va='baseline', fontsize=9, color='black', xytext=(0, 5),
                    textcoords='offset points')
    plt.title(f'Distribution Of Patients By {column}')
    plt.xlabel(column)
    plt.ylabel('Number Of Patients')
    plt.xticks(rotation=90)
plt.tight_layout(h_pad=4)
plt.show()
```


Gender Distribution
M
F
54%
46%


Age Group Distribution
>80
61-70
71-80
31-60
0-30
34%
25%
20%
17%
4%


Distribution Of Patients By ethnicity
Number Of Patients
ethnicity
0
20
40
60
80
7.0
11.0
86.0
3.0
2.0
2.0
15.0
1.0
2.0
BLACK/AFRICAN AMERICAN
UNKNOWN/NOT SPECIFIED
WHITE
OTHER
ASIAN
HISPANIC OR LATINO
HISPANIC/LATINO - PUERTO RICAN
UNABLE TO OBTAIN
AMERICAN INDIAN/ALASKA NATIVE FEDERALLY RECOGNIZED TRIBE


Distribution Of Patients By marital_status
Number Of Patients
marital_status
0
10
20
30
40
50
60
1.0
26.0
6.0
60.0
15.0
5.0
SEPARATED
SINGLE
DIVORCED
MARRIED
WIDOWED
UNKNOWN (DEFAULT)

Admission Characteristics

Readmission Rate

In [34]:
```
ion pattern')
bject_id').agg({'admittime': 'count'}).reset_index().rename({'admittime': 'admissioncount'}, axis=1)['admissioncount'].value_counts()
```

```
Readmission pattern
```

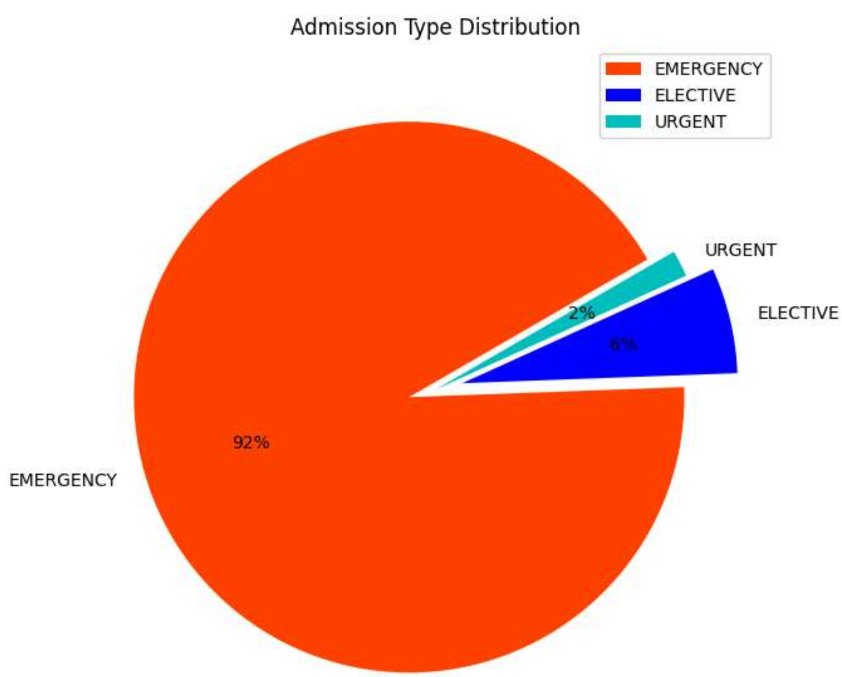
Out[34]:
```
1     86
2     11
3      2
15     1
Name: admissioncount, dtype: int64
```

Insights:

- One patient was admitted 15 times to the hospital and two patients were admitted three times.
- Eleven patients were admitted twice and rest of the patients were admitted only once.
- The data shows that the redmission rates are pretty less provided a few number of patients were admitted more than once.

