Predictive Modeling - Logistic Regression

The point of this project is to build on initial data preparation, cleaning, and analysis, enabling us to make assertions vital to organizational needs. In this project, I conduct logistic regression and multiple regression to model the phenomena revealed by data. This project covers normality, homoscedasticity, and significance, preparing us to communicate findings and the limitations of those findings accurately to organizational leaders.

Competencies

Logistic Regression
Employs logistic regression algorithms in describing phenomena.

Multiple Regression
Employs multiple regression algorithms with categorical and numerical predictors in describing phenomena.

Regression Implications
Makes assertions based on regression modeling.

Write Up

Research Question
What variables influence higher additional charges throughout this hospital chain?

Goals
The goal and objective of my analysis is to gain a fundamental understanding of the variables that do and do not have an impact on readmission within this hospital.

Summary of Assumptions

- Categorical y variable
- Linearity with logit(p)
- Low Multicollinearity
- Independent Observations

Logistic regression deals only with a categorical y variable meaning it would be inaccurate to perform logistic regression on a continuous y variable. There is also a linear relationship between the x variable or the explanatory variables and the logit function. “Multicollinearity refers to a linear relationship between any of the x variables,” (Straw, 2023) and these relationships negatively affect the coefficients and therefore negatively affect the overall model. Lastly, the observations should be independent of each other.

My research question focuses on variables that are influential to readmission to the hospital or the main categorical variable. The use of logistic regression helps, “to analyze and understand the relationship between two or more variables of interest.” (Middleton, 2022) Logistic regression looks at relationships between variables through the prediction of outcomes of the categorical response variable. Due to our response variable being categorical, we can perform logistic regression to analyze the research question and predict outcomes of whether a patient will be readmitted to the hospital or not.

Code

In [3]:
```
# Importing packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import missingno as msno
import seaborn as sns
```

In [4]:
```
# Importing medical data CSV and creating the medical_data DataFrame
medical_data = pd.read_csv("C:/Users/Makayla Avendano/Desktop/medical_clean.csv")
```

In [5]:
```
# Looking at columns, non-null counts and data types
medical_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 50 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   CaseOrder           10000 non-null  int64
 1   Customer_id         10000 non-null  object
 2   Interaction         10000 non-null  object
 3   UID                 10000 non-null  object
 4   City                10000 non-null  object
 5   State               10000 non-null  object
 6   County              10000 non-null  object
 7   Zip                 10000 non-null  int64
 8   Lat                 10000 non-null  float64
 9   Lng                 10000 non-null  float64
 10  Population          10000 non-null  int64
 11  Area                10000 non-null  object
 12  TimeZone            10000 non-null  object
 13  Job                 10000 non-null  object
 14  Children            10000 non-null  int64
 15  Age                 10000 non-null  int64
 16  Income              10000 non-null  float64
 17  Marital             10000 non-null  object
 18  Gender              10000 non-null  object
 19  ReAdmis             10000 non-null  object
 20  VitD_levels         10000 non-null  float64
 21  Doc_visits          10000 non-null  int64
 22  Full_meals_eaten    10000 non-null  int64
 23  vitD_supp           10000 non-null  int64
 24  Soft_drink          10000 non-null  object
 25  Initial_admin       10000 non-null  object
 26  HighBlood           10000 non-null  object
 27  Stroke              10000 non-null  object
 28  Complication_risk   10000 non-null  object
 29  Overweight          10000 non-null  object
 30  Arthritis           10000 non-null  object
 31  Diabetes            10000 non-null  object
 32  Hyperlipidemia      10000 non-null  object
 33  BackPain            10000 non-null  object
 34  Anxiety             10000 non-null  object
 35  Allergic_rhinitis   10000 non-null  object
 36  Reflux_esophagitis  10000 non-null  object
 37  Asthma              10000 non-null  object
 38  Services            10000 non-null  object
 39  Initial_days        10000 non-null  float64
 40  TotalCharge         10000 non-null  float64
 41  Additional_charges  10000 non-null  float64
 42  Item1               10000 non-null  int64
 43  Item2               10000 non-null  int64
 44  Item3               10000 non-null  int64
 45  Item4               10000 non-null  int64
 46  Item5               10000 non-null  int64
 47  Item6               10000 non-null  int64
 48  Item7               10000 non-null  int64
 49  Item8               10000 non-null  int64
dtypes: float64(7), int64(16), object(27)
memory usage: 3.8+ MB
```

In [6]:

```
# Drop columns that are not needed
new_med_data = medical_data.drop(columns=['Interaction', 'UID', 'City', 'State', 'Cour
```

In [7]:
```
# Updated data frame
new_med_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 27 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Children            10000 non-null  int64  
 1   Age                 10000 non-null  int64  
 2   Income              10000 non-null  float64
 3   Gender              10000 non-null  object 
 4   ReAdmis             10000 non-null  object 
 5   VitD_levels         10000 non-null  float64
 6   Doc_visits          10000 non-null  int64  
 7   Full_meals_eaten    10000 non-null  int64  
 8   vitD_supp           10000 non-null  int64  
 9   Soft_drink          10000 non-null  object 
 10  Initial_admin       10000 non-null  object 
 11  HighBlood           10000 non-null  object 
 12  Stroke              10000 non-null  object 
 13  Complication_risk   10000 non-null  object 
 14  Overweight          10000 non-null  object 
 15  Arthritis           10000 non-null  object 
 16  Diabetes            10000 non-null  object 
 17  Hyperlipidemia      10000 non-null  object 
 18  BackPain            10000 non-null  object 
 19  Anxiety             10000 non-null  object 
 20  Allergic_rhinitis   10000 non-null  object 
 21  Reflux_esophagitis  10000 non-null  object 
 22  Asthma              10000 non-null  object 
 23  Services            10000 non-null  object 
 24  Initial_days        10000 non-null  float64
 25  TotalCharge         10000 non-null  float64
 26  Additional_charges  10000 non-null  float64
dtypes: float64(5), int64(5), object(17)
memory usage: 2.1+ MB
```

Data Cleaning

Data cleaning is an integral part of any data analysis. To make my analysis as accurate as possible, it is necessary to verify that the data is clean. Cleaning the data involves looking at duplicates, missing values, and outliers.

Duplicates

With duplicates in the data, we are exposed to potential integrity threats including causing inaccuracies and skewing the data with unnecessary inflation. The steps used to clean duplicates in the data include the use of .duplicated and .value_counts to look at the counts of duplicates within each variable.

In [8]:
```
# Duplicates
medical_duplicates = new_med_data.duplicated()
print(medical_duplicates.value_counts())
```

```
False    10000
Name: count, dtype: int64
```

Missing Values

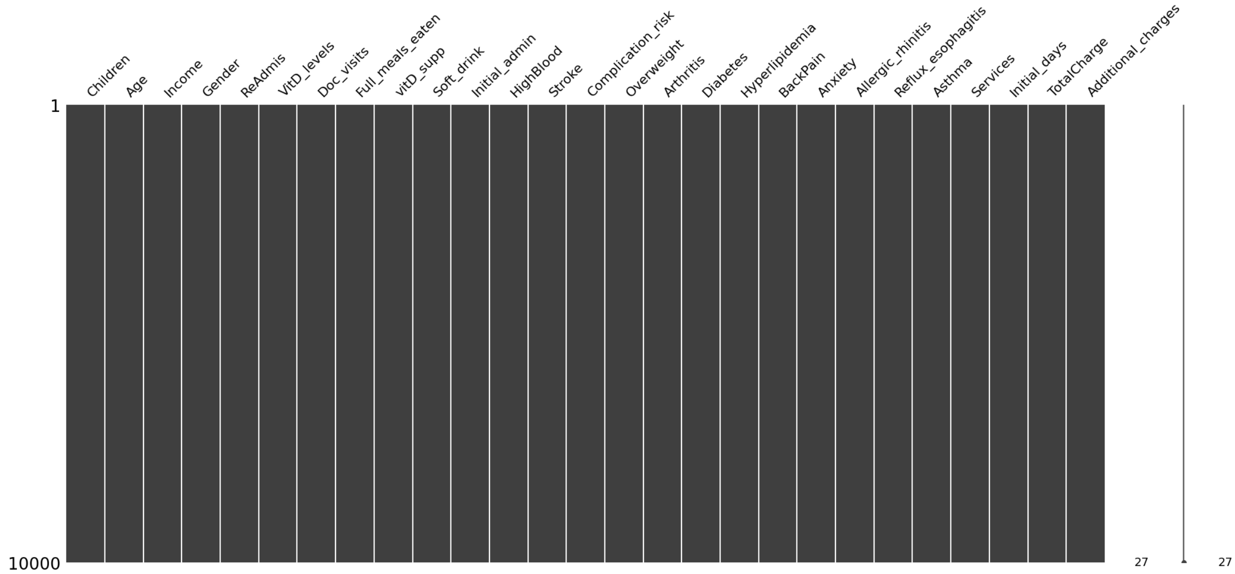
Missing values can also negatively influence the data similar to duplicates through possible integrity threats like inaccuracies and inflation or deflation of values. Missing values were addressed using the pair of the .isnull() and .sum() function. This looked at each variable and indicated whether any values were missing within that variable. I also verified this information with the use of the missingno library and the msno function to create a matrix to indicate no values were missing.

In [9]:
```
# Missing Values
# Sum of all null values within each column
new_med_data.isnull().sum()
```

Out[9]:
```
Children              0
Age                   0
Income                0
Gender                0
ReAdmis               0
VitD_levels           0
Doc_visits            0
Full_meals_eaten      0
vitD_supp             0
Soft_drink            0
Initial_admin         0
HighBlood             0
Stroke                0
Complication_risk     0
Overweight            0
Arthritis             0
Diabetes              0
Hyperlipidemia        0
BackPain              0
Anxiety               0
Allergic_rhinitis     0
Reflux_esophagitis    0
Asthma                0
Services              0
Initial_days          0
TotalCharge           0
Additional_charges    0
dtype: int64
```

In [10]:
```
# Double checking no missing values
msno.matrix(new_med_data)
```

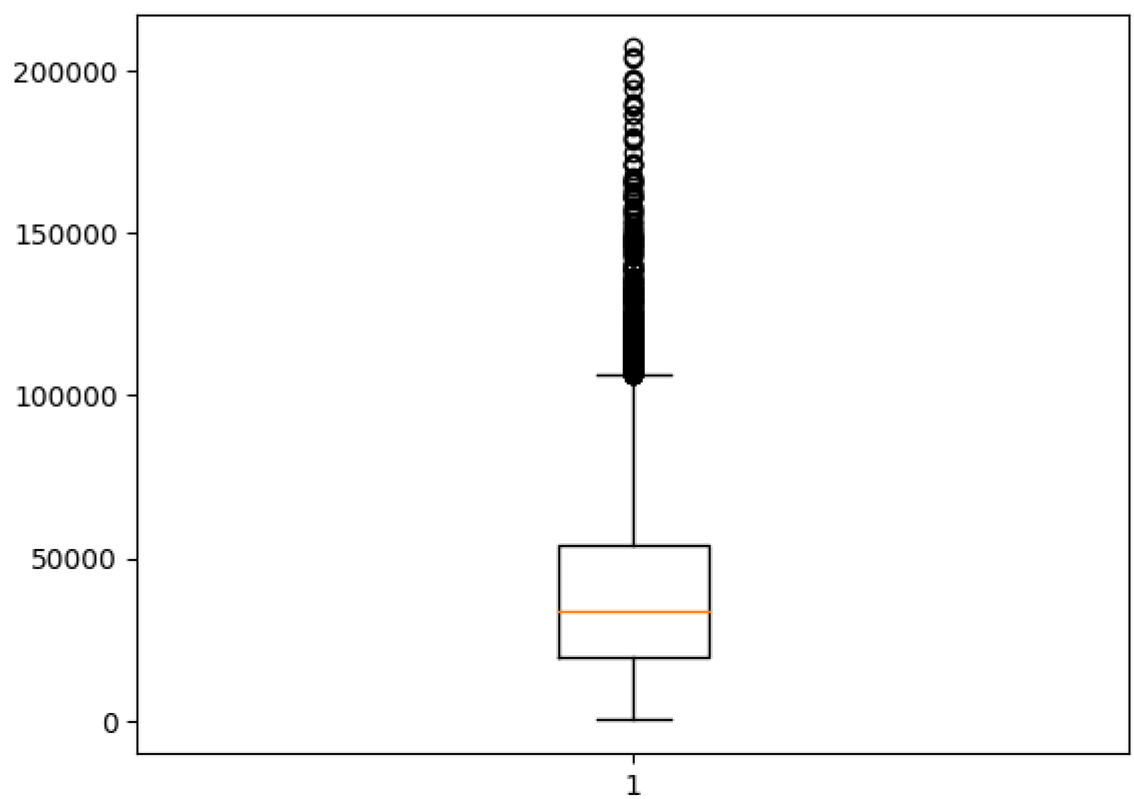
Out[10]:
```
<Axes: >
```



Outliers

Lastly, outliers can distort relationships or individual measurements which would be detrimental to a multiple linear regression model. The outliers were found using box plots and treated using the replace or imputation technique. I used the 95th percentile of the box plot and used NumPy's .where() function to replace all values above the 95th percentile with the median of the variable.

In [12]:
```
IncomePlot = plt.boxplot(x='Income', data = new_med_data)
```



In [13]:
```
# Treat outliers with imputation
percentile_income = np.percentile(new_med_data['Income'], 95)
print(percentile_income)
```

```
96071.83099999995
```

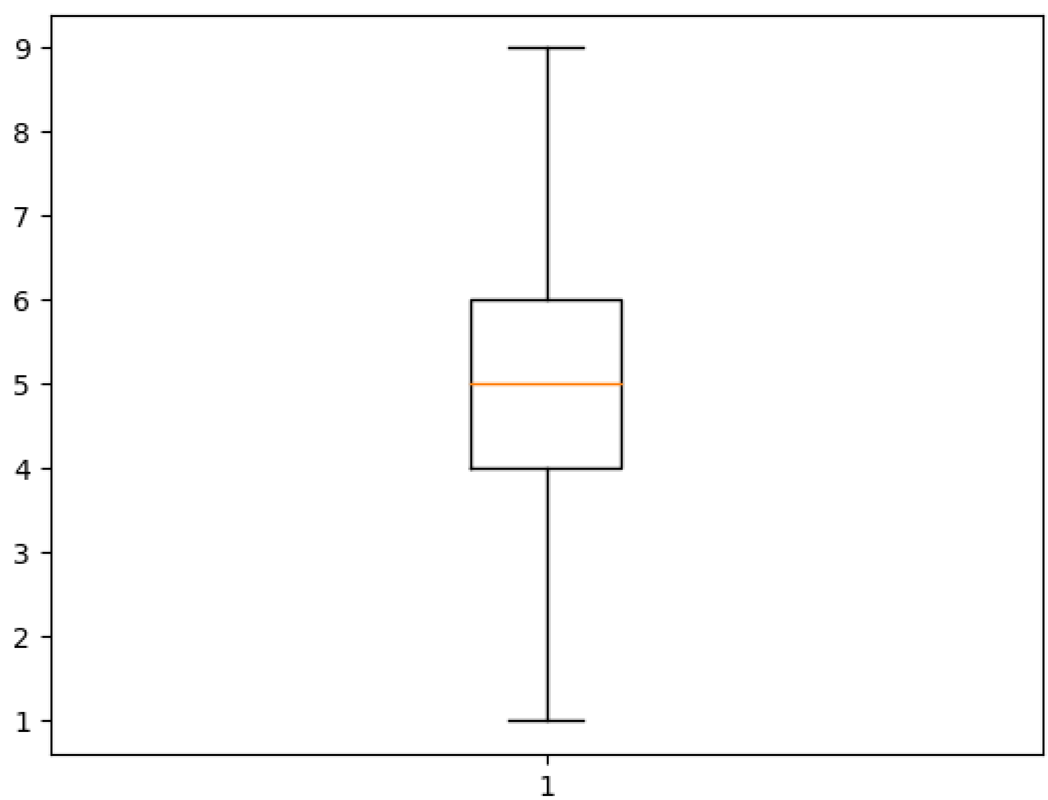
In [14]:
```
# Replacing with the median
median = float(new_med_data['Income'].median())
new_med_data['Income'] = np.where(new_med_data['Income'] > percentile_income, median,
```

In [15]:
```
# Verifying the max value
new_med_data.describe()
```

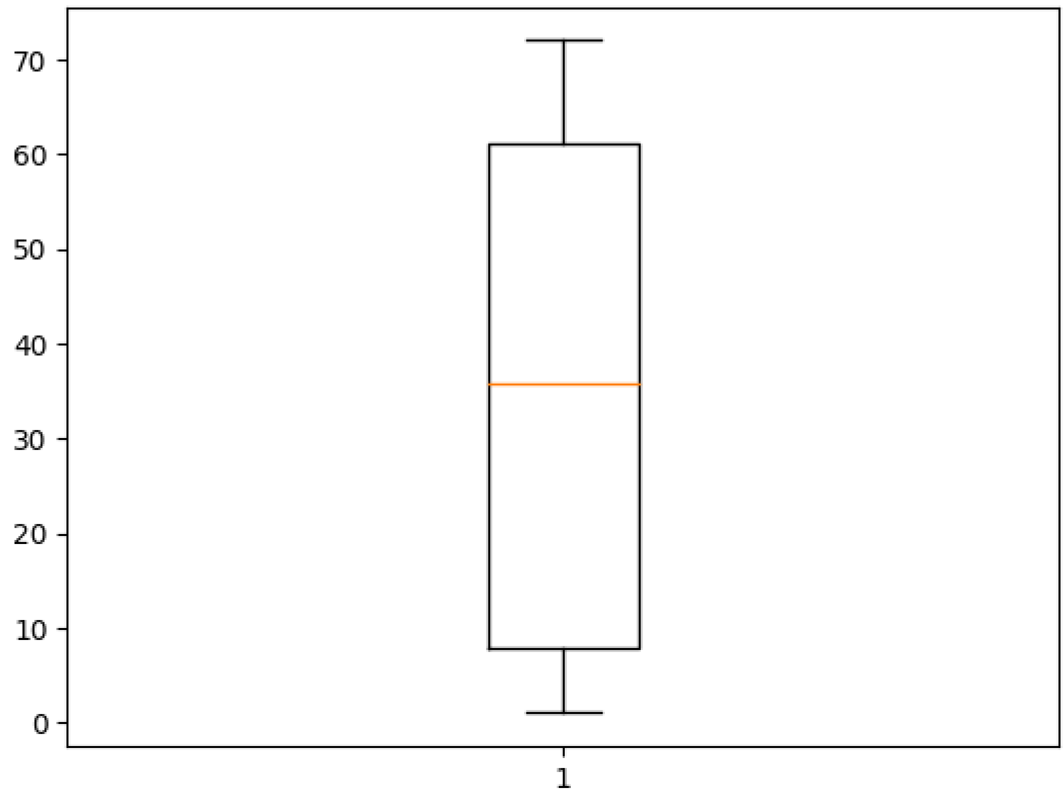
Out[15]:

	Income	Doc_visits	Initial_days	TotalCharge	Additional_charges
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	36188.024603	5.012200	34.455299	5312.172769	12934.528587
std	21376.715194	1.045734	26.309341	2180.393838	6542.601544
min	154.080000	1.000000	1.001981	1938.312067	3125.703000
25%	19598.775000	4.000000	7.896215	3179.374015	7986.487755
50%	33766.005000	5.000000	35.836244	5213.952000	11573.977735
75%	49348.447500	6.000000	61.161020	7459.699750	15626.490000
max	96067.940000	9.000000	71.981490	9180.728000	30566.070000