Admission type frequency

In [35]:
```
plt.figure(figsize=(8,6))
admpt['admission_type'].value_counts().plot(kind='pie',
                                            autopct='%1.0f%%',
                                            legend=True,
                                            explode = (0.1, 0.1, 0),
                                            colors=['orangered','b','c'],
                                             startangle=30,
                                            ylabel='')
plt.title('Admission Type Distribution')
plt.tight_layout()
plt.show()
```



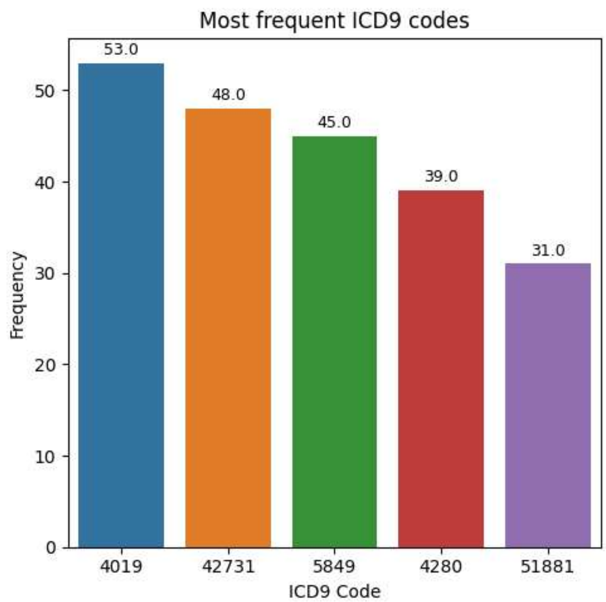
Insights:

- 92% of the admission types of the given dataset is emergency.
- Only 2% of the admissions are urgent and 6% are elective.

Diagnosis Analysis

Most Frequent ICD9 Diagnosis

In [107]:
```
d = diagnosis.groupby('icd9_code').agg({'subject_id': 'count'}).reset_index().rename({'subject_id': 'frequency'}, axis=1).sort_values(
plt.figure(figsize=(5,5))
ax = sns.barplot(data=d, x='icd9_code', y='frequency')
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=9, color='black', xytext=(0, 5),
                textcoords='offset points')
plt.title('Most frequent ICD9 codes')
plt.xlabel('ICD9 Code')
plt.ylabel('Frequency')
plt.tight_layout()
plt.show()
```



Insights:

- The most frequent ICD9 diagnosis is 4019 wich was diagnosed 53 times.
- The top 5 frequent ICD9 diagnosis are 4019, 42731, 5849, 4280 and 51881 with a frequency of 53, 48, 45, 39 and 31 times diagnosed respectively.

Associations between Diagnosis and Patient Outcomes

Diagnosis vs Length of stay

In [141]:
```
#Creating the length of stay column form discchrge time and admit time
admpt['stay_length'] = (admpt['dischtime'] - admpt['admittime']).astype('timedelta64[D]').astype(int)
```

In [143]:
```
#Joining the Patients table, Admissions table and Diagnosis for further analysis
admptdiag = admpt.merge(diagnosis[['hadm_id', 'icd9_code']], how='right', on='hadm_id')
```

In [205]:

```
# Association between diagnosis and length of stay
admptdiag.groupby(['diagnosis']).agg({'stay_length':'max', 'subject_id': 'nunique', 'icd9_code': 'nunique'}).reset_index().sort_values
```

Out[205]:

	diagnosis	stay_length	subject_id	icd9_code
28	FACIAL NUMBNESS	123	1	36
26	ESOPHAGEAL CA/SDA	39	2	19
5	ACUTE RESPIRATORY DISTRESS SYNDROME;ACUTE RENA...	36	1	24
46	LIVER FAILURE	35	2	26
72	SEIZURE;STATUS EPILEPTICUS	32	1	19
...	...	...	...	...
57	PLEURAL EFFUSION	0	1	8
79	STEMI;	0	1	14
78	STATUS POST MOTOR VEHICLE ACCIDENT WITH INJURIES	0	1	5
60	PNEUMONIA;TELEMETRY	0	1	9
94	VOLVULUS	0	1	19

95 rows × 4 columns

Insights:

- A paatient with Facial Numbness diagnosis was admitted with 36 different ICD9 codes with a stay length of 123 days which is the highest of all admissions.
- The diagnosis ESOPHAGEAL CA/SDA has the second highest stay length with 39 days.