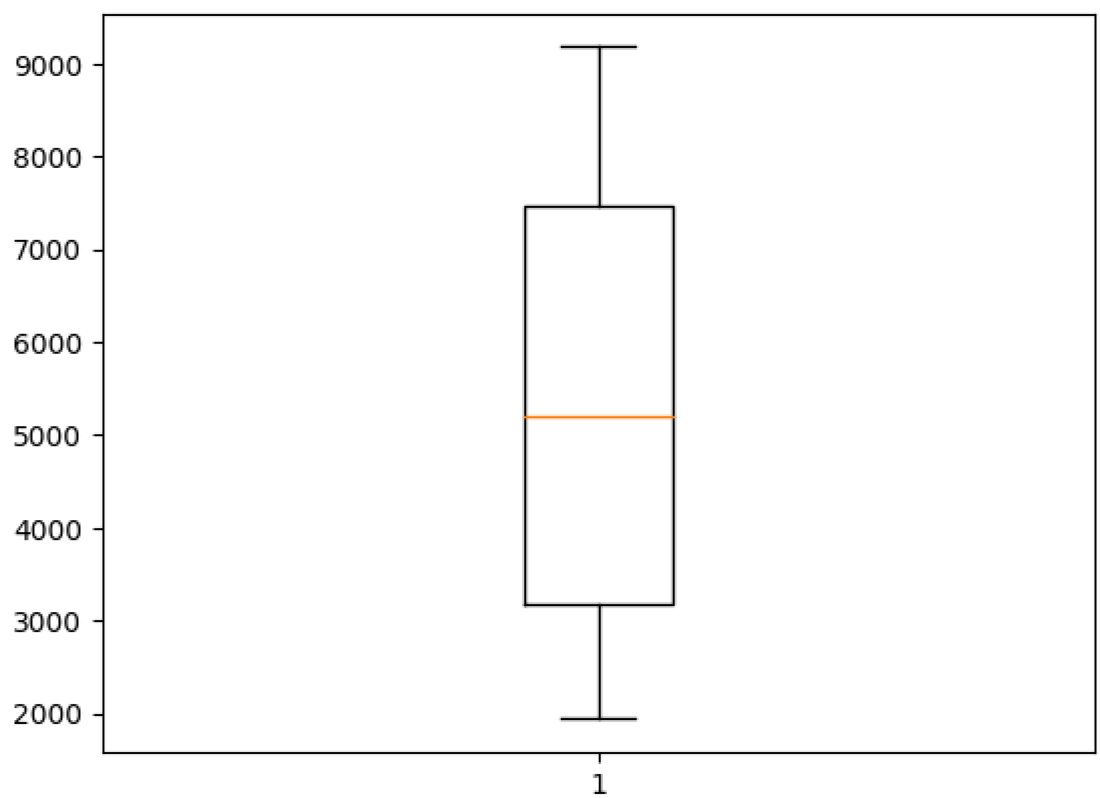
In [16]:
```
Doc_visitsPlot = plt.boxplot(x='Doc_visits', data = new_med_data)
```



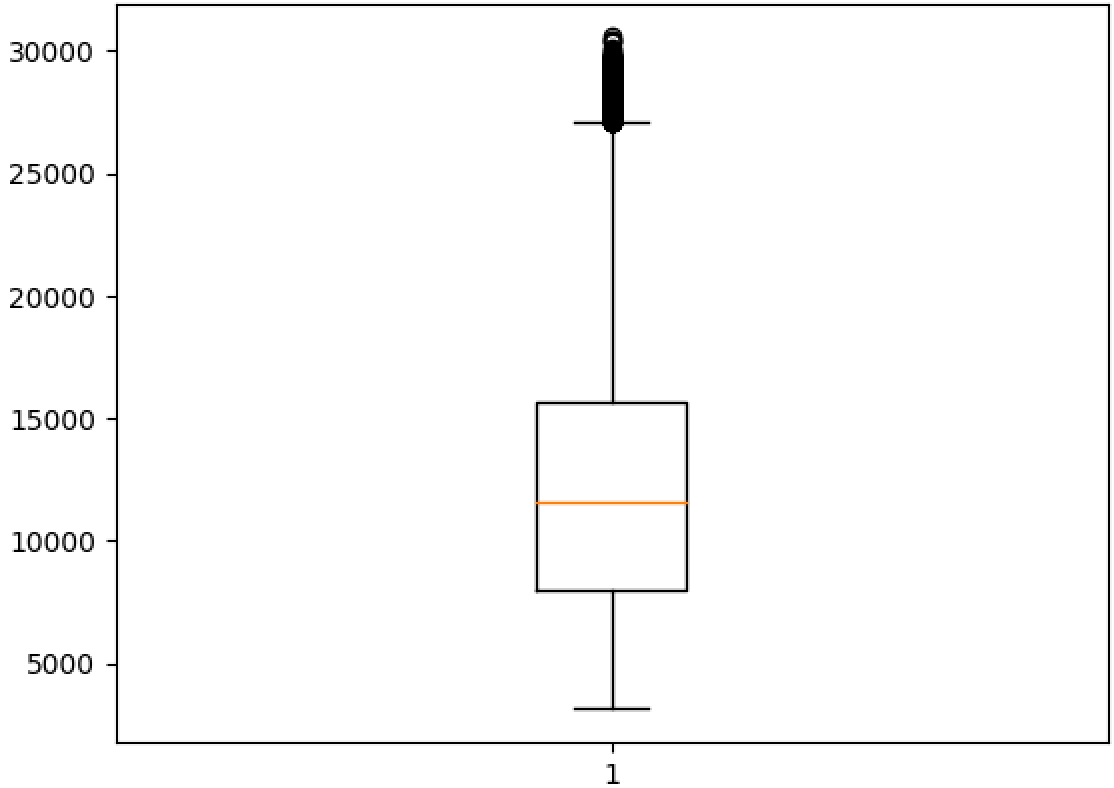
In [17]:
```
Initial_daysPlot = plt.boxplot(x='Initial_days', data = new_med_data)
```



In [18]:
```
TotalChargePlot = plt.boxplot(x='TotalCharge', data = new_med_data)
```



In [19]:
```
Additional_chargesPlot = plt.boxplot(x='Additional_charges', data = new_med_data)
```



In [20]:
```
# Treat outliers with imputation
percentile_addcharges = np.percentile(new_med_data['Additional_charges'], 95)
print(percentile_addcharges)
```

```
26604.554999999997
```

In [21]:
```
# Replacing with the median
median = float(new_med_data['Additional_charges'].median())
new_med_data['Additional_charges'] = np.where(new_med_data['Additional_charges'] > per
```

In [22]:
```
# Verifying the max value
new_med_data.describe()
```

Out[22]:

	Income	Doc_visits	Initial_days	TotalCharge	Additional_charges
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	36188.024603	5.012200	34.455299	5312.172769	12108.260572
std	21376.715194	1.045734	26.309341	2180.393838	5538.630675
min	154.080000	1.000000	1.001981	1938.312067	3125.703000
25%	19598.775000	4.000000	7.896215	3179.374015	7986.487755
50%	33766.005000	5.000000	35.836244	5213.952000	11573.938868
75%	49348.447500	6.000000	61.161020	7459.699750	14535.582983
max	96067.940000	9.000000	71.981490	9180.728000	26604.310000

In [23]:
```
# EDA - Looking at descriptive statistics
new_med_data.describe()
```

Out[23]:

	Income	Doc_visits	Initial_days	TotalCharge	Additional_charges
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	36188.024603	5.012200	34.455299	5312.172769	12108.260572
std	21376.715194	1.045734	26.309341	2180.393838	5538.630675
min	154.080000	1.000000	1.001981	1938.312067	3125.703000
25%	19598.775000	4.000000	7.896215	3179.374015	7986.487755
50%	33766.005000	5.000000	35.836244	5213.952000	11573.938868
75%	49348.447500	6.000000	61.161020	7459.699750	14535.582983
max	96067.940000	9.000000	71.981490	9180.728000	26604.310000

In [24]:

```
# Qualitative/categorical descriptive data
new_med_data.describe(include='object')
```

Out[24]:

	HighBlood	Stroke	Complication_risk	Overweight	Arthritis	Diabetes	Anxiety	Services
count	10000	10000	10000	10000	10000	10000	10000	10000
unique	2	2	3	2	2	2	2	4
top	No	No	Medium	Yes	No	No	No	Blood Work
freq	5910	8007	4517	7094	6426	7262	6785	5265

In [25]:

```
# Univariate - Additional Charges
new_med_data['Additional_charges'].describe()
```

Out[25]:

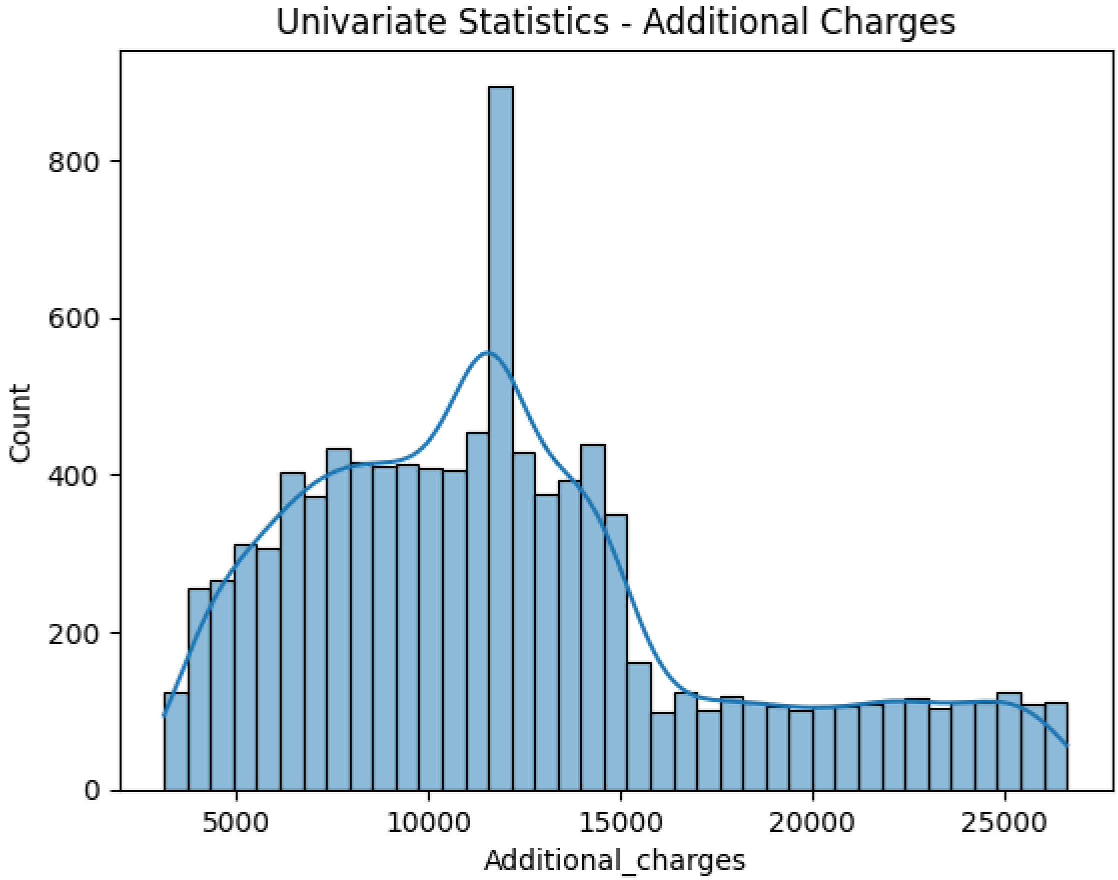
```
count    10000.000000
mean     12108.260572
std       5538.630675
min       3125.703000
25%       7986.487755
50%      11573.938868
75%      14535.582983
max      26604.310000
Name: Additional_charges, dtype: float64
```

In [26]:

```
# Histogram Plot - Additional Charges
sns.histplot(new_med_data.Additional_charges,kde=True)
plt.title("Univariate Statistics - Additional Charges")
```

Out[26]:

```
Text(0.5, 1.0, 'Univariate Statistics - Additional Charges')
```

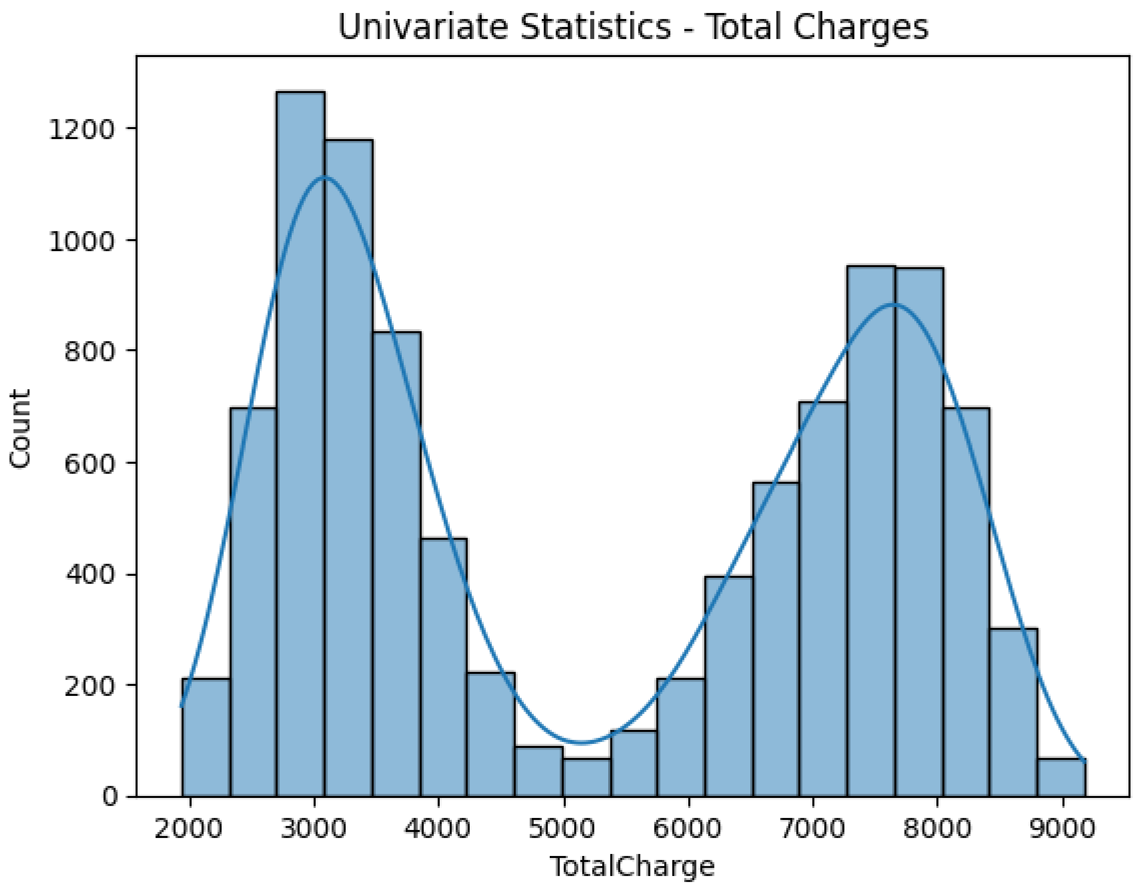


In [27]:
```
# Univariate - Total Charges
new_med_data['TotalCharge'].describe()
```

Out[27]:
```
count    10000.000000
mean      5312.172769
std       2180.393838
min       1938.312067
25%       3179.374015
50%       5213.952000
75%       7459.699750
max       9180.728000
Name: TotalCharge, dtype: float64
```

In [28]:
```
# Histogram - Total Charges
sns.histplot(new_med_data.TotalCharge,kde=True)
plt.title("Univariate Statistics - Total Charges")
```

Out[28]:
```
Text(0.5, 1.0, 'Univariate Statistics - Total Charges')
```

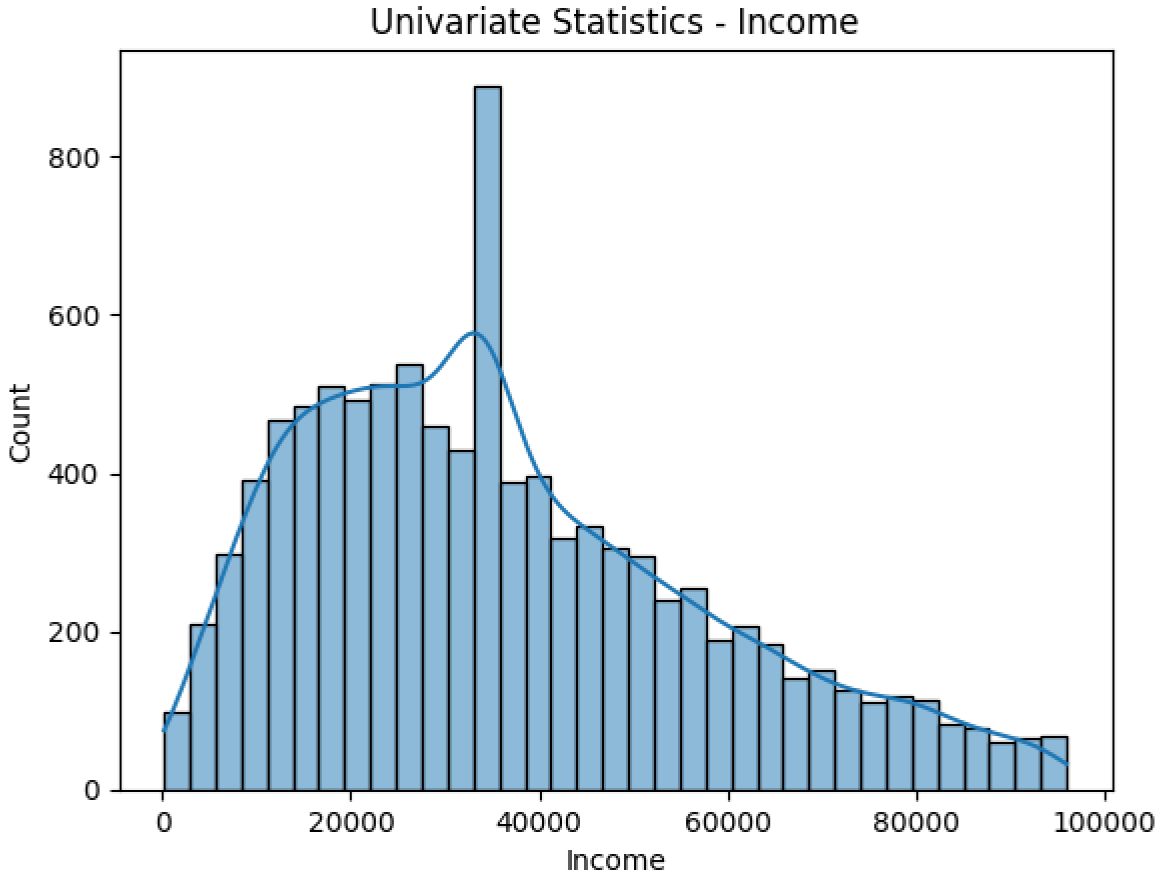


In [29]:
```
# Univariate - Income
new_med_data['Income'].describe()
```

Out[29]:
```
count    10000.000000
mean     36188.024603
std      21376.715194
min        154.080000
25%      19598.775000
50%      33766.005000
75%      49348.447500
max      96067.940000
Name: Income, dtype: float64
```

In [30]:
```
# Histogram - Income
sns.histplot(new_med_data.Income,kde=True)
plt.title("Univariate Statistics - Income")
```

Out[30]:
```
Text(0.5, 1.0, 'Univariate Statistics - Income')
```

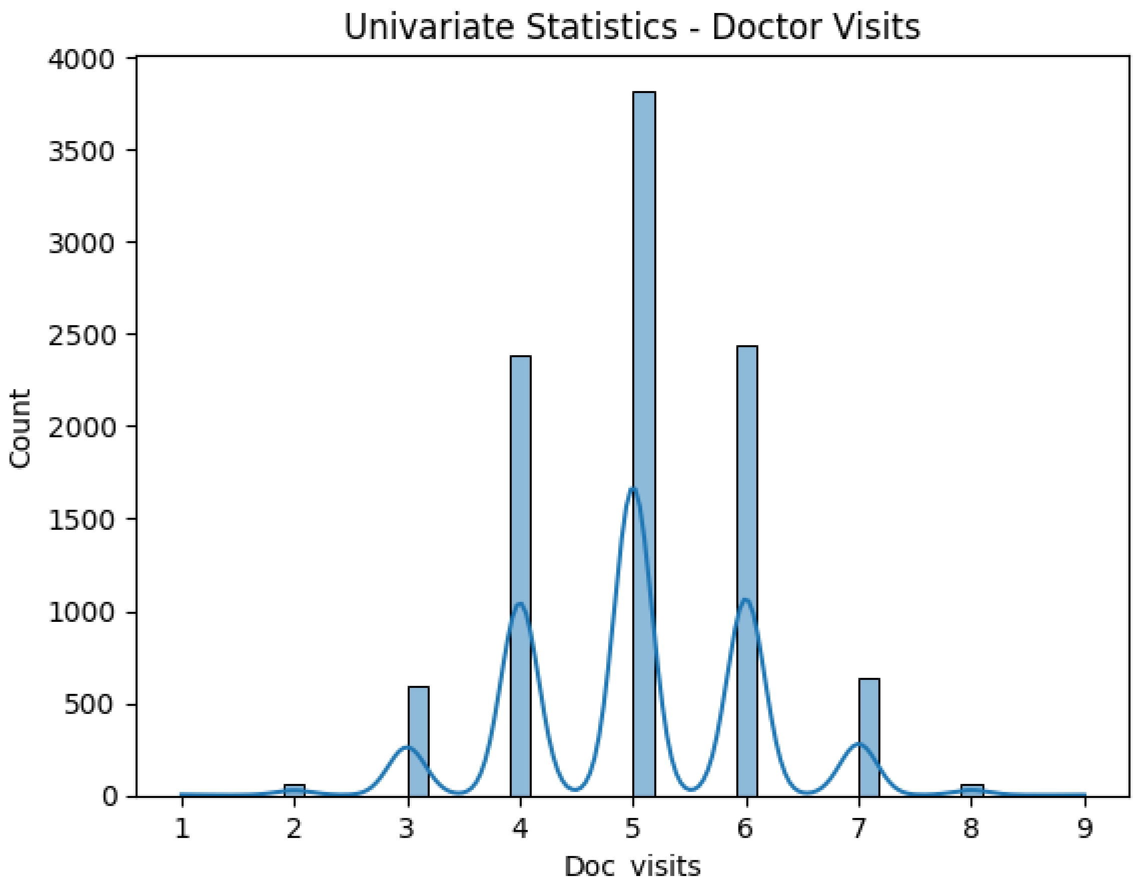


In [31]:
```
# Univariate - Doctor Visits
new_med_data['Doc_visits'].describe()
```

Out[31]:
```
count    10000.000000
mean         5.012200
std          1.045734
min          1.000000
25%          4.000000
50%          5.000000
75%          6.000000
max          9.000000
Name: Doc_visits, dtype: float64
```

In [32]:
```
# Histogram - Doctor Visits
sns.histplot(new_med_data.Doc_visits,kde=True)
plt.title("Univariate Statistics - Doctor Visits")
```

Out[32]:
```
Text(0.5, 1.0, 'Univariate Statistics - Doctor Visits')
```

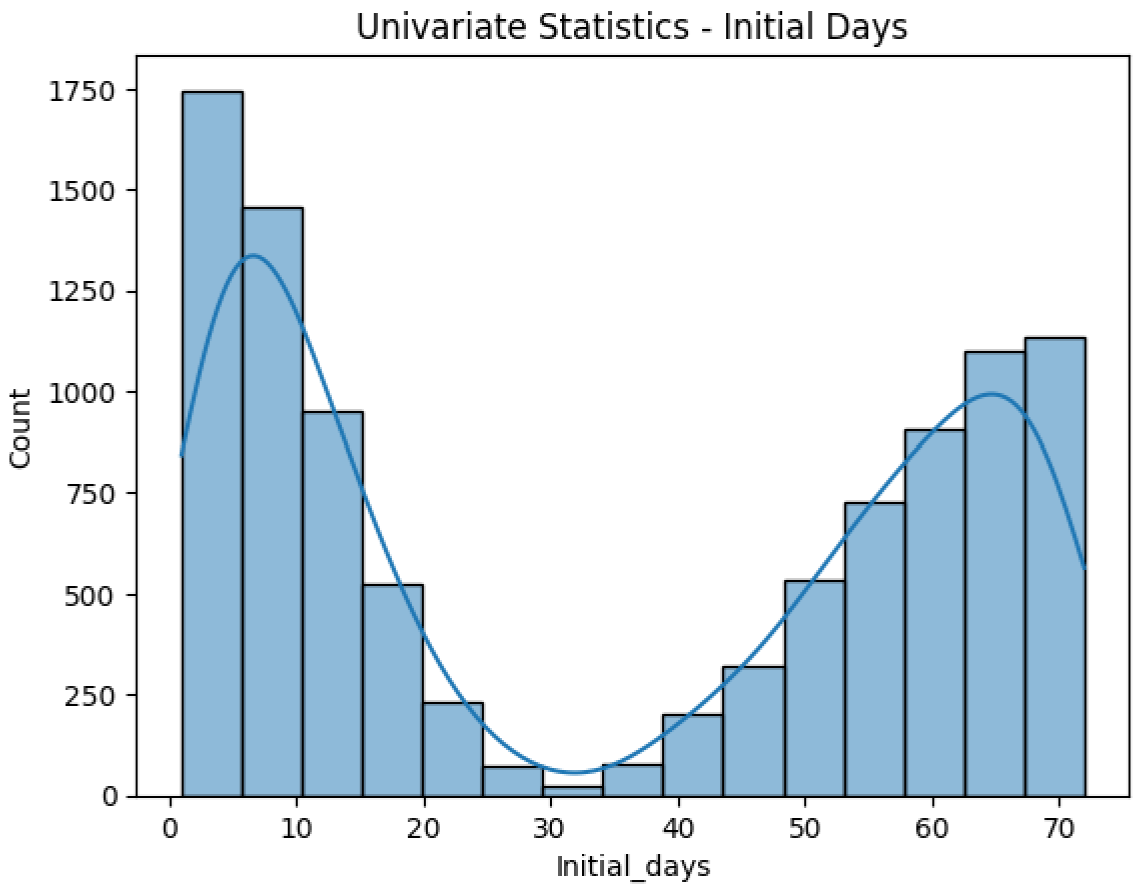


In [33]:
```python
# Univariate - Initial Days
new_med_data['Initial_days'].describe()
```

Out[33]:
```
count    10000.000000
mean        34.455299
std         26.309341
min          1.001981
25%          7.896215
50%         35.836244
75%         61.161020
max         71.981490
Name: Initial_days, dtype: float64
```

In [34]:
```python
# Histogram - Initial Days
sns.histplot(new_med_data.Initial_days,kde=True)
plt.title("Univariate Statistics - Initial Days")
```

Out[34]:
```
Text(0.5, 1.0, 'Univariate Statistics - Initial Days')
```

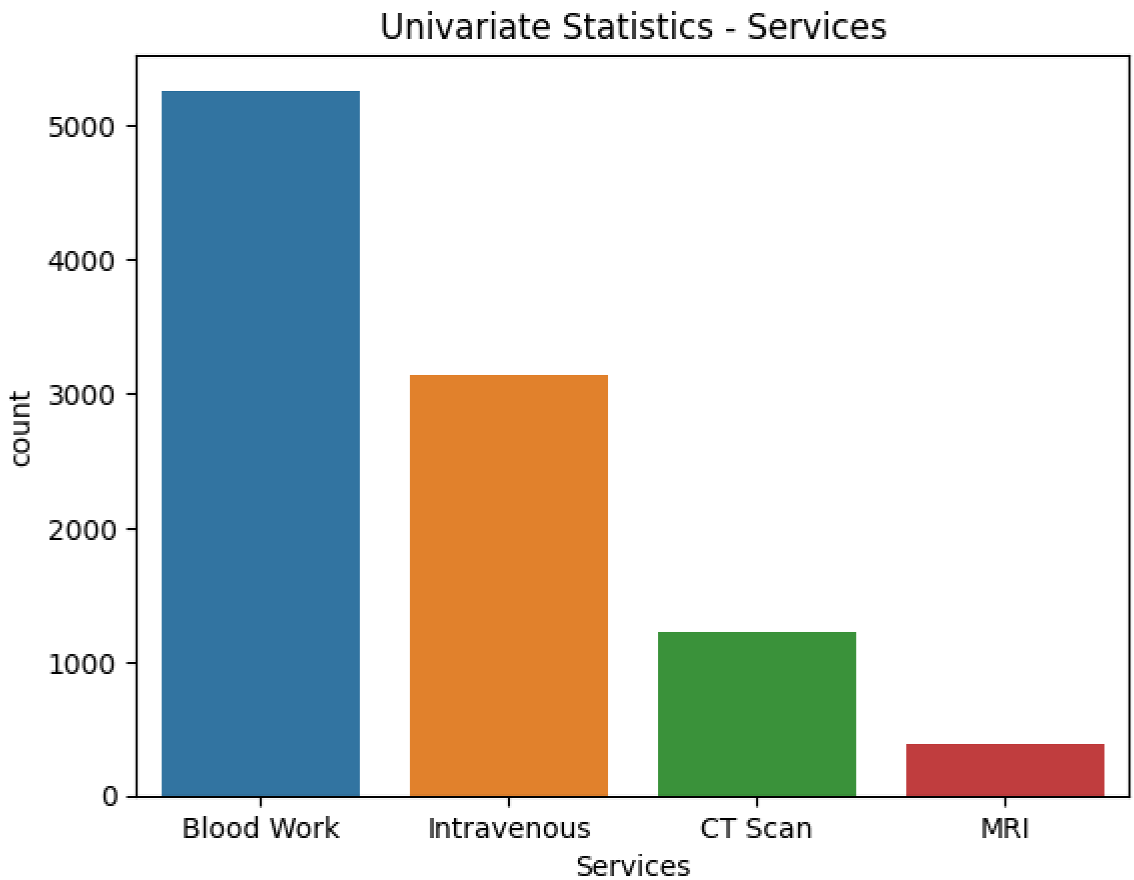


In [35]:
```
# Univariate - Services Variable
new_med_data['Services'].describe()
```

Out[35]:
```
count          10000
unique             4
top       Blood Work
freq            5265
Name: Services, dtype: object
```

In [36]:
```
# Count Plot - Services
sns.countplot(data=new_med_data, x='Services')
plt.title("Univariate Statistics - Services")
```

Out[36]:
```
Text(0.5, 1.0, 'Univariate Statistics - Services')
```

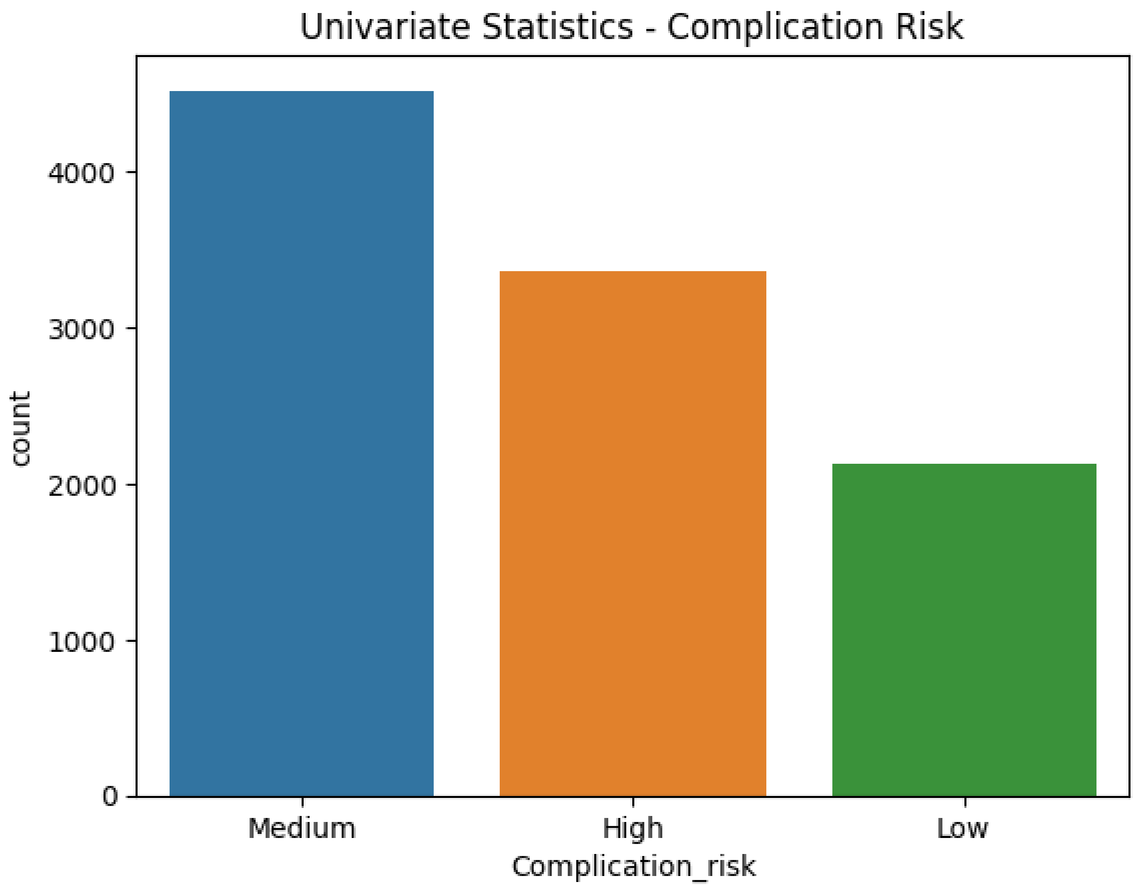


In [37]:
```
# Univariate - Complication Risk
new_med_data['Complication_risk'].describe()
```

Out[37]:
```
count      10000
unique         3
top       Medium
freq        4517
Name: Complication_risk, dtype: object
```

In [38]:
```
# Count Plot - Complication Risk
sns.countplot(data=new_med_data, x='Complication_risk')
plt.title("Univariate Statistics - Complication Risk")
```

Out[38]:
```
Text(0.5, 1.0, 'Univariate Statistics - Complication Risk')
```

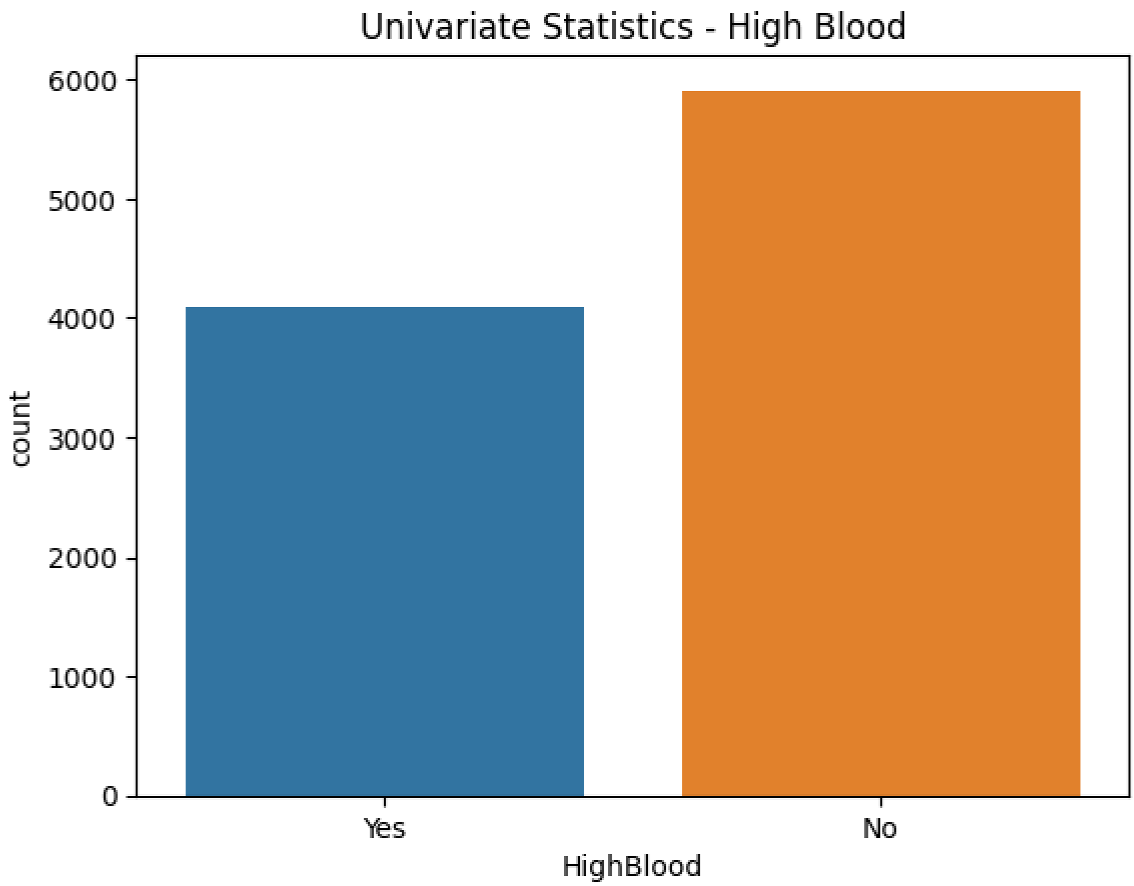


In [39]:
```
# Univariate - High Blood Pressure
new_med_data['HighBlood'].describe()
```

Out[39]:
```
count     10000
unique        2
top          No
freq       5910
Name: HighBlood, dtype: object
```

In [40]:
```
# Count Plot - High Blood Pressure
sns.countplot(data=new_med_data, x='HighBlood')
plt.title("Univariate Statistics - High Blood")
```

Out[40]:
```
Text(0.5, 1.0, 'Univariate Statistics - High Blood')
```

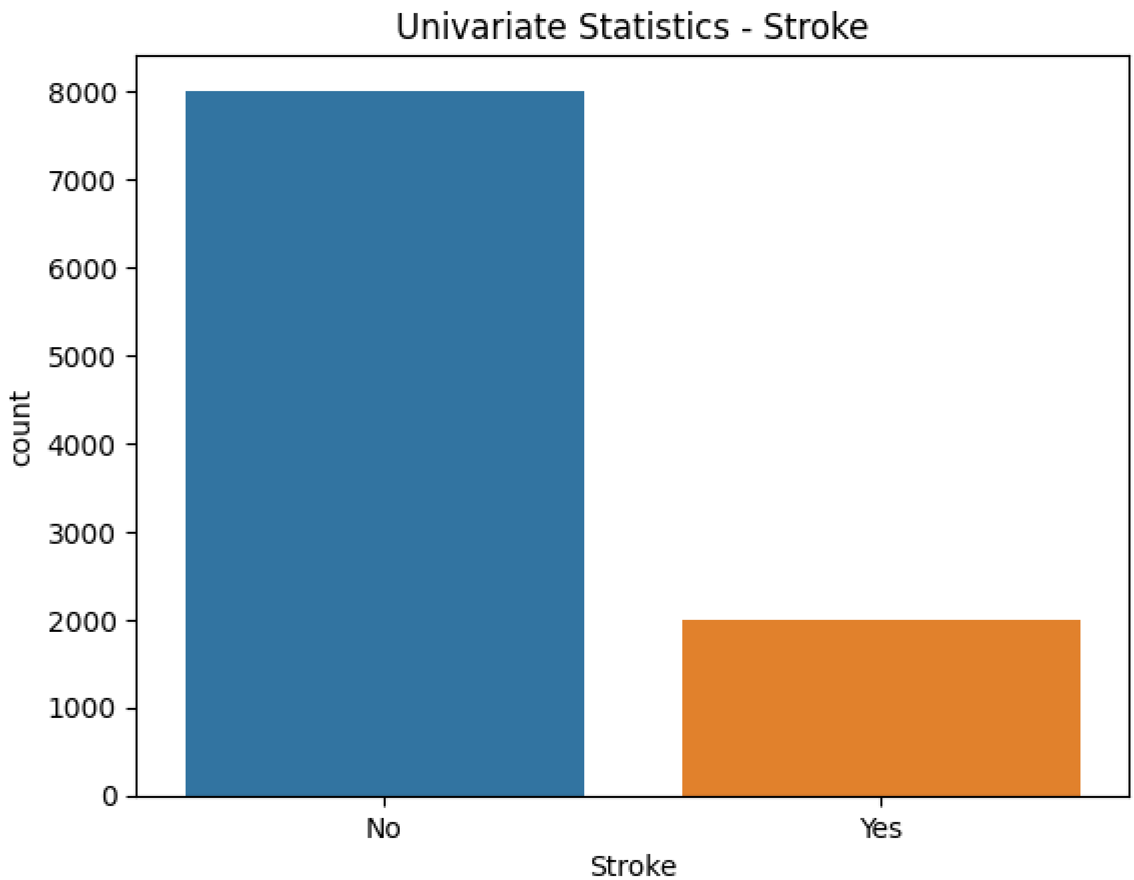


In [41]:
```
# Univariate - Stroke
new_med_data['Stroke'].describe()
```

Out[41]:
```
count     10000
unique        2
top          No
freq       8007
Name: Stroke, dtype: object
```

In [42]:
```
# Count Plot - Stroke
sns.countplot(data=new_med_data, x='Stroke')
plt.title("Univariate Statistics - Stroke")
```