Diagnosis vs Readmission Rate

In [242]:

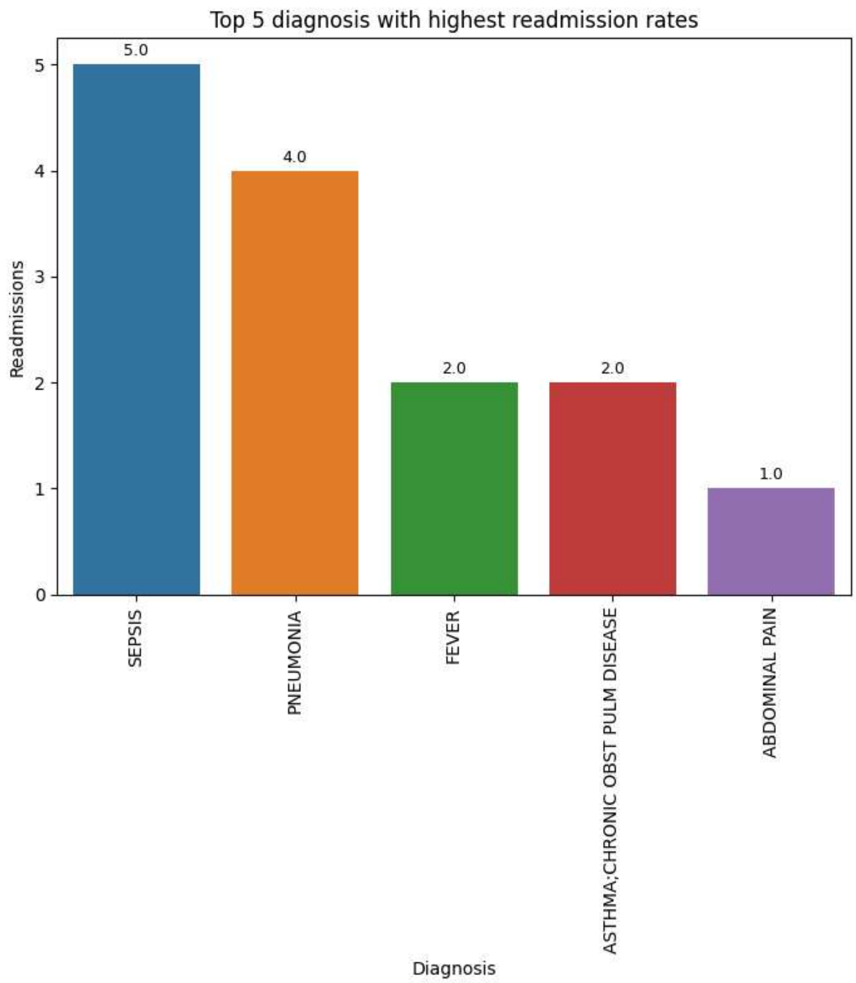
```
#Top 5 diagnosis with highest readmission rates
top5readm = admpt.groupby(['diagnosis', 'subject_id']).agg({'hadm_id': 'count'}).reset_index().rename({'hadm_id': 'readmissions'}, axi
top5readm
```

Out[242]:

	diagnosis	subject_id	readmissions
93	SEPSIS	41976	5
70	PNEUMONIA	41976	4
36	FEVER	10117	2
11	ASTHMA;CHRONIC OBST PULM DISEASE	41795	2
0	ABDOMINAL PAIN	40687	1

In [247]:

```
plt.figure(figsize=(7,8))
ax = sns.barplot(data=top5readm, x='diagnosis', y='readmissions')
for p in ax.patches:
    ax.annotate(f'{p.get_height()}', (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=9, color='black', xytext=(0, 5),
                textcoords='offset points')
plt.title('Top 5 diagnosis with highest readmission rates')
plt.xlabel('Diagnosis')
plt.ylabel('Readmissions')
plt.xticks(rotation=90)
plt.tight_layout()
plt.show()
```



Mortality Analysis

Mortality Rates for Different Diagnosis and Admission Types

In [268]:
```
admpt.groupby(['diagnosis', 'admission_type']).agg({'hospital_expire_flag': 'sum'}).reset_index().sort_values(by='hospital_expire_flag
```

Out[268]:

	diagnosis	admission_type	no_of_deaths
22	CONGESTIVE HEART FAILURE	EMERGENCY	2
46	LIVER FAILURE	EMERGENCY	2
73	SEPSIS	EMERGENCY	2
30	FEVER	EMERGENCY	2
0	ABDOMINAL PAIN	EMERGENCY	1
71	SEIZURE	EMERGENCY	1
35	HEPATITIS B	EMERGENCY	1
39	HYPOTENSION	EMERGENCY	1
43	INFERIOR MYOCARDIAL INFARCTION\CATH	EMERGENCY	1
48	LUNG CANCER;SHORTNESS OF BREATH	EMERGENCY	1
51	METASTIC MELANOMA;ANEMIA	EMERGENCY	1
60	PNEUMONIA;TELEMETRY	EMERGENCY	1
68	S/P FALL	EMERGENCY	1
70	S/P MOTORCYCLE ACCIDENT	EMERGENCY	1
72	SEIZURE;STATUS EPILEPTICUS	EMERGENCY	1
76	SEPSIS;TELEMETRY	EMERGENCY	1
77	SHORTNESS OF BREATH	EMERGENCY	1
78	STATUS POST MOTOR VEHICLE ACCIDENT WITH INJURIES	EMERGENCY	1
79	STEMI;	EMERGENCY	1
80	STROKE/TIA	EMERGENCY	1
81	SUBDURAL HEMATOMA/S/P FALL	EMERGENCY	1
84	TACHYPNEA;TELEMETRY	EMERGENCY	1
86	TRACHEAL STENOSIS	EMERGENCY	1
88	UPPER GI BLEED	EMERGENCY	1
93	VF ARREST	URGENT	1
34	HEPATIC ENCEP	EMERGENCY	1
47	LOWER GI BLEED	EMERGENCY	1
94	VOLVULUS	EMERGENCY	1
24	CRITICAL AORTIC STENOSIS/HYPOTENSION	EMERGENCY	1
16	CEREBROVASCULAR ACCIDENT	EMERGENCY	1
12	BASAL GANGLIN BLEED	EMERGENCY	1
9	AROMEGLEY;BURKITTS LYMPHOMA	EMERGENCY	1
8	ALTERED MENTAL STATUS	EMERGENCY	1
21	CHRONIC MYELOGENOUS LEUKEMIA;TRANSFUSION REACTION	EMERGENCY	1
7	ALCOHOLIC HEPATITIS	EMERGENCY	1
2	ACUTE CHOLANGITIS	EMERGENCY	1
3	ACUTE CHOLECYSTITIS	EMERGENCY	0
75	SEPSIS;PNEUMONIA;TELEMETRY	EMERGENCY	0
64	RENAL CANCER/SDA	ELECTIVE	0
65	RENAL FAILIURE-SYNCOPE-HYPERKALEMIA	EMERGENCY	0

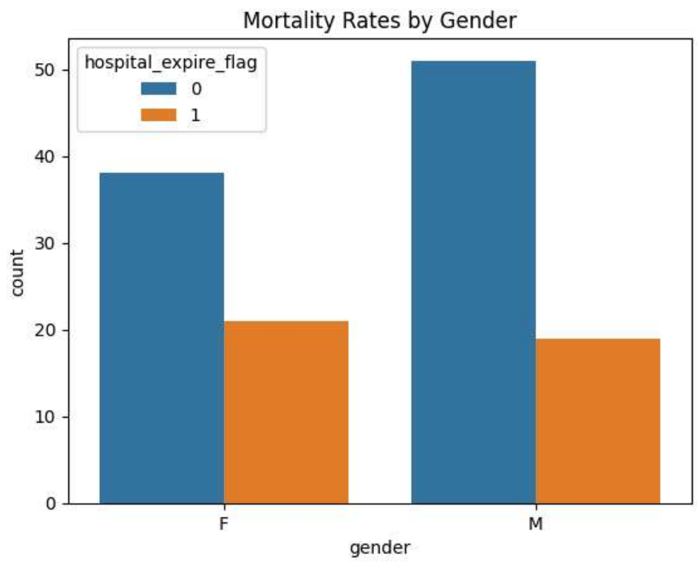
Insights:

- Most of the deaths happened with the admission type Emergency.
- Congestive heart failure, liver failure, sepsis and fever has the highest number of deaths of 2 in each.