Out[42]:
```
Text(0.5, 1.0, 'Univariate Statistics - Stroke')
```

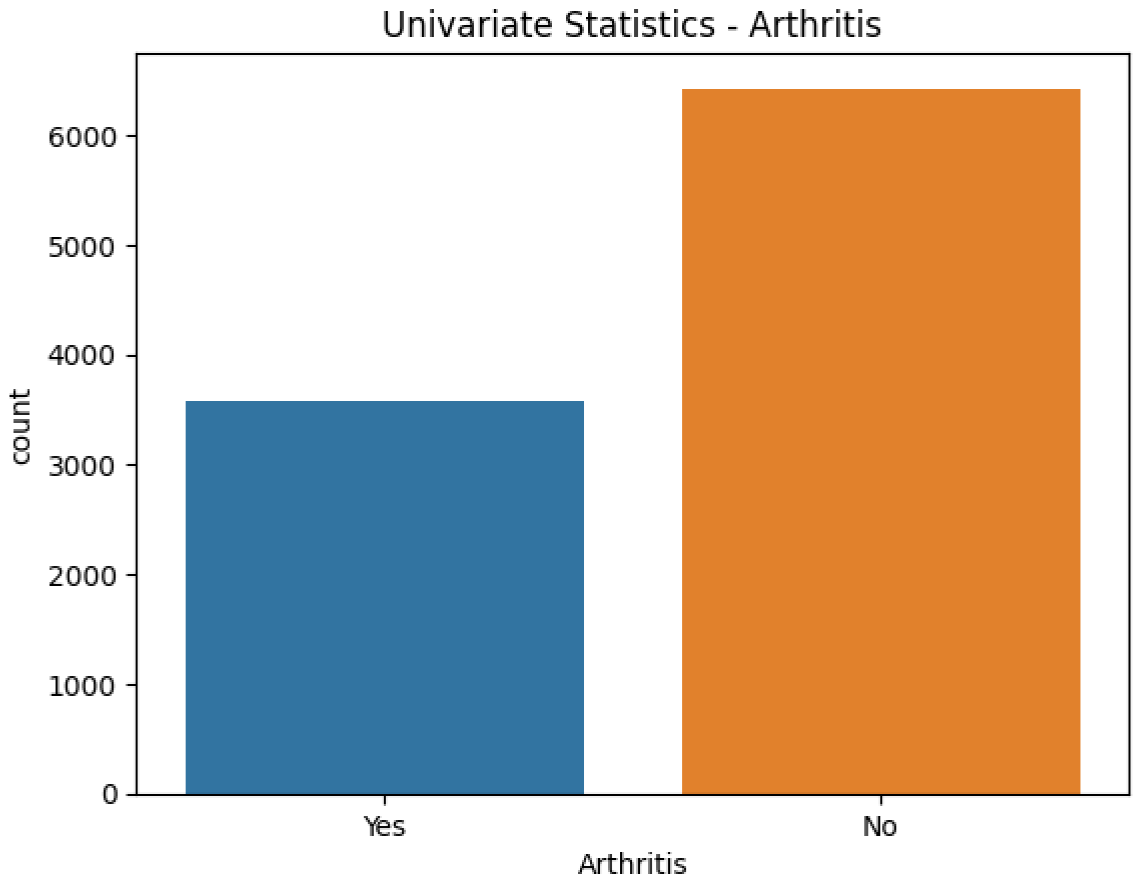


In [43]:
```python
# Univariate - Arthritis
new_med_data['Arthritis'].describe()
```

Out[43]:
```
count     10000
unique        2
top          No
freq       6426
Name: Arthritis, dtype: object
```

In [44]:
```python
# Count Plot - Arthritis
sns.countplot(data=new_med_data, x='Arthritis')
plt.title("Univariate Statistics - Arthritis")
```

Out[44]:
```
Text(0.5, 1.0, 'Univariate Statistics - Arthritis')
```

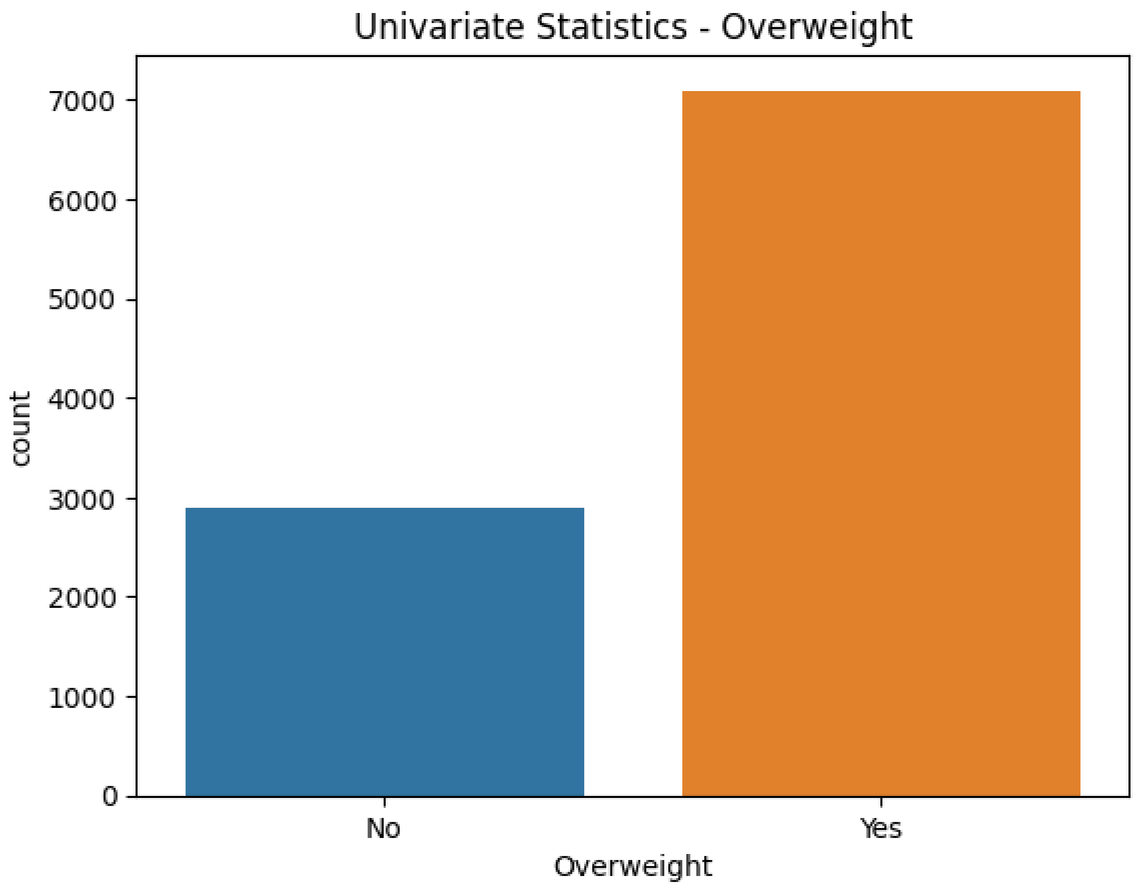


In [45]:
```
# Univariate - Overweight
new_med_data['Overweight'].describe()
```

Out[45]:
```
count     10000
unique        2
top         Yes
freq       7094
Name: Overweight, dtype: object
```

In [46]:
```
# Count Plot - Overweight
sns.countplot(data=new_med_data, x='Overweight')
plt.title("Univariate Statistics - Overweight")
```

Out[46]:
```
Text(0.5, 1.0, 'Univariate Statistics - Overweight')
```

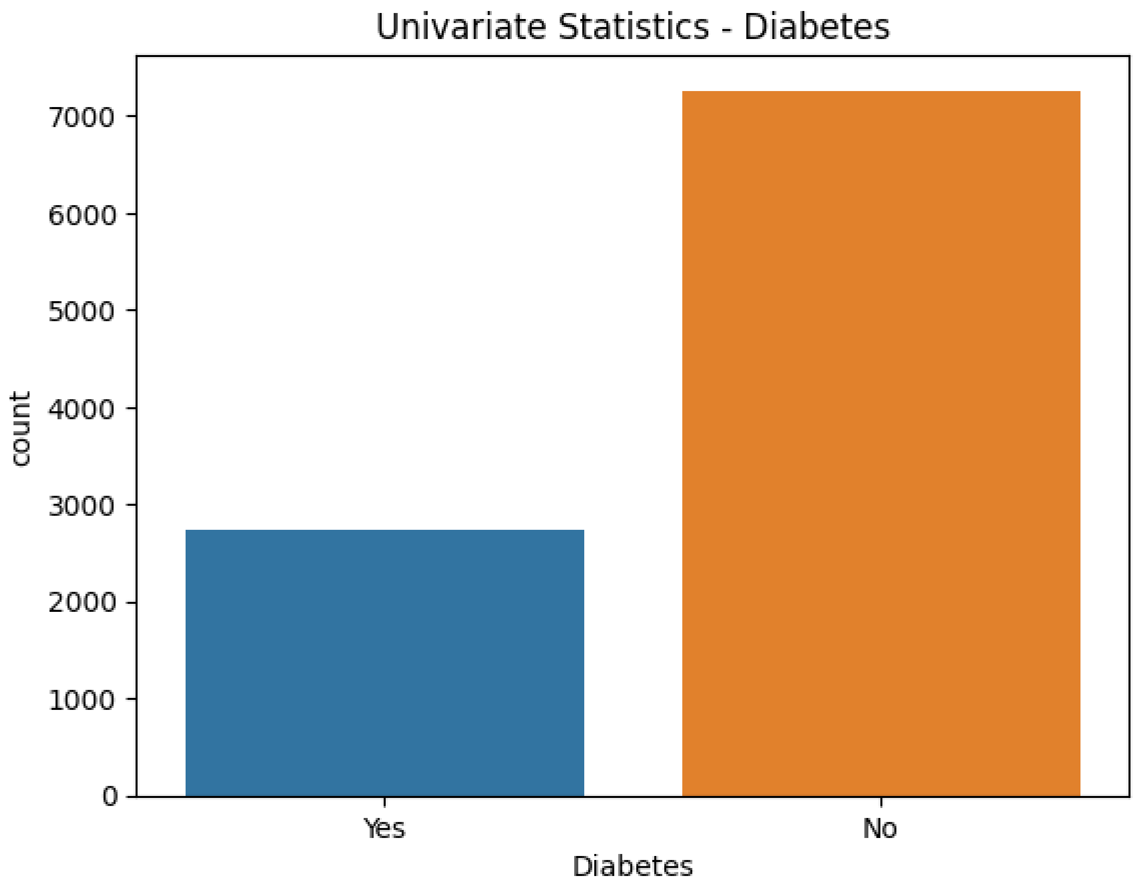


In [47]:
```
# Univariate - Diabetes
new_med_data['Diabetes'].describe()
```

Out[47]:
```
count     10000
unique        2
top          No
freq       7262
Name: Diabetes, dtype: object
```

In [48]:
```
# Count Plot - Diabetes
sns.countplot(data=new_med_data, x='Diabetes')
plt.title("Univariate Statistics - Diabetes")
```

Out[48]:
```
Text(0.5, 1.0, 'Univariate Statistics - Diabetes')
```

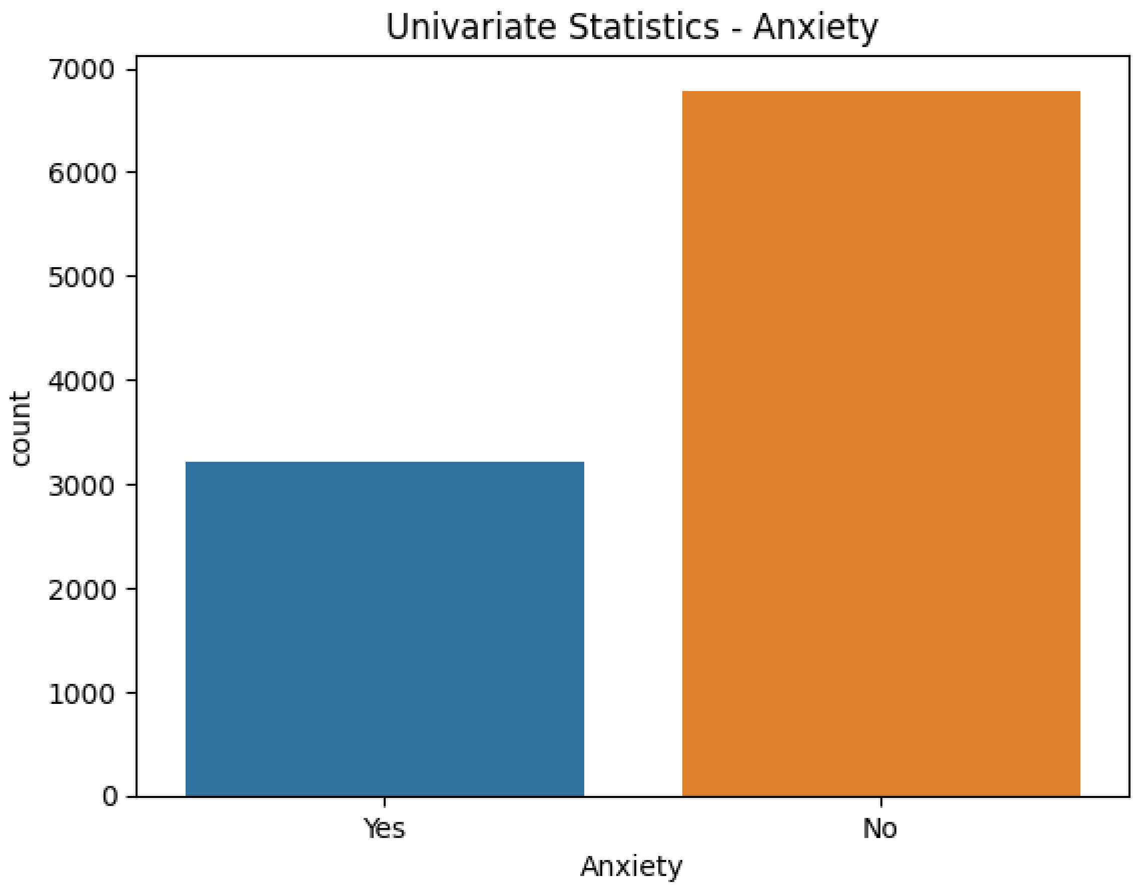


In [49]:
```
# Univariate - Anxiety
new_med_data['Anxiety'].describe()
```

Out[49]:
```
count     10000
unique        2
top          No
freq       6785
Name: Anxiety, dtype: object
```

In [50]:
```
# Count Plot - Anxiety
sns.countplot(data=new_med_data, x='Anxiety')
plt.title("Univariate Statistics - Anxiety")
```

Out[50]:
```
Text(0.5, 1.0, 'Univariate Statistics - Anxiety')
```



In [51]:
```
# Bivariate Statistics
# Additional Charges vs Total Charges
new_med_data[['Additional_charges', 'TotalCharge']].describe()
```

Out[51]:

	Additional_charges	TotalCharge
count	10000.000000	10000.000000
mean	12108.260572	5312.172769
std	5538.630675	2180.393838
min	3125.703000	1938.312067
25%	7986.487755	3179.374015
50%	11573.938868	5213.952000
75%	14535.582983	7459.699750
max	26604.310000	9180.728000

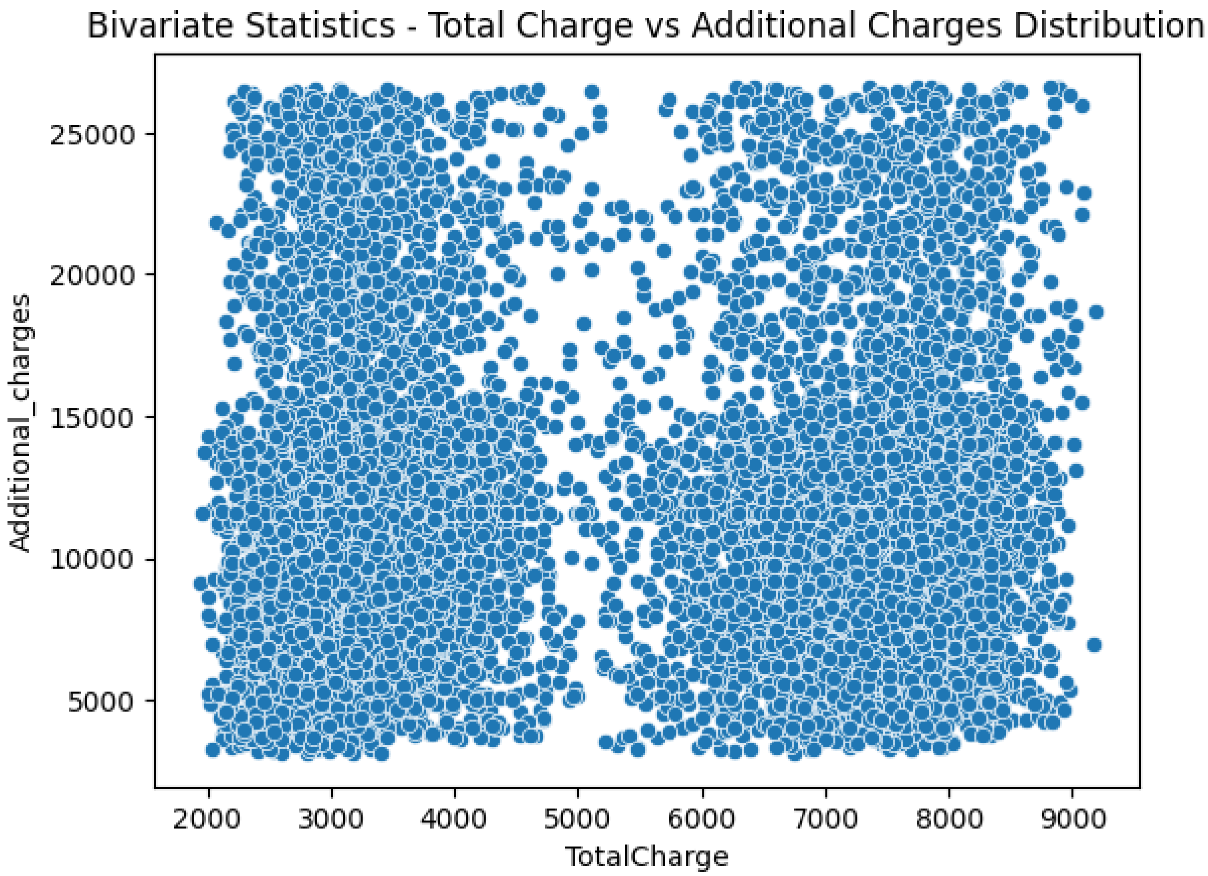
In [52]:
```
# Additional Charges vs Total Charges correlation
new_med_data[['Additional_charges', 'TotalCharge']].corr()
```

Out[52]:

	Additional_charges	TotalCharge
Additional_charges	1.000000	0.028396
TotalCharge	0.028396	1.000000

In [53]:
```
# Additional Charges vs Total Charges scatterplot
sns.scatterplot(data=new_med_data, x='TotalCharge', y='Additional_charges')
plt.title("Bivariate Statistics - Total Charge vs Additional Charges Distribution")
```

Out[53]:
```
Text(0.5, 1.0, 'Bivariate Statistics - Total Charge vs Additional Charges Distributio
n')
```



In [54]:
```
# Bivariate Statistics
# Additional Charges vs Income
new_med_data[['Additional_charges', 'Income']].describe()
```

Out[54]:

	Additional_charges	Income
count	10000.000000	10000.000000
mean	12108.260572	36188.024603
std	5538.630675	21376.715194
min	3125.703000	154.080000
25%	7986.487755	19598.775000
50%	11573.938868	33766.005000
75%	14535.582983	49348.447500
max	26604.310000	96067.940000

In [55]:
```
# Additional Charges vs Income correlation
new_med_data[['Additional_charges', 'Income']].corr()
```

Out[55]:

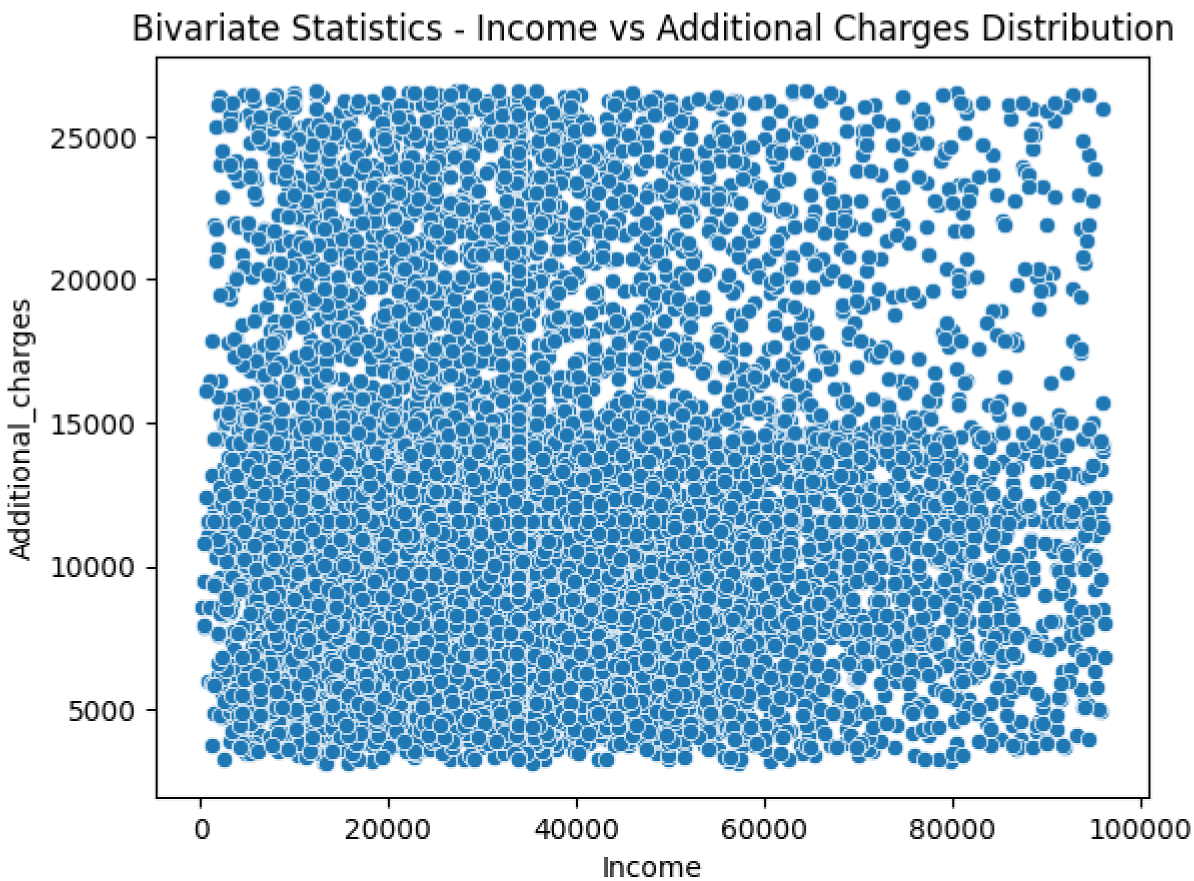
	Additional_charges	Income
Additional_charges	1.000000	-0.005247
Income	-0.005247	1.000000

In [56]:

```
# Additional Charges vs Income plot
sns.scatterplot(data=new_med_data, x='Income', y='Additional_charges')
plt.title("Bivariate Statistics - Income vs Additional Charges Distribution")
```

Out[56]:

```
Text(0.5, 1.0, 'Bivariate Statistics - Income vs Additional Charges Distribution')
```



In [57]:

```
# Bivariate Statistics
# Additional charges vs doc visits
new_med_data[['Additional_charges', 'Doc_visits']].describe()
```

Out[57]:

	Additional_charges	Doc_visits
count	10000.000000	10000.000000
mean	12108.260572	5.012200
std	5538.630675	1.045734
min	3125.703000	1.000000
25%	7986.487755	4.000000
50%	11573.938868	5.000000
75%	14535.582983	6.000000
max	26604.310000	9.000000

In [58]:

```
# Additional charges vs doc visits correlation
new_med_data[['Additional_charges', 'Doc_visits']].corr()
```

Out[58]:

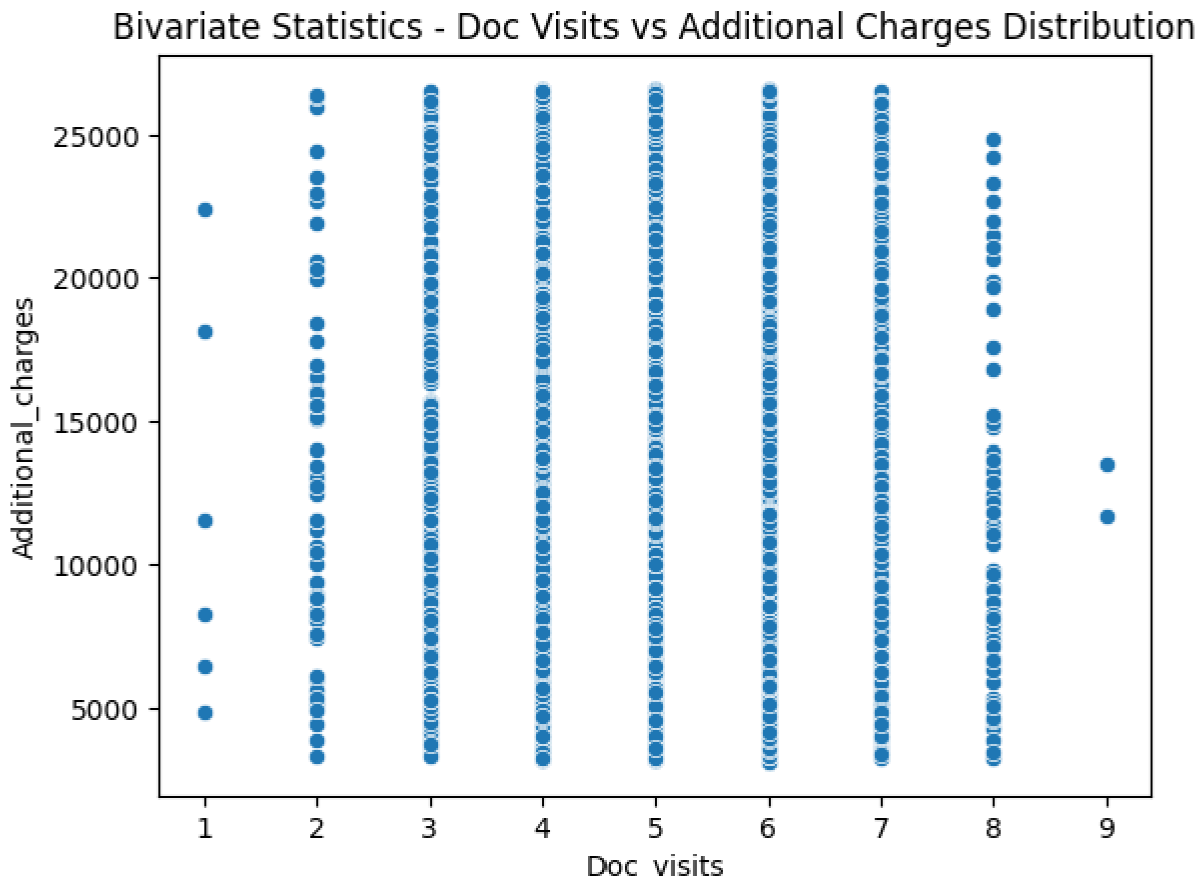
	Additional_charges	Doc_visits
Additional_charges	1.000000	0.009862
Doc_visits	0.009862	1.000000

In [59]:

```
# Additional charges vs doc visits plot
sns.scatterplot(data=new_med_data, x='Doc_visits', y='Additional_charges')
plt.title("Bivariate Statistics - Doc Visits vs Additional Charges Distribution")
```

Out[59]:

```
Text(0.5, 1.0, 'Bivariate Statistics - Doc Visits vs Additional Charges Distributio
n')
```



In [60]:
```
# Bivariate Statistics
# Additional Charges vs Initial days
new_med_data[['Additional_charges', 'Initial_days']].describe()
```

Out[60]:

	Additional_charges	Initial_days
count	10000.000000	10000.000000
mean	12108.260572	34.455299
std	5538.630675	26.309341
min	3125.703000	1.001981
25%	7986.487755	7.896215
50%	11573.938868	35.836244
75%	14535.582983	61.161020
max	26604.310000	71.981490

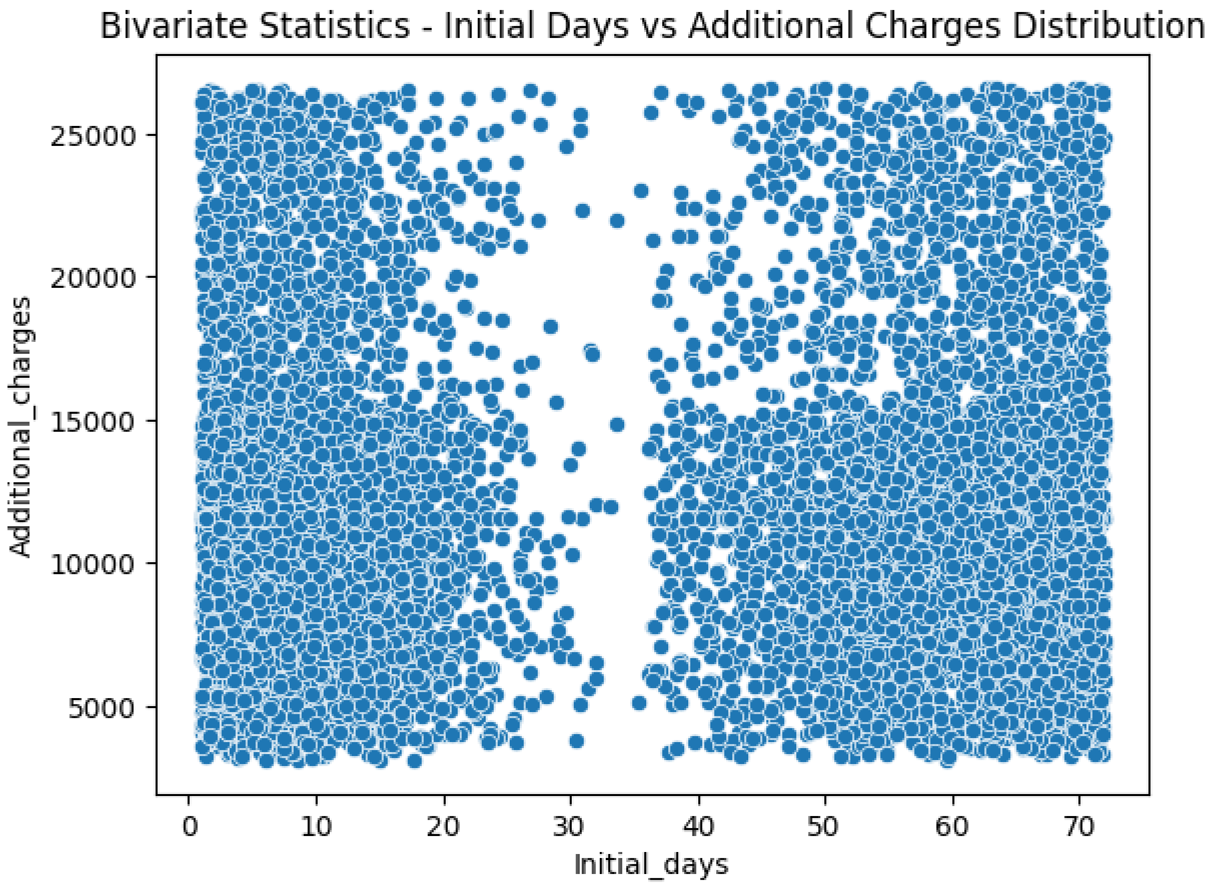
In [61]:
```
# Additional Charges vs Initial days correlation
new_med_data[['Additional_charges', 'Initial_days']].corr()
```

Out[61]:

	Additional_charges	Initial_days
Additional_charges	1.00000	0.00634
Initial_days	0.00634	1.00000

In [62]:
```
# Additional Charges vs Initial days plot
sns.scatterplot(data=new_med_data, x='Initial_days', y='Additional_charges')
plt.title("Bivariate Statistics - Initial Days vs Additional Charges Distribution")
```

Out[62]:
```
Text(0.5, 1.0, 'Bivariate Statistics - Initial Days vs Additional Charges Distributio
n')
```



In [63]:
```
# Bivariate (categorical values)
# Additional charges vs Services
pd.crosstab(new_med_data.Additional_charges, new_med_data.Services, margins=True)
```

Out[63]:

Services	Blood Work	CT Scan	Intravenous	MRI	All
Additional_charges					
3125.703	1	0	0	0	1
3132.25999	1	0	1	0	2
3139.049369	2	0	0	0	2
3173.112679	0	1	0	0	1
3213.0799	1	0	0	0	1
...	...	...	...	...	...
26592.28	1	0	0	0	1
26594.73	0	1	0	0	1
26601.03	0	0	0	1	1
26604.31	1	0	1	0	2
All	5265	1225	3130	380	10000

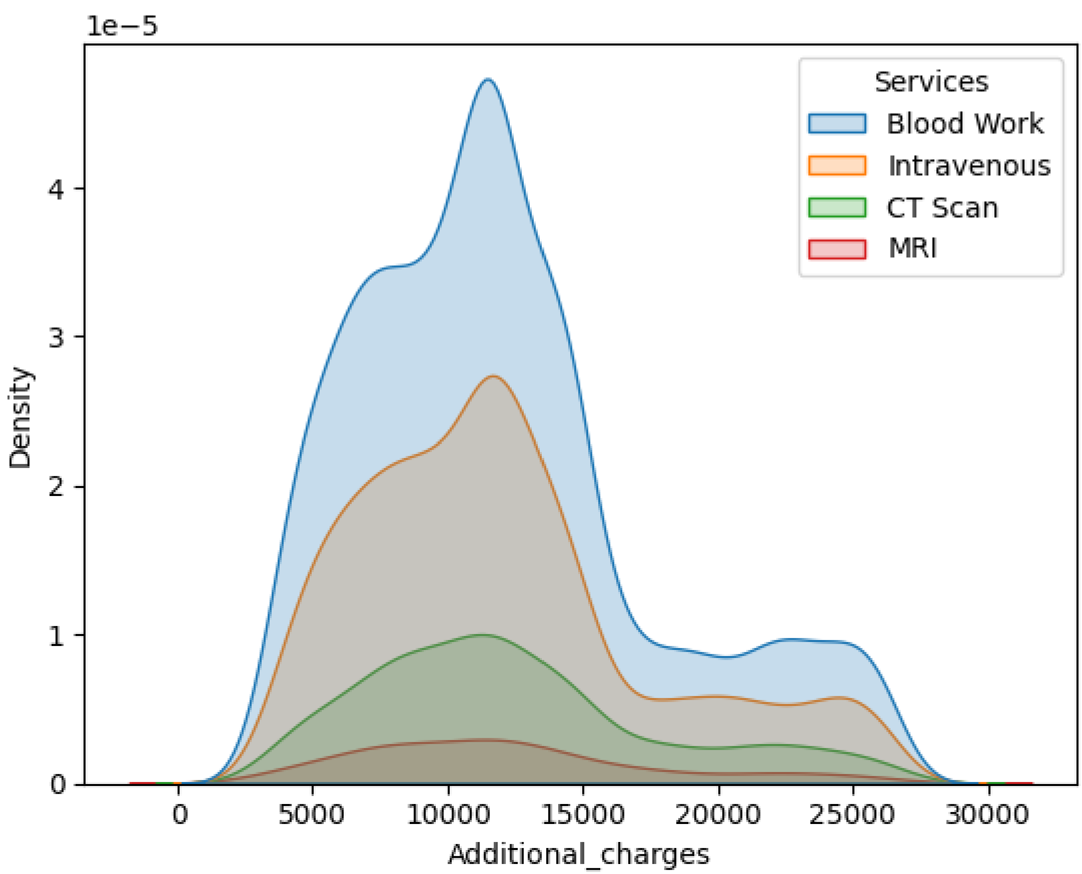
8934 rows × 5 columns

In [64]:

```
# Bivariate (categorical values)
# Additional charges vs Services
sns.kdeplot(data=new_med_data, x='Additional_charges', hue='Services', fill=True)
```

Out[64]:

```
<Axes: xlabel='Additional_charges', ylabel='Density'>
```



In [65]:
```
# Bivariate (categorical values)
# Additional charges vs Complication risk
pd.crosstab(new_med_data.Additional_charges, new_med_data.Complication_risk, margins=T
```

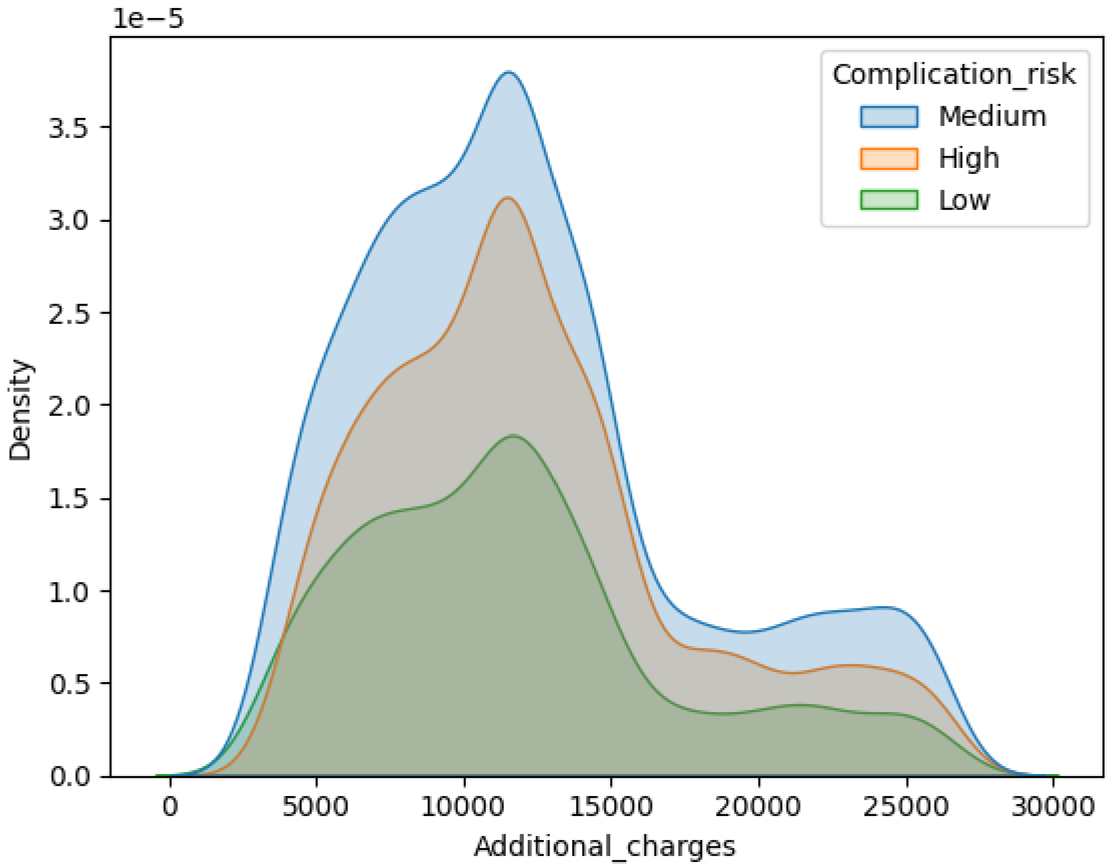
Out[65]:

Complication_risk	High	Low	Medium	All
Additional_charges				
3125.703	0	1	0	1
3132.25999	0	2	0	2
3139.049369	0	2	0	2
3173.112679	0	1	0	1
3213.0799	0	0	1	1
...	...	...	...	...
26592.28	0	0	1	1
26594.73	1	0	0	1
26601.03	1	0	0	1
26604.31	2	0	0	2
All	3358	2125	4517	10000

8934 rows × 4 columns

In [66]:
```
# Bivariate (categorical values)
# Additional charges vs Complication risk
sns.kdeplot(data=new_med_data, x='Additional_charges', hue='Complication_risk', fill=T
```

Out[66]:
```
<Axes: xlabel='Additional_charges', ylabel='Density'>
```



In [67]:
```
# Bivariate (categorical values)
# Additional charges vs High Blood
pd.crosstab(new_med_data.Additional_charges, new_med_data.HighBlood, margins=True)
```

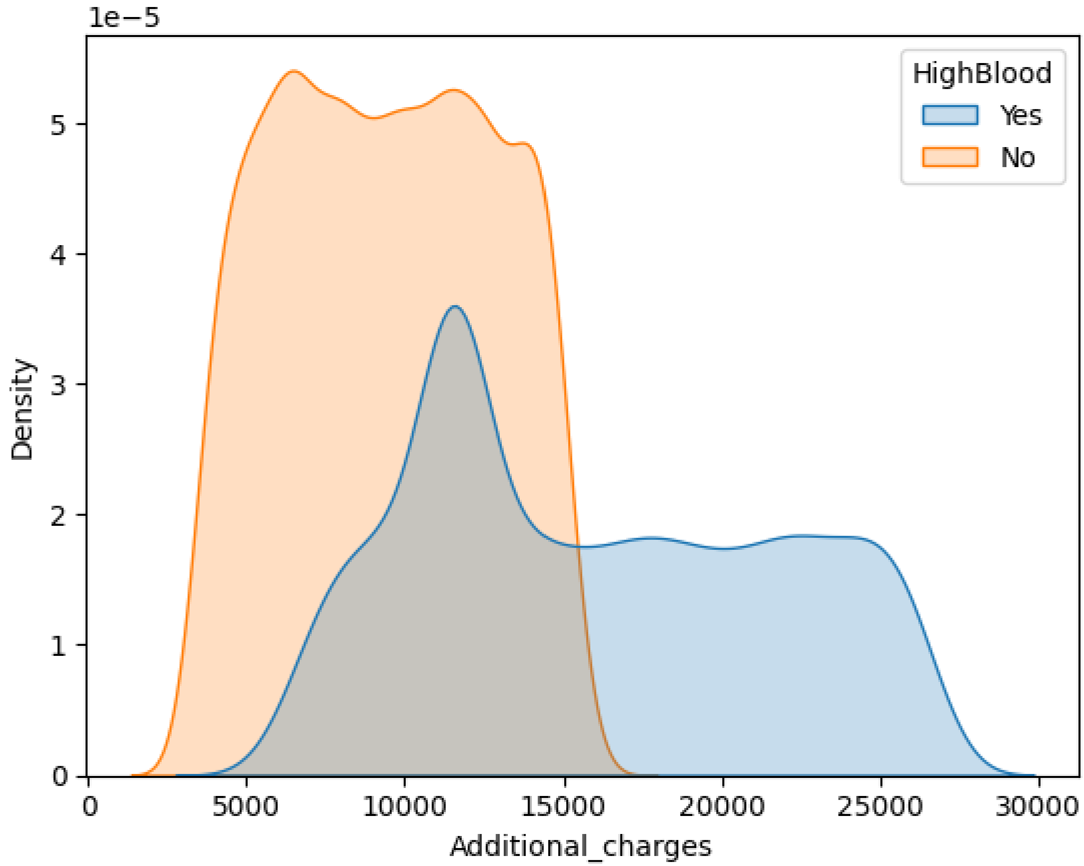
Out[67]:

HighBlood	No	Yes	All
Additional_charges			
3125.703	1	0	1
3132.25999	2	0	2
3139.049369	2	0	2
3173.112679	1	0	1
3213.0799	1	0	1
...	...	...	...
26592.28	0	1	1
26594.73	0	1	1
26601.03	0	1	1
26604.31	0	2	2
All	5910	4090	10000

8934 rows × 3 columns

In [68]:
```
# Bivariate (categorical values)
# Additional charges vs High Blood
sns.kdeplot(data=new_med_data, x='Additional_charges', hue='HighBlood', fill=True)
```

Out[68]: <Axes: xlabel='Additional_charges', ylabel='Density'>



In [69]:
```
# Bivariate (categorical values)
# Additional charges vs Stroke
pd.crosstab(new_med_data.Additional_charges, new_med_data.Stroke, margins=True)
```

Out[69]:

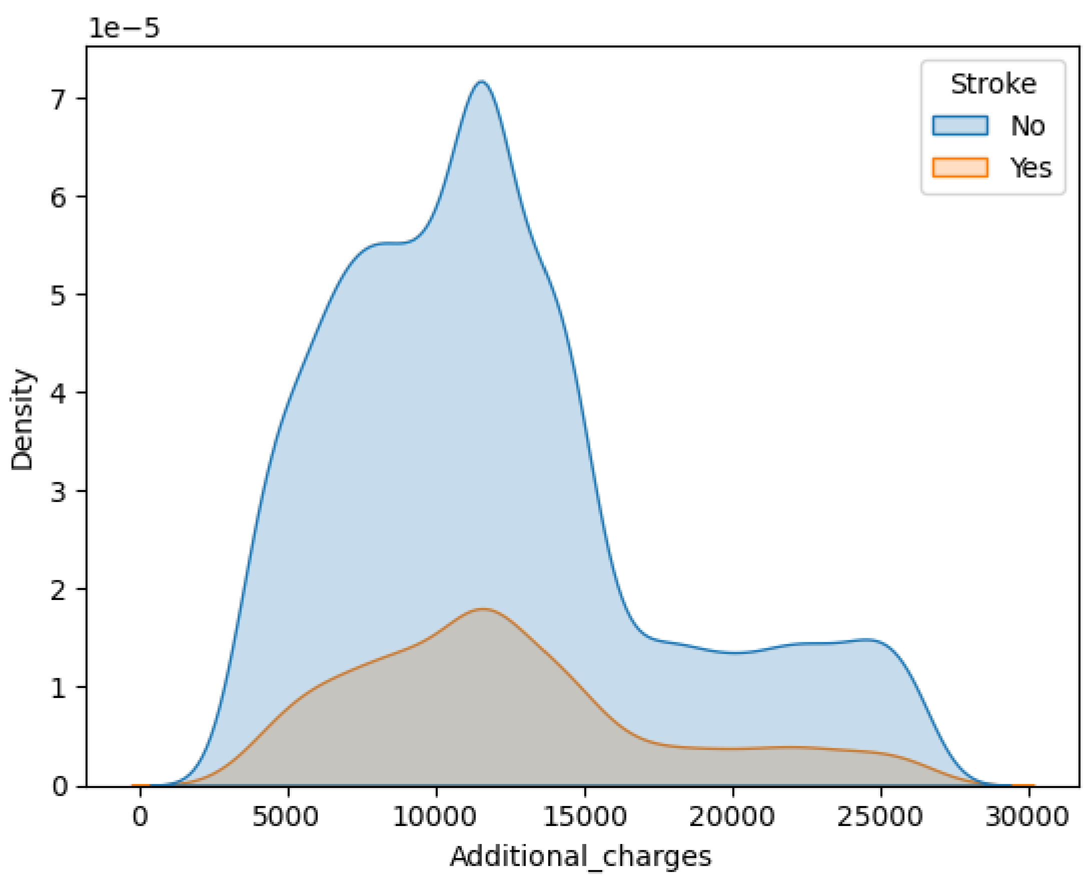
Stroke	No	Yes	All
Additional_charges			
3125.703	1	0	1
3132.25999	2	0	2
3139.049369	2	0	2
3173.112679	1	0	1
3213.0799	1	0	1
...	...	...	...
26592.28	0	1	1
26594.73	0	1	1
26601.03	1	0	1
26604.31	2	0	2
All	8007	1993	10000

8934 rows × 3 columns

In [70]:

```
# Bivariate (categorical values)
# Additional charges vs Stroke
sns.kdeplot(data=new_med_data, x='Additional_charges', hue='Stroke', fill=True)
```

Out[70]: <Axes: xlabel='Additional_charges', ylabel='Density'>



In [71]:
```
# Bivariate (categorical values)
# Additional charges vs Arthritis
pd.crosstab(new_med_data.Additional_charges, new_med_data.Arthritis, margins=True)
```

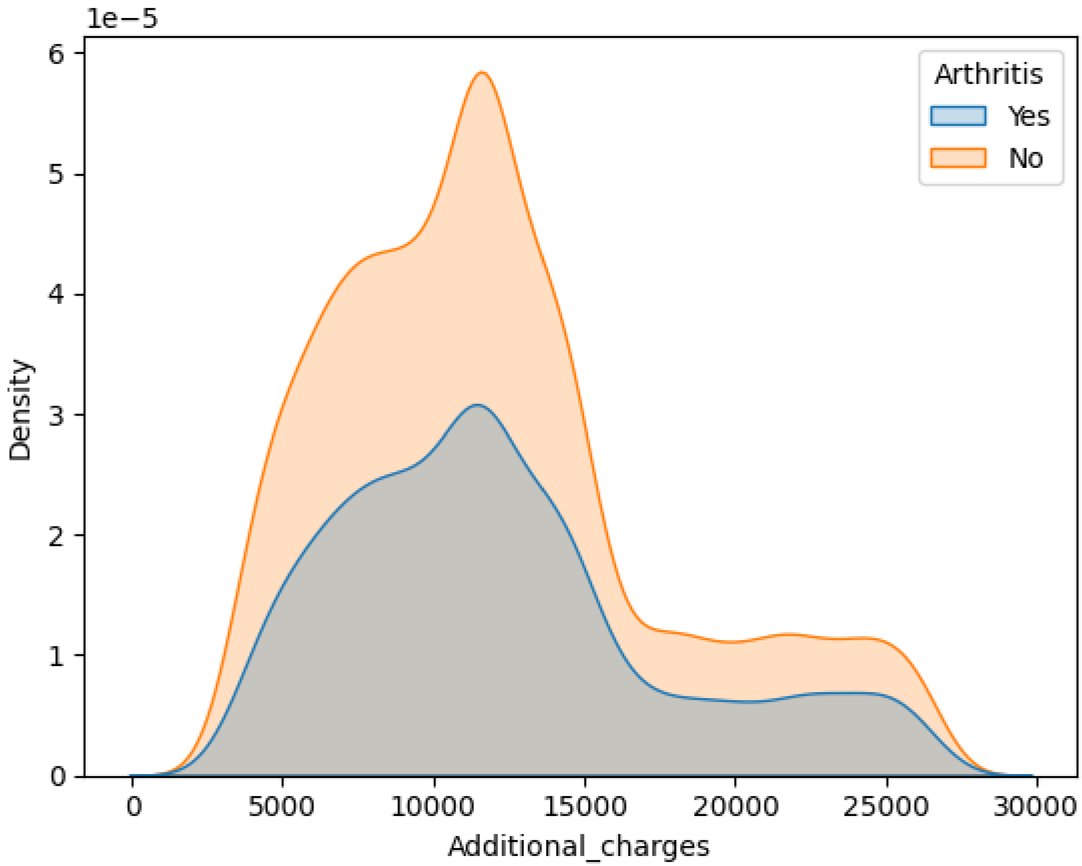
Out[71]:

Arthritis	No	Yes	All
Additional_charges			
3125.703	1	0	1
3132.25999	2	0	2
3139.049369	1	1	2
3173.112679	1	0	1
3213.0799	1	0	1
...	...	...	...
26592.28	1	0	1
26594.73	0	1	1
26601.03	1	0	1
26604.31	1	1	2
All	6426	3574	10000

8934 rows × 3 columns

In [72]:
```
# Bivariate (categorical values)
# Additional charges vs Arthritis
sns.kdeplot(data=new_med_data, x='Additional_charges', hue='Arthritis', fill=True)
```

Out[72]: <Axes: xlabel='Additional_charges', ylabel='Density'>



In [73]:
```
# Bivariate (categorical values)
# Additional charges vs Overweight
pd.crosstab(new_med_data.Additional_charges, new_med_data.Overweight, margins=True)
```

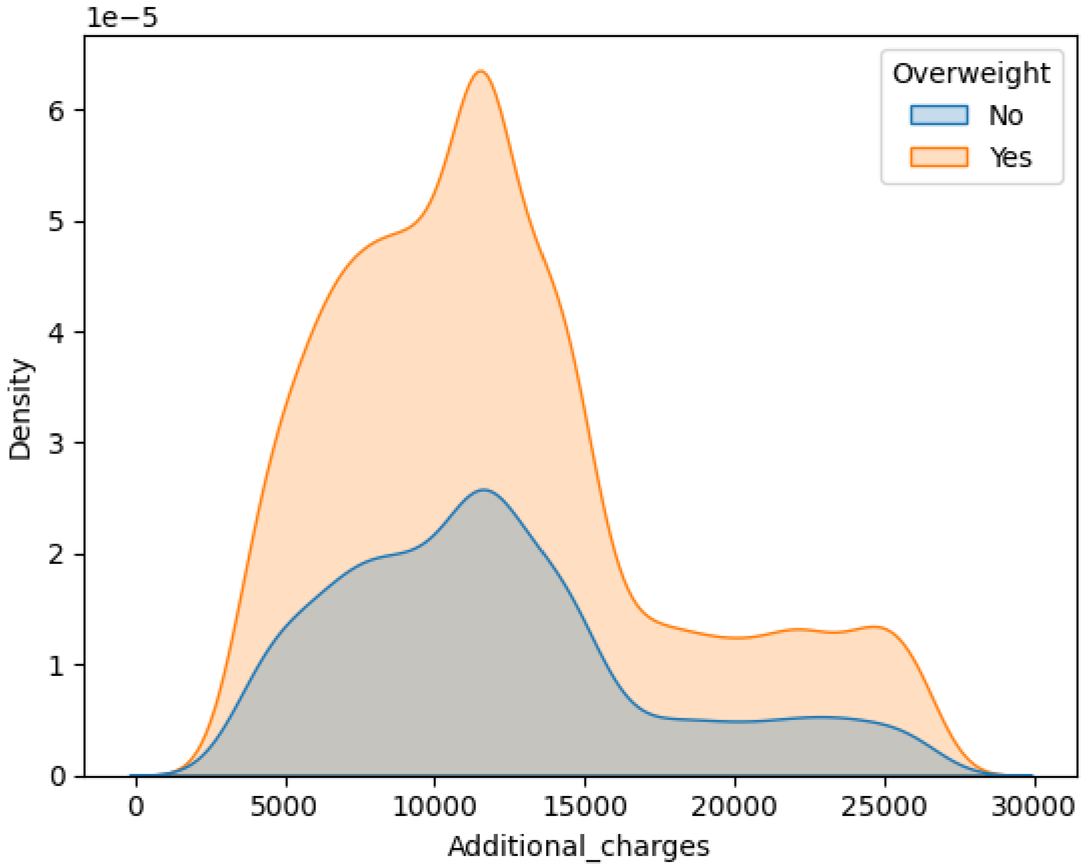
Out[73]:

Overweight	No	Yes	All
Additional_charges			
3125.703	1	0	1
3132.25999	0	2	2
3139.049369	0	2	2
3173.112679	1	0	1
3213.0799	0	1	1
...	...	...	...
26592.28	0	1	1
26594.73	0	1	1
26601.03	0	1	1
26604.31	0	2	2
All	2906	7094	10000

8934 rows × 3 columns

In [74]:
```
# Bivariate (categorical values)
# Additional charges vs Overweight
sns.kdeplot(data=new_med_data, x='Additional_charges', hue='Overweight', fill=True)
```

Out[74]: <Axes: xlabel='Additional_charges', ylabel='Density'>



In [75]:
```
# Bivariate (categorical values)
# Additional charges vs Diabetes
pd.crosstab(new_med_data.Additional_charges, new_med_data.Diabetes, margins=True)
```

Out[75]:

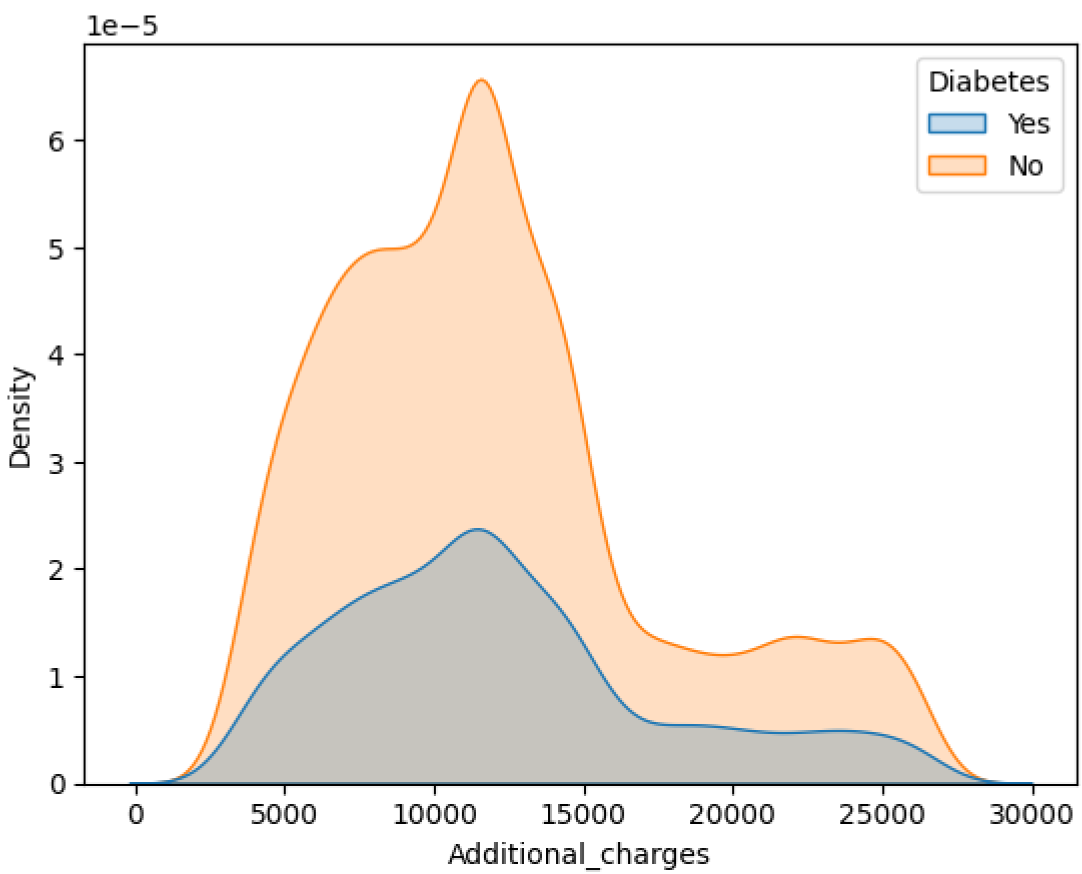
Diabetes	No	Yes	All
Additional_charges			
3125.703	1	0	1
3132.25999	2	0	2
3139.049369	2	0	2
3173.112679	1	0	1
3213.0799	1	0	1
...	...	...	...
26592.28	1	0	1
26594.73	0	1	1
26601.03	1	0	1
26604.31	2	0	2
All	7262	2738	10000

8934 rows × 3 columns

In [76]:

```
# Bivariate (categorical values)
# Additional charges vs Diabetes
sns.kdeplot(data=new_med_data, x='Additional_charges', hue='Diabetes', fill=True)
```

Out[76]: <Axes: xlabel='Additional_charges', ylabel='Density'>



In [77]:
```
# Bivariate (categorical values)
# Additional charges vs Anxiety
pd.crosstab(new_med_data.Additional_charges, new_med_data.Anxiety, margins=True)
```

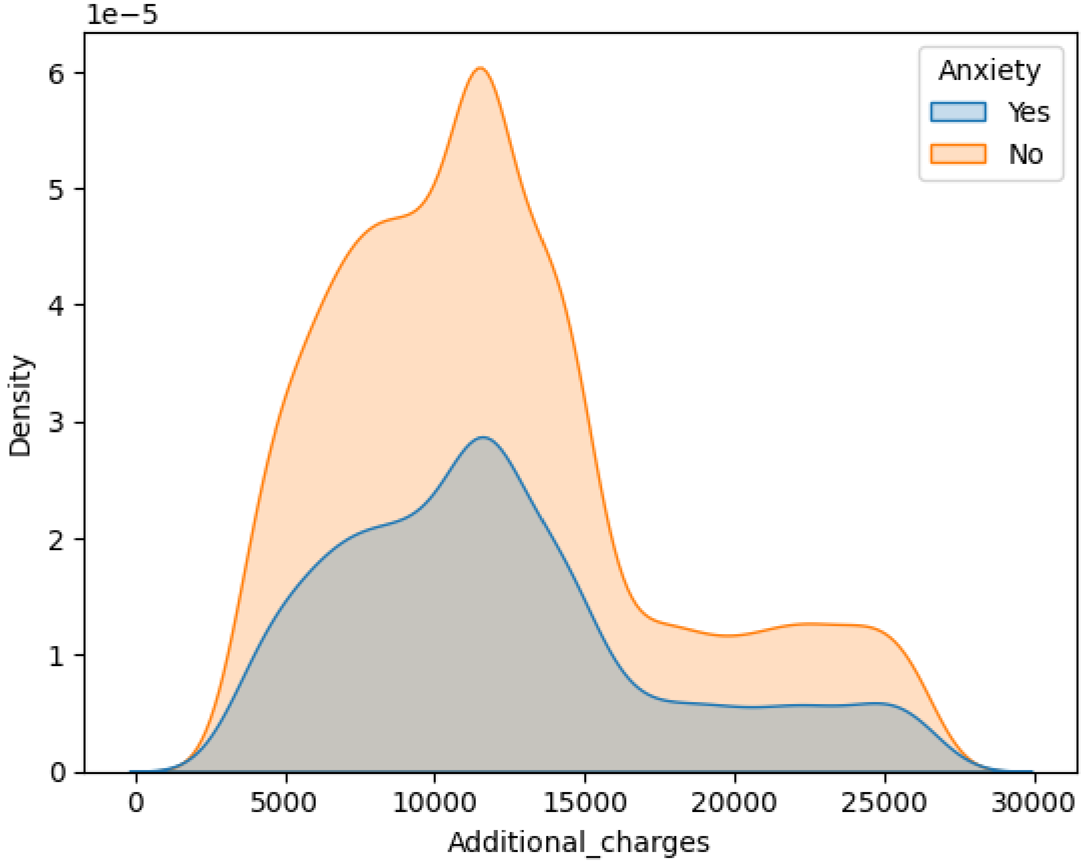
Out[77]:

Anxiety	No	Yes	All
Additional_charges			
3125.703	1	0	1
3132.25999	1	1	2
3139.049369	1	1	2
3173.112679	1	0	1
3213.0799	0	1	1
...	...	...	...
26592.28	1	0	1
26594.73	1	0	1
26601.03	0	1	1
26604.31	2	0	2
All	6785	3215	10000

8934 rows × 3 columns

In [78]:
```
# Bivariate (categorical values)
# Additional charges vs Anxiety
sns.kdeplot(data=new_med_data, x='Additional_charges', hue='Anxiety', fill=True)
```

Out[78]: <Axes: xlabel='Additional_charges', ylabel='Density'>



Data Transformation

My data transformation goals include changing categorical data to numerical data through the re-expression of categorical variables. Due to most statistical methods only working with numerical data, we had to change the categorical data to represent numerical values. I performed re-expression on ordinal data and nominal categorical data using the ordinal encoder technique and one hot encoding.

Ordinal data was re-expressed with an ordinal encoder technique. This technique started with creating a new column to insert the new values into. Next, a dictionary was created to easily distinguish the most valuable to the least valuable or in this case yes as the most valuable or 1 and no as the least valuable or 0. It is also worth mentioning the one other instance of ordinal data that included low, medium, and high values instead of Boolean values that were encoded as 0,1,2 respectively. The last step was to use the replace function in Python to replace the categorical values with the defined numerical values.

Nominal data was re-expressed with one hot encoding. There was one variable that had categorical data that was nominal: services. I used the function get dummies within the pandas library to create new variables called dummy variables that, “contain a binary encoding (0 or 1) to denote whether a particular row belongs to this category.” (Middleton, 2022) The services variable had four possible values and with the get dummies function, we can follow the k-1 rule to mitigate multicollinearity and retain 3 of the 4 dummy variables using the drop_first=True rule. Instead of using the services categorical variable, we now were able to use the 3 remaining dummy variables.

In [79]:
```
# Data Wrangling
# Re-expression
new_med_data.HighBlood.unique()
```

Out[79]:
```
array(['Yes', 'No'], dtype=object)
```

In [80]:
```
# 2. Create new column to input into
new_med_data['HighBlood_numeric'] = new_med_data['HighBlood']
```

In [81]:
```
# 3. Create dictionary for the values
dict_highblood = {"HighBlood_numeric": {"Yes": 1, "No": 0}}
new_med_data.replace(dict_highblood, inplace = True)
```

In [82]:
```
new_med_data.HighBlood_numeric.unique()
```

Out[82]:
```
array([1, 0], dtype=int64)
```

In [83]:
```
# Data Wrangling
# Re-expression
new_med_data.Stroke.unique()
```

Out[83]:
```
array(['No', 'Yes'], dtype=object)
```

In [84]:
```
# 2. Create new column to input into
new_med_data['Stroke_numeric'] = new_med_data['Stroke']
```

In [85]:
```
# 3. Create dictionary for the values
dict_stroke = {"Stroke_numeric": {"Yes": 1, "No": 0}}
new_med_data.replace(dict_stroke, inplace = True)
```

In [86]:
```
# Data Wrangling
# Re-expression
new_med_data.Arthritis.unique()
```

Out[86]:
```
array(['Yes', 'No'], dtype=object)
```

In [87]:
```
# 2. Create new column to input into
new_med_data['Arthritis_numeric'] = new_med_data['Arthritis']
```

In [88]:
```
# 3. Create dictionary for the values
dict_arthritis = {"Arthritis_numeric": {"Yes": 1, "No": 0}}
new_med_data.replace(dict_arthritis, inplace = True)
```

In [89]:
```
# Data Wrangling
# Re-expression
new_med_data.Overweight.unique()
```

Out[89]:
```
array(['No', 'Yes'], dtype=object)
```

In [90]:
```
# 2. Create new column to input into
new_med_data['Overweight_numeric'] = new_med_data['Overweight']
```

In [91]:
```
# 3. Create dictionary for the values
dict_overweight = {"Overweight_numeric": {"Yes": 1, "No": 0}}
new_med_data.replace(dict_overweight, inplace = True)
```

In [92]:
```
# Data Wrangling
# Re-expression
new_med_data.Diabetes.unique()
```

Out[92]:
```
array(['Yes', 'No'], dtype=object)
```

In [93]:
```
# 2. Create new column to input into
new_med_data['Diabetes_numeric'] = new_med_data['Diabetes']
```

In [94]:
```
# 3. Create dictionary for the values
dict_diabetes = {"Diabetes_numeric": {"Yes": 1, "No": 0}}
new_med_data.replace(dict_diabetes, inplace = True)
```

In [95]:
```
# Data Wrangling
# Re-expression
new_med_data.Anxiety.unique()
```

Out[95]:
```
array(['Yes', 'No'], dtype=object)
```

In [96]:
```
# 2. Create new column to input into
new_med_data['Anxiety_numeric'] = new_med_data['Anxiety']
```

In [97]:
```
# 3. Create dictionary for the values
dict_anxiety = {"Anxiety_numeric": {"Yes": 1, "No": 0}}
new_med_data.replace(dict_anxiety, inplace = True)
```

In [98]:
```
# Data Wrangling
# Re-expression
new_med_data.Complication_risk.unique()
```

Out[98]:
```
array(['Medium', 'High', 'Low'], dtype=object)
```

In [99]:
```
# 2. Create new column to input into
new_med_data['Complication_risk_numeric'] = new_med_data['Complication_risk']
```

In [100…
```
# 3. Create dictionary for the values
dict_complication = {"Complication_risk_numeric": {"Low": 0, "Medium": 1, "High": 2}}
new_med_data.replace(dict_complication, inplace = True)
```

In [102…
```
# Look at all column names to start developing the model
new_med_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 20 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Income                   10000 non-null  float64
 1   Doc_visits               10000 non-null  int64  
 2   HighBlood                10000 non-null  object 
 3   Stroke                   10000 non-null  object 
 4   Complication_risk        10000 non-null  object 
 5   Overweight               10000 non-null  object 
 6   Arthritis                10000 non-null  object 
 7   Diabetes                 10000 non-null  object 
 8   Anxiety                  10000 non-null  object 
 9   Services                 10000 non-null  object 
 10  Initial_days             10000 non-null  float64
 11  TotalCharge              10000 non-null  float64
 12  Additional_charges       10000 non-null  float64
 13  HighBlood_numeric        10000 non-null  int64  
 14  Stroke_numeric           10000 non-null  int64  
 15  Arthritis_numeric        10000 non-null  int64  
 16  Overweight_numeric       10000 non-null  int64  
 17  Diabetes_numeric         10000 non-null  int64  
 18  Anxiety_numeric          10000 non-null  int64  
 19  Complication_risk_numeric  10000 non-null  int64  
dtypes: float64(4), int64(8), object(8)
memory usage: 1.5+ MB
```

In [103…

```
# Drop columns that are not needed
new_med_data = new_med_data.drop(columns=['HighBlood','Stroke','Complication_risk','Ov
```

In [104…

```
new_med_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 13 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Income                   10000 non-null  float64
 1   Doc_visits               10000 non-null  int64  
 2   Services                 10000 non-null  object 
 3   Initial_days             10000 non-null  float64
 4   TotalCharge              10000 non-null  float64
 5   Additional_charges       10000 non-null  float64
 6   HighBlood_numeric        10000 non-null  int64  
 7   Stroke_numeric           10000 non-null  int64  
 8   Arthritis_numeric        10000 non-null  int64  
 9   Overweight_numeric       10000 non-null  int64  
 10  Diabetes_numeric         10000 non-null  int64  
 11  Anxiety_numeric          10000 non-null  int64  
 12  Complication_risk_numeric  10000 non-null  int64  
dtypes: float64(4), int64(8), object(1)
memory usage: 1015.8+ KB
```

In [105…

```
# Using get dummies pandas function to get numerical values for the one categorical va
new_med_data = pd.get_dummies(new_med_data, columns=['Services'], prefix='Services', c
new_med_data.head()
```

Out[105]:

	Income	Doc_visits	Initial_days	TotalCharge	Additional_charges	HighBlood_numeric	Stroke_num
0	86575.93	6	10.585770	3726.702860	17939.403420	1	
1	46805.99	4	15.129562	4193.190458	17612.998120	1	
2	14370.14	4	4.772177	2434.234222	17505.192460	1	
3	39741.49	4	1.714879	2127.830423	12993.437350	0	
4	1209.56	5	1.254807	2113.073274	3716.525786	0	

In [107…

```
# Multiple linear regression
y = new_med_data.Additional_charges
X = new_med_data[['Income','Initial_days','Doc_visits','TotalCharge', 'HighBlood_numer

model = sm.OLS(y,X.astype(float))
results_initial = model.fit()
print(results_initial.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     Additional_charges   R-squared:                       0.355
Model:                            OLS   Adj. R-squared:                  0.355
Method:                 Least Squares   F-statistic:                     393.3
Date:                Mon, 07 Aug 2023   Prob (F-statistic):               0.00
Time:                        23:26:49   Log-Likelihood:                -98188.
No. Observations:               10000   AIC:                         1.964e+05
Df Residuals:                    9985   BIC:                         1.965e+05
Df Model:                          14
Covariance Type:            nonrobust
==============================================================================
========
                               coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
--------
Income                      -0.0030      0.002     -1.457      0.145      -0.007
0.001
Initial_days               -51.6074     12.793     -4.034      0.000     -76.684
-26.530
Doc_visits                  22.4108     42.577      0.526      0.599     -61.049
105.870
TotalCharge                  0.6558      0.155      4.236      0.000       0.352
0.959
HighBlood_numeric         6609.2288     92.124     71.743      0.000    6428.647
6789.811
Stroke_numeric             348.0033    111.460      3.122      0.002     129.519
566.487
Arthritis_numeric           93.0304     93.494      0.995      0.320     -90.237
276.298
Overweight_numeric         -61.5910     98.083     -0.628      0.530    -253.853
130.671
Diabetes_numeric            97.9816    100.445      0.975      0.329     -98.910
294.873
Anxiety_numeric            -15.1317     96.307     -0.157      0.875    -203.913
173.650
Complication_risk_numeric   22.9094     70.331      0.326      0.745    -114.953
160.772
Services_CT Scan           270.6102    141.224      1.916      0.055      -6.218
547.438
Services_Intravenous        69.1391    100.474      0.688      0.491    -127.810
266.088
Services_MRI               120.6894    236.466      0.510      0.610    -342.832
584.211
const                     7531.1395    424.239     17.752      0.000    6699.546
8362.733
==============================================================================
Omnibus:                      523.454   Durbin-Watson:                   2.017
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              254.932
Skew:                           0.201   Prob(JB):                     4.39e-56
Kurtosis:                       2.329   Cond. No.                     4.05e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 4.05e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Model

An initial multiple linear regression model was created using all variables listed above in C2 with the dependent (y) variable as additional charges and the remaining variables as the independent (x) variables. Screenshot of the initial model summary below.

In [108…

```
# Reducing the model - Backward Stepwise Elimination
X = new_med_data.drop(columns=['Additional_charges','Anxiety_numeric']).assign(const=1

results_reduced = sm.OLS(y,X.astype(float)).fit()
print(results_reduced.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     Additional_charges   R-squared:                       0.355
Model:                            OLS   Adj. R-squared:                  0.355
Method:                 Least Squares   F-statistic:                     423.6
Date:                Mon, 07 Aug 2023   Prob (F-statistic):               0.00
Time:                        23:27:50   Log-Likelihood:                -98188.
No. Observations:               10000   AIC:                         1.964e+05
Df Residuals:                    9986   BIC:                         1.965e+05
Df Model:                          13
Covariance Type:            nonrobust
=====================================================================================
========
                             coef    std err          t      P>|t|      [0.025
0.975]
-------------------------------------------------------------------------------------
--------
Income                    -0.0030      0.002     -1.459      0.145      -0.007
0.001
Doc_visits                22.4238     42.575      0.527      0.598     -61.031
105.879
Initial_days             -51.3247     12.665     -4.052      0.000     -76.151
-26.498
TotalCharge                0.6523      0.153      4.258      0.000       0.352
0.953
HighBlood_numeric       6609.4835     92.105     71.760      0.000    6428.938
6790.029
Stroke_numeric           348.2084    111.447      3.124      0.002     129.750
566.667
Arthritis_numeric         93.0995     93.489      0.996      0.319     -90.157
276.356
Overweight_numeric       -61.4540     98.074     -0.627      0.531    -253.699
130.791
Diabetes_numeric          98.2633    100.424      0.978      0.328     -98.587
295.114
Complication_risk_numeric  23.7046    70.145      0.338      0.735    -113.794
161.203
Services_CT Scan         270.7416    141.215      1.917      0.055      -6.068
547.551
Services_Intravenous      69.0548    100.467      0.687      0.492    -127.881
265.991
Services_MRI             120.9551    236.449      0.512      0.609    -342.532
584.442
const                   7533.8507    423.867     17.774      0.000    6702.986
8364.715
==============================================================================
Omnibus:                      523.697   Durbin-Watson:                   2.018
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              254.976
Skew:                           0.201   Prob(JB):                     4.29e-56
Kurtosis:                       2.329   Cond. No.                     4.04e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 4.04e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [109…

```
# Reducing model - Backward Stepwise Elimination
X = new_med_data.drop(columns=['Additional_charges','Anxiety_numeric','Complication_ri
```

```
results_reduced = sm.OLS(y,X.astype(float)).fit()
print(results_reduced.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     Additional_charges   R-squared:                       0.355
Model:                            OLS   Adj. R-squared:                  0.355
Method:                 Least Squares   F-statistic:                     459.0
Date:                Mon, 07 Aug 2023   Prob (F-statistic):               0.00
Time:                        23:28:02   Log-Likelihood:                -98188.
No. Observations:               10000   AIC:                         1.964e+05
Df Residuals:                    9987   BIC:                         1.965e+05
Df Model:                          12
Covariance Type:            nonrobust
=====================================================================================
===
                          coef    std err          t      P>|t|      [0.025      0.9
75]
-------------------------------------------------------------------------------------
---
Income                 -0.0030      0.002     -1.455      0.146      -0.007       0.
001
Doc_visits             22.5528     42.571      0.530      0.596     -60.895     106.
001
Initial_days          -53.4272     11.031     -4.843      0.000     -75.051     -31.
803
TotalCharge             0.6779      0.133      5.089      0.000       0.417       0.
939
HighBlood_numeric    6607.2555     91.865     71.923      0.000    6427.181    6787.
330
Stroke_numeric        348.4727    111.439      3.127      0.002     130.030     566.
916
Arthritis_numeric      90.9398     93.266      0.975      0.330     -91.880     273.
760
Overweight_numeric    -61.2423     98.068     -0.624      0.532    -253.475     130.
990
Diabetes_numeric       96.2747    100.247      0.960      0.337    -100.229     292.
778
Services_CT Scan      271.1344    141.204      1.920      0.055      -5.654     547.
922
Services_Intravenous   69.1849    100.462      0.689      0.491    -127.741     266.
111
Services_MRI          120.0647    236.423      0.508      0.612    -343.373     583.
502
const                7498.1024    410.436     18.269      0.000    6693.564    8302.
640
==============================================================================
Omnibus:                      523.938   Durbin-Watson:                   2.018
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              255.026
Skew:                           0.201   Prob(JB):                     4.19e-56
Kurtosis:                       2.329   Cond. No.                     3.91e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 3.91e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [110…

```
# Reducing model - Backward Stepwise Elimination
X = new_med_data.drop(columns=['Additional_charges','Anxiety_numeric','Complication_ri

results_reduced = sm.OLS(y,X.astype(float)).fit()
print(results_reduced.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     Additional_charges   R-squared:                       0.355
Model:                            OLS   Adj. R-squared:                  0.355
Method:                 Least Squares   F-statistic:                     500.7
Date:                Mon, 07 Aug 2023   Prob (F-statistic):               0.00
Time:                        23:28:07   Log-Likelihood:                -98188.
No. Observations:               10000   AIC:                         1.964e+05
Df Residuals:                    9988   BIC:                         1.965e+05
Df Model:                          11
Covariance Type:            nonrobust
=====================================================================================
===
                           coef    std err          t      P>|t|      [0.025      0.9
75]
-------------------------------------------------------------------------------------
---
Income                  -0.0030      0.002     -1.457      0.145      -0.007       0.
001
Doc_visits              22.2734     42.566      0.523      0.601     -61.165     105.
711
Initial_days           -53.4092     11.031     -4.842      0.000     -75.032     -31.
786
TotalCharge              0.6777      0.133      5.088      0.000       0.417       0.
939
HighBlood_numeric     6607.3722     91.861     71.928      0.000    6427.305    6787.
439
Stroke_numeric         348.1563    111.433      3.124      0.002     129.725     566.
588
Arthritis_numeric       90.7257     93.261      0.973      0.331     -92.085     273.
537
Overweight_numeric     -61.3345     98.064     -0.625      0.532    -253.559     130.
890
Diabetes_numeric        97.3597    100.220      0.971      0.331     -99.092     293.
811
Services_CT Scan       263.0416    140.296      1.875      0.061     -11.968     538.
051
Services_Intravenous    61.0961     99.188      0.616      0.538    -133.332     255.
524
const                 7507.8168    409.975     18.313      0.000    6704.183    8311.
451
==============================================================================
Omnibus:                      523.437   Durbin-Watson:                   2.018
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              254.750
Skew:                           0.201   Prob(JB):                     4.81e-56
Kurtosis:                       2.329   Cond. No.                     3.91e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 3.91e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [111…

```
# Reducing model - Backward Stepwise Elimination
X = new_med_data.drop(columns=['Additional_charges','Anxiety_numeric','Complication_ri


results_reduced = sm.OLS(y,X.astype(float)).fit()
print(results_reduced.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     Additional_charges   R-squared:                       0.355
Model:                            OLS   Adj. R-squared:                  0.355
Method:                 Least Squares   F-statistic:                     550.8
Date:                Mon, 07 Aug 2023   Prob (F-statistic):               0.00
Time:                        23:28:11   Log-Likelihood:                -98188.
No. Observations:               10000   AIC:                         1.964e+05
Df Residuals:                    9989   BIC:                         1.965e+05
Df Model:                          10
Covariance Type:            nonrobust
=====================================================================================
===
                           coef    std err          t      P>|t|      [0.025      0.9
75]
-------------------------------------------------------------------------------------
---
Income                  -0.0030      0.002     -1.451      0.147      -0.007       0.
001
Initial_days           -53.4603     11.030     -4.847      0.000     -75.082     -31.
839
TotalCharge              0.6783      0.133      5.093      0.000       0.417       0.
939
HighBlood_numeric     6607.7052     91.856     71.936      0.000    6427.649    6787.
761
Stroke_numeric         348.0037    111.429      3.123      0.002     129.581     566.
427
Arthritis_numeric       90.6451     93.258      0.972      0.331     -92.159     273.
449
Overweight_numeric     -60.7201     98.053     -0.619      0.536    -252.924     131.
484
Diabetes_numeric        97.9942    100.209      0.978      0.328     -98.436     294.
424
Services_CT Scan       263.9627    140.280      1.882      0.060     -11.015     538.
940
Services_Intravenous    60.8084     99.183      0.613      0.540    -133.610     255.
226
const                 7617.1069    352.771     21.592      0.000    6925.605    8308.
609
==============================================================================
Omnibus:                      524.525   Durbin-Watson:                   2.018
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              255.155
Skew:                           0.201   Prob(JB):                     3.92e-56
Kurtosis:                       2.329   Cond. No.                     3.36e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 3.36e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [112…