Correlations between Patient Demographics and Mortality Rates

Gender vs Mortality rates

In [271]:
```
# Visualize mortality rates by gender
sns.countplot(data=admpt, x="gender", hue="hospital_expire_flag")
plt.title("Mortality Rates by Gender")
plt.show()
```



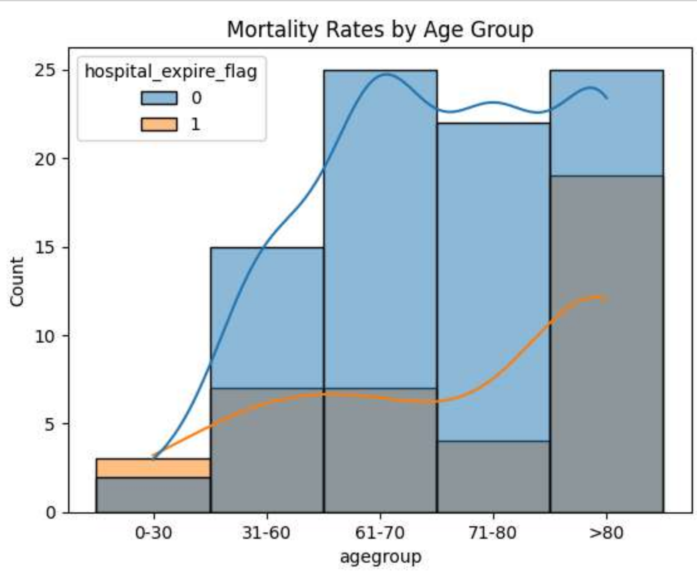
In [285]:
```
# Chi-square test for gender and mortality
gender_mortality_contingency = pd.crosstab(admpt["gender"], admpt["hospital_expire_flag"])
chi2, p, _, _ = chi2_contingency(gender_mortality_contingency)
print("Chi-square p-value for gender and mortality:", p)
```

```
Chi-square p-value for gender and mortality: 0.3993917889521913
```

Insights:

- A p-value of 0.39 suggests that there is no significant association between gender and mortality rates

In [274]:
```
# Explore mortality rates by age group
sns.histplot(data=admpt, x="agegroup", hue="hospital_expire_flag", kde=True)
plt.title("Mortality Rates by Age Group")
plt.show()
```



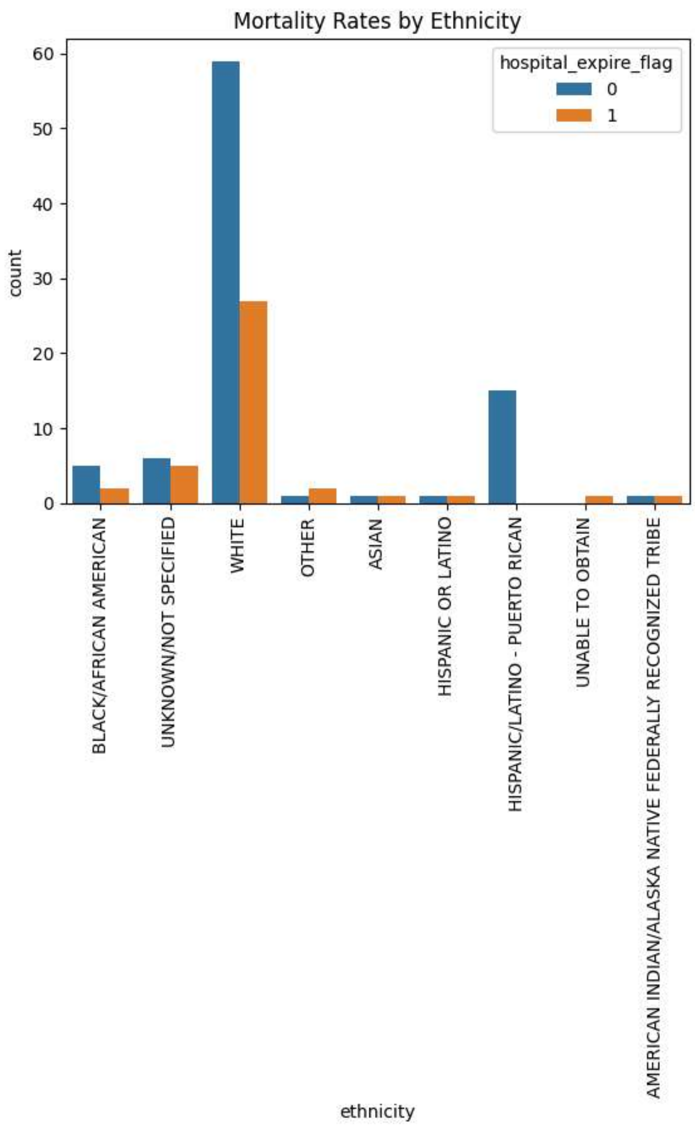
In [291]:
```
agegroup_mortality_contingency = pd.crosstab(admpt["agegroup"], admpt["hospital_expire_flag"])
chi2, p, _, _ = chi2_contingency(agegroup_mortality_contingency)
print("Chi-square p-value for age group and mortality:", p)
```

```
Chi-square p-value for age group and mortality: 0.055517169568212364
```

Insights:

- A chi-square p-value of 0.0555 suggests that there is a borderline significant association between age group and mortality rates.