```
# Reducing model - Backward Stepwise Elimination
X = new_med_data.drop(columns=['Additional_charges','Anxiety_numeric','Complication_ri

results_reduced = sm.OLS(y,X.astype(float)).fit()
print(results_reduced.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     Additional_charges   R-squared:                       0.355
Model:                            OLS   Adj. R-squared:                  0.355
Method:                 Least Squares   F-statistic:                     612.0
Date:                Mon, 07 Aug 2023   Prob (F-statistic):               0.00
Time:                        23:28:21   Log-Likelihood:                -98188.
No. Observations:               10000   AIC:                         1.964e+05
Df Residuals:                    9990   BIC:                         1.965e+05
Df Model:                           9
Covariance Type:            nonrobust
==============================================================================
=
                        coef    std err          t      P>|t|      [0.025      0.97
5]
------------------------------------------------------------------------------
-
Income               -0.0030      0.002     -1.444      0.149      -0.007       0.00
1
Initial_days        -53.4682     11.030     -4.848      0.000     -75.089     -31.84
8
TotalCharge           0.6782      0.133      5.092      0.000       0.417       0.93
9
HighBlood_numeric  6607.3919     91.852     71.936      0.000    6427.344    6787.43
9
Stroke_numeric      346.8382    111.409      3.113      0.002     128.454     565.22
3
Arthritis_numeric    90.5828     93.255      0.971      0.331     -92.216     273.38
1
Overweight_numeric  -60.4248     98.049     -0.616      0.538    -252.620     131.77
1
Diabetes_numeric     98.3584    100.204      0.982      0.326     -98.062     294.77
9
Services_CT Scan    242.3134    135.759      1.785      0.074     -23.802     508.42
8
const              7638.9813    350.951     21.767      0.000    6951.046    8326.91
6
==============================================================================
Omnibus:                      524.822   Durbin-Watson:                   2.018
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              255.200
Skew:                           0.201   Prob(JB):                     3.84e-56
Kurtosis:                       2.329   Cond. No.                     3.34e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 3.34e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [113…

```
# Reducing model - Backward Stepwise Elimination
X = new_med_data.drop(columns=['Additional_charges','Anxiety_numeric','Complication_ri
```

```
results_reduced = sm.OLS(y,X.astype(float)).fit()
print(results_reduced.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:     Additional_charges   R-squared:                       0.355
Model:                            OLS   Adj. R-squared:                  0.355
Method:                 Least Squares   F-statistic:                     688.5
Date:                Mon, 07 Aug 2023   Prob (F-statistic):               0.00
Time:                        23:28:29   Log-Likelihood:                -98189.
No. Observations:               10000   AIC:                         1.964e+05
Df Residuals:                    9991   BIC:                         1.965e+05
Df Model:                           8                                         
Covariance Type:            nonrobust                                         
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
Income               -0.0030      0.002     -1.436      0.151      -0.007       0.001
Initial_days        -53.5656     11.028     -4.857      0.000     -75.183     -31.948
TotalCharge           0.6795      0.133      5.103      0.000       0.419       0.941
HighBlood_numeric  6605.7739     91.811     71.950      0.000    6425.805    6785.742
Stroke_numeric      346.9266    111.406      3.114      0.002     128.549     565.304
Arthritis_numeric    90.2648     93.251      0.968      0.333     -92.525     273.055
Diabetes_numeric     98.7377    100.199      0.985      0.324     -97.673     295.148
Services_CT Scan    242.1478    135.755      1.784      0.074     -23.958     508.254
const              7592.4255    342.713     22.154      0.000    6920.638    8264.213
==============================================================================
Omnibus:                      525.871   Durbin-Watson:                   2.017
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              255.454
Skew:                           0.201   Prob(JB):                     3.38e-56
Kurtosis:                       2.328   Cond. No.                     3.26e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 3.26e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [114…

```
X = new_med_data.drop(columns=['Additional_charges','Anxiety_numeric','Complication_ri
results_reduced = sm.OLS(y,X.astype(float)).fit()
print(results_reduced.summary())
```

```
                             OLS Regression Results
==============================================================================
Dep. Variable:     Additional_charges   R-squared:                       0.355
Model:                            OLS   Adj. R-squared:                  0.355
Method:                 Least Squares   F-statistic:                     786.7
Date:                Mon, 07 Aug 2023   Prob (F-statistic):               0.00
Time:                        23:28:33   Log-Likelihood:                -98189.
No. Observations:               10000   AIC:                         1.964e+05
Df Residuals:                    9992   BIC:                         1.965e+05
Df Model:                           7
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
Income               -0.0030      0.002     -1.431      0.152      -0.007       0.001
Initial_days        -54.4878     10.987     -4.959      0.000     -76.025     -32.951
TotalCharge           0.6912      0.133      5.212      0.000       0.431       0.951
HighBlood_numeric  6605.0850     91.808     71.944      0.000    6425.122    6785.047
Stroke_numeric      345.0462    111.388      3.098      0.002     126.703     563.390
Diabetes_numeric     98.8433    100.199      0.986      0.324     -97.567     295.253
Services_CT Scan    242.0549    135.754      1.783      0.075     -24.050     508.160
const              7594.8889    342.703     22.162      0.000    6923.122    8266.656
==============================================================================
Omnibus:                      527.024   Durbin-Watson:                   2.017
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              255.722
Skew:                           0.201   Prob(JB):                     2.96e-56
Kurtosis:                       2.328   Cond. No.                     3.26e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 3.26e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [115…

```
X = new_med_data.drop(columns=['Additional_charges','Anxiety_numeric','Complication_ri
results_reduced = sm.OLS(y,X.astype(float)).fit()
print(results_reduced.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     Additional_charges   R-squared:                       0.355
Model:                            OLS   Adj. R-squared:                  0.355
Method:                 Least Squares   F-statistic:                     917.7
Date:                Mon, 07 Aug 2023   Prob (F-statistic):               0.00
Time:                        23:28:37   Log-Likelihood:                -98189.
No. Observations:               10000   AIC:                         1.964e+05
Df Residuals:                    9993   BIC:                         1.964e+05
Df Model:                           6
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
Income               -0.0030      0.002     -1.440      0.150      -0.007       0.001
Initial_days        -55.4650     10.942     -5.069      0.000     -76.914     -34.016
TotalCharge           0.7031      0.132      5.324      0.000       0.444       0.962
HighBlood_numeric  6603.1710     91.788     71.940      0.000    6423.249    6783.093
Stroke_numeric      345.7949    111.386      3.104      0.002     127.457     564.133
Services_CT Scan    243.7301    135.743      1.796      0.073     -22.354     509.814
const              7593.6153    342.700     22.158      0.000    6921.854    8265.376
==============================================================================
Omnibus:                      527.158   Durbin-Watson:                   2.017
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              255.718
Skew:                           0.201   Prob(JB):                     2.96e-56
Kurtosis:                       2.328   Cond. No.                     3.26e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 3.26e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [116…

```
X = new_med_data.drop(columns=['Additional_charges','Anxiety_numeric','Complication_ri
results_reduced = sm.OLS(y,X.astype(float)).fit()
print(results_reduced.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     Additional_charges   R-squared:                       0.355
Model:                            OLS   Adj. R-squared:                  0.355
Method:                 Least Squares   F-statistic:                     1101.
Date:                Mon, 07 Aug 2023   Prob (F-statistic):               0.00
Time:                        23:28:39   Log-Likelihood:                -98191.
No. Observations:               10000   AIC:                         1.964e+05
Df Residuals:                    9994   BIC:                         1.964e+05
Df Model:                           5
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
Initial_days        -55.4593     10.943     -5.068      0.000     -76.910     -34.009
TotalCharge           0.7033      0.132      5.325      0.000       0.444       0.962
HighBlood_numeric  6601.6885     91.787     71.924      0.000    6421.768    6781.609
Stroke_numeric      345.4016    111.391      3.101      0.002     127.052     563.751
Services_CT Scan    246.2365    135.739      1.814      0.070     -19.840     512.313
const              7484.2218    334.196     22.395      0.000    6829.130    8139.314
==============================================================================
Omnibus:                      528.319   Durbin-Watson:                   2.017
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              255.626
Skew:                           0.200   Prob(JB):                     3.10e-56
Kurtosis:                       2.327   Cond. No.                     4.32e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 4.32e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [117…

```
X = new_med_data.drop(columns=['Additional_charges','Anxiety_numeric','Complication_ri
results_reduced = sm.OLS(y,X.astype(float)).fit()
print(results_reduced.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     Additional_charges   R-squared:                       0.355
Model:                            OLS   Adj. R-squared:                  0.355
Method:                 Least Squares   F-statistic:                     1375.
Date:                Mon, 07 Aug 2023   Prob (F-statistic):               0.00
Time:                        23:28:45   Log-Likelihood:                -98192.
No. Observations:               10000   AIC:                         1.964e+05
Df Residuals:                    9995   BIC:                         1.964e+05
Df Model:                           4
Covariance Type:            nonrobust
=====================================================================================
                        coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------
Initial_days        -55.7636     10.943     -5.096      0.000     -77.214     -34.313
TotalCharge           0.7073      0.132      5.355      0.000       0.448       0.966
HighBlood_numeric  6603.1470     91.794     71.935      0.000    6423.213    6783.081
Stroke_numeric      348.1834    111.393      3.126      0.002     129.830     566.537
const              7502.4044    334.084     22.457      0.000    6847.532    8157.276
==============================================================================
Omnibus:                      531.346   Durbin-Watson:                   2.017
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              255.867
Skew:                           0.199   Prob(JB):                     2.75e-56
Kurtosis:                       2.325   Cond. No.                     4.32e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
[2] The condition number is large, 4.32e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [118…

```
# VIF (variance inflation factor) - looks at multicolinearity
from statsmodels.stats.outliers_influence import variance_inflation_factor
# Independent Variables Set
X = X.astype(float)

# VIF Data Frame
vif_data = pd.DataFrame()
vif_data["Feature"] = X.columns

# Calculate VIF for each feature
vif_data["VIF"] = [variance_inflation_factor(X.values, i)
for i in range(len(X.columns))]

vif_data = vif_data.sort_values(by='VIF', ascending=False)

print(vif_data)
```

```
             Feature        VIF
4              const  56.377480
1        TotalCharge  41.878499
0       Initial_days  41.863125
2  HighBlood_numeric   1.028799
3     Stroke_numeric   1.000208
```

In [119…

```
# Final reduced model
X = new_med_data.drop(columns=['Additional_charges','Anxiety_numeric','Diabetes_numeri
results_reduced = sm.OLS(y,X.astype(float)).fit()
print(results_reduced.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     Additional_charges   R-squared:                       0.353
Model:                            OLS   Adj. R-squared:                  0.353
Method:                 Least Squares   F-statistic:                     2727.
Date:                Mon, 07 Aug 2023   Prob (F-statistic):               0.00
Time:                        23:29:19   Log-Likelihood:                -98207.
No. Observations:               10000   AIC:                         1.964e+05
Df Residuals:                    9997   BIC:                         1.964e+05
Df Model:                           2
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
HighBlood_numeric  6684.5358     90.630     73.756      0.000    6506.882    6862.189
Stroke_numeric      340.6685    111.542      3.054      0.002     122.023     559.314
const              9306.3902     61.976    150.160      0.000    9184.904    9427.876
==============================================================================
Omnibus:                      535.698   Durbin-Watson:                   2.015
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              253.995
Skew:                           0.193   Prob(JB):                     7.01e-56
Kurtosis:                       2.322   Cond. No.                         2.89
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
```

In [120…

```
# Calculating RSE
mse = results_initial.mse_resid
print('mse: ',mse)

rse = np.sqrt(mse)
print('rse: ',rse)
```

```
mse:  19799875.768461548
rse:  4449.705132754478
```

In [122…

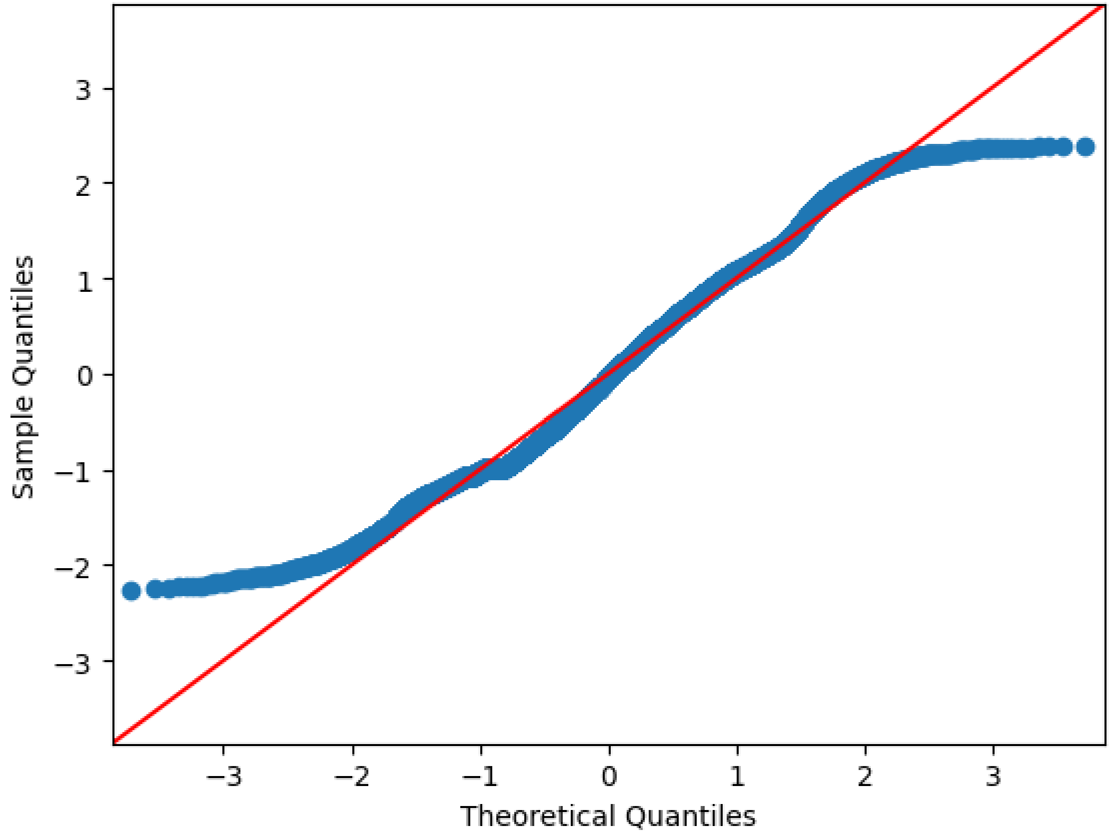
```
# Calculating RSE
mse = results_reduced.mse_resid
print('mse: ',mse)

rse = np.sqrt(mse)
print('rse: ',rse)
```

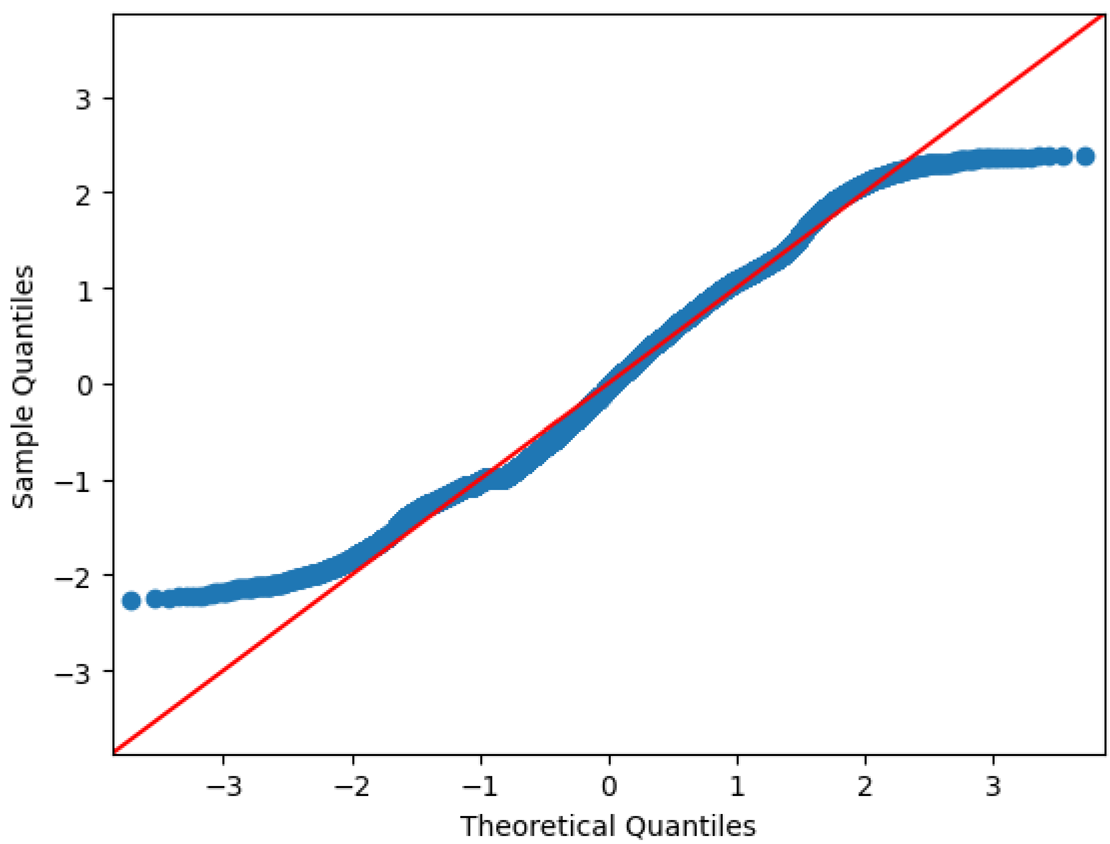
```
mse:  19853294.35214707
rse:  4455.703575435317
```

In [123…

```
# Visualizing model fit of reduced model
sm.qqplot(data=results_reduced.resid, fit=True, line="45")
```

Out[123]:





Justification of Model Reduction

The feature selection procedure that I initially used to reduce the linear regression model was backward stepwise elimination. Backward stepwise elimination is defined as a wrapper method that, “feed the features (variables) for your model and based on the model performance you add/remove the features.” (Middleton, 2022) This was performed by evaluating the initial model variables and their corresponding p-values. I made comparisons and started eliminating variables one by one starting with the highest p-value first until there were no variables that were above 0.05. At the end of the evaluation, I removed a total of ten variables. With this technique, we were able to reduce the model and focus on those variables that have more influence on the dependent variable and get rid of those variables that do not.

Lastly, I used the Variance Inflation Factor (VIF) to look at multicollinearity and reduce the model further. Multicollinearity is important to address to adhere to the initial assumption that multicollinearity is low. When performing VIF, there were two variables with a value of above 10 which were then dropped from the model. (Sewell, n.d.)

Model Comparison

Looking at the initial model and the reduced model, it appears that the model decreased in strength and validity by a small amount. The model evaluation metric I chose to focus on was the residual standard error. The residual standard error (RSE) is, “Used to measure how well a regression model fits a dataset. In simple terms, it measures the standard deviation of the residuals in a regression model.” (Middleton, 2022) The initial model RSE was 4449.71 and the reduced model RSE was 4455.70. Since a lower RSE is better, it appears that the model got slightly worse after reduction.

Results

An interpretation of the coefficients of the reduced model
HighBlood_numeric: 6684.54
Stroke_numeric : 340.67

The coefficients listed above are for all remaining variables within the reduced model. These coefficients indicate the effect that each variable has on the dependent variable additional charges in parallel with what direction the effect is. (Middleton, 2022) This means that a one-unit increase of the independent variable results in the value of the coefficients increase in the dependent variable. When an individual is characterized as having high blood pressure, there is an associated increase of additional charges by 6684.54. Similarly, when an individual is characterized as having a stroke there is an increase of additional charges by 340.67.

The statistical and practical significance of the reduced model
The model does have statistical significance. To determine statistical model significance, I focused on the F-statistic and the p-value. The p-value or Prob(F-statistic) in the summary of the reduced model indicated a value of 0.0. This value is less than the significance level of 0.05 and

therefore leads to the conclusion that we reject the null hypothesis and determine that there is a relationship that exists within this model. (Straw, 2023) As mentioned above, another evaluation metric to look at would be the F-statistic which was 2727. Utilizing the F-table of critical values, I discovered that the F-statistic (2727) was greater than the critical value (3) leading to the conclusion that the model is statistically significant. (Straw, 2023)

Now, looking at practical significance I do not believe that this model is practically significant. This model is looking at the relationship between additional hospital charges and the reduced models independent variables high blood pressure and stroke. The independent variables high blood pressure and stroke are too complex to condemn it to a simple linear regression model. When it comes to medical issues like high blood pressure and stroke, there are almost always other underlying factors and variables to consider that would cause an affect on additional hospital charges. This could be underlying diseases or even certain treatment protocols for these certain medical conditions.

Limitations of the data analysis

With data analysis, there are always advantages and disadvantages of each method used. I would like to focus on the methods used for outliers treatment, re-expression of categorical data, backward stepwise elimination, and variance inflation factor (VIF).

Outliers: The treatment I chose for the outliers within this data analysis was replacing them with the median or imputation. This method has drawbacks that stem from causing unnecessary influence on the data, skewing the data improperly, or adding bias.

Re-expression of categorical data: Due to the process of ordinal encoding, with larger data sets and more unique values this method could turn into a lengthy process in the future. One hot encoding increases dimensionality and decreases optimization with the increase in columns and lack of new information.

Backward Stepwise Elimination: Using this method could cause the elimination of explanatory variables that do have causal effects on the dependent variable with the lack of statistical significance and, “nuisance variables may be coincidentally significant.” (Smith, 2018)

Variance Inflation Factor (VIF): I performed VIF after backward stepwise elimination which could have had an influence on the VIF values and caused incorrect interpretation.

Recommendations

Based on my results, I would recommend focusing on the creation and maintenance of a more exhaustive list of variables. Due to the complexity of these variables within the model created, it is important to zoom in on other underlying variables like billing practices or necessary treatment protocols when faced with these complicated variables.

In [ ]:

```
```