In [295]:
```
# Visualize mortality rates by ethicity
sns.countplot(data=admpt, x="ethnicity", hue="hospital_expire_flag")
plt.title("Mortality Rates by Ethnicity")
plt.xticks(rotation=90)
plt.show()
```



In [296]:
```
ethnicity_mortality_contingency = pd.crosstab(admpt["ethnicity"], admpt["hospital_expire_flag"])
chi2, p, _, _ = chi2_contingency(ethnicity_mortality_contingency)
print("Chi-square p-value for ethnicity and mortality:", p)
```

```
Chi-square p-value for ethnicity and mortality: 0.11675823784989112
```

Insights:

- A chi-square p-value of 0.1168 suggests that there is no significant association between ethnicity and mortality rates.

Overall Insights:

Patient Demographics:

1. The patient population comprises 54% males and 46% females.
2. Age Distribution: 34% of the patients are aged over 80, 25% belong to the 61-70 age group, and 20% fall within the 71-80 age range.
3. Ethnicity: A significant majority (86 patients) are identified as White.
4. Marital Status: 60 patients are married, 26 are single, and 15 are widowed.

Patient Admissions:

1. The dataset includes information on 100 unique patients.
2. A notable observation is the variability in hospital admissions among these patients; one patient was admitted 15 times, two patients were admitted three times each, eleven patients were admitted twice, and the remaining patients had a single admission.

ICD-9 Codes Usage:

1. From a total of 14,567 ICD-9 codes available, only 580 distinct codes are utilized in the dataset.
2. The most frequently recorded ICD-9 code is 4019, documented 53 times. The other common codes include 42731, 5849, 4280, and 51881, highlighting prevalent health issues related to heart and kidney diseases.

Admission Types:

1. The overwhelming majority of admissions (92%) were categorized as emergency, indicating urgent and unplanned medical care. Only 6% were elective, and 2% were urgent admissions.

Length of Stay:

1. A patient diagnosed with Facial Numbness had the longest hospital stay of 123 days, associated with 36 different ICD-9 codes.
2. The second-longest stay was 39 days for a patient with the diagnosis ESOPHAGEAL CA/SDA.

Mortality Rates and Admission Types:

1. Most in-hospital deaths occurred under emergency admissions.
2. Specific conditions such as congestive heart failure, liver failure, sepsis, and fever each recorded two deaths, indicating critical areas of concern.

Statistical Associations:

1. Gender does not show a significant association with mortality rates (p-value: 0.39).
2. There is a borderline significant association between age groups and mortality rates (p-value: 0.0555).
3. No significant association was found between ethnicity and mortality rates (p-value: 0.1168).

Recommendations:

Focus on High-Risk Conditions:

- Implement targeted interventions for conditions frequently leading to readmissions (e.g., heart and kidney diseases), aiming to improve patient outcomes and reduce the burden on healthcare resources.

Enhance Emergency Care:

- Given the high percentage of emergency admissions, enhancing emergency department efficiency and response times could potentially reduce mortality rates and improve patient care.

Monitor and Support Frequent Admitters:

- Develop specialized care plans for patients with multiple admissions to manage their conditions more effectively, possibly involving more rigorous follow-up routines and outpatient support.

Address Age-Specific Needs:

- Considering the borderline significance of age with mortality rates, develop age-specific medical protocols to better address the unique needs of different age groups.

In [ ]: