Data Mining - K-Nearest Neighbor

Data Mining I expands predictive modeling into nonlinear dimensions, enhancing the capabilities and effectiveness of the data analytics lifecycle. In this course, learners implement supervised models—specifically classification and prediction data mining models—to unearth relationships among variables that are not apparent with more surface-level techniques. The course provides frameworks for assessing models' sensitivity and specificity.

Competencies

Classification Data Mining Models
Applies observations to appropriate classes and categories using classification models.

Predictive Data Mining Models
Implements prediction data mining models to find hard-to-spot relationships among variables.

Data Mining Model Performance
Evaluates data mining model performance for precision, accuracy, and model comparison.

Write Up

Research Question
Can the classification method K-Nearest Neighbor be used to predict readmission of patients?

Goal
One goal of the data analysis is to determine if the K-Nearest Neighbors classification method can produce a model that can predict readmission of patients.

Explanation of Classification Method
The classification method I chose is K-Nearest Neighbor. This method classifies, "a record in accordance with how similar records are classified." (Bruce et al, 2020) K-Nearest Neighbor works by calculating the distance of a test observation from other observations within the dataset and then finding the data points label, "by looking at the 'k' closest labeled data point and getting them to vote on what the unlabeled point should have." (Elleh, 2022) The distance calculation used is called Euclidean distance and is used to calculate the distance between the data points mentioned above. The expected outcome will be a model that can make accurate predictions for the target categorical variable readmission of patients.

Summary of Method Assumption
One assumption of the K-Nearest Neighbors classification method is, "The K-nearest neighbors classification method assumes that similar things exist in proximity to each other." (Elleh, 2022)

This assumption is important as the basis of K-NN is classifying a record in accordance with how similar records are classified so we must assume that close records are similar.

Code

In [1]:
```
# Importing packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import missingno as msno
import seaborn as sns
```

In [2]:
```
# Importing medical data CSV and creating the medical_data DataFrame
medical_data = pd.read_csv("C:/Users/Makayla Avendano/Desktop/medical_clean.csv")
```

In [3]:
```
# 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 [4]:
```
# Drop columns that are not needed
medical_data = medical_data.drop(columns=['Interaction', 'UID', 'City', 'State', 'Cour
```

In [5]:
```
# Updated data frame
medical_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
```

In [6]:
```
# Duplicates
medical_duplicates = medical_data.duplicated()
print(medical_duplicates.value_counts())
```

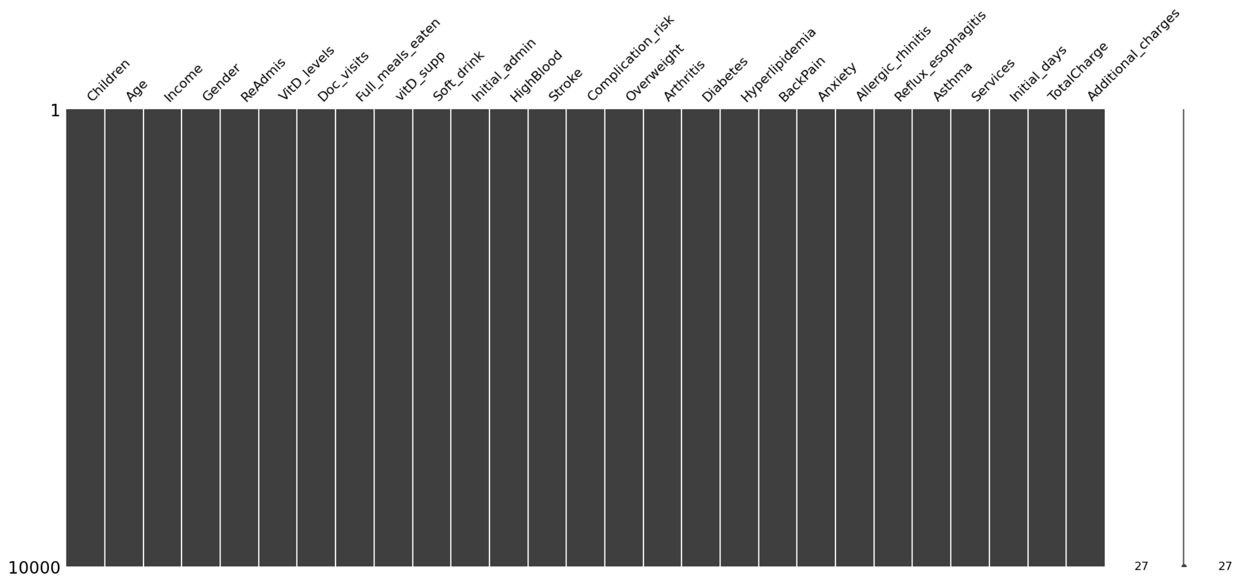
```
False    10000
Name: count, dtype: int64
```

In [7]:
```
# Missing Values
# Sum of all null values within each column
medical_data.isnull().sum()
```

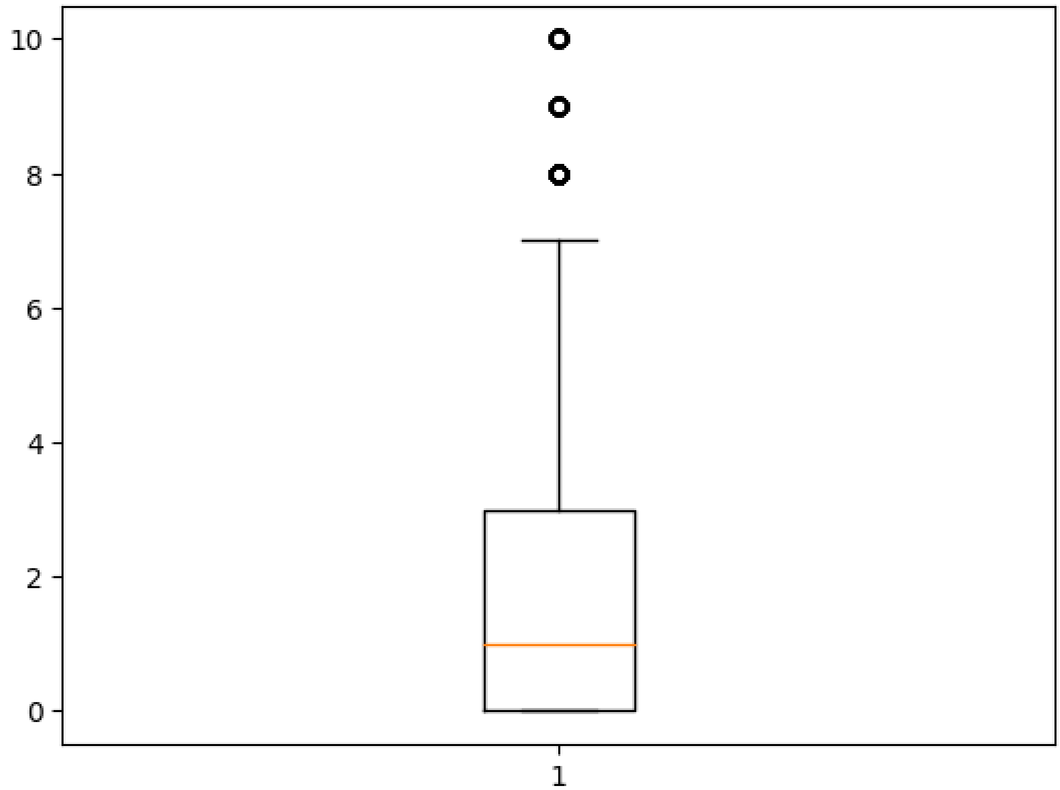
Out[7]:
```
Children              0
Age                   0
Income                0
Gender                0
ReAdmis               0
VitD_levels           0
Doc_visits            0
Full_meals_eaten      0
vitD_supp             0
Soft_drink            0
Initial_admin         0
HighBlood             0
Stroke                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 [8]:
```
# Double checking no missing values
msno.matrix(medical_data)
```

Out[8]: <Axes: >



In [9]:
```
# Outliers
ChildrenPlot = plt.boxplot(x='Children', data = medical_data)
```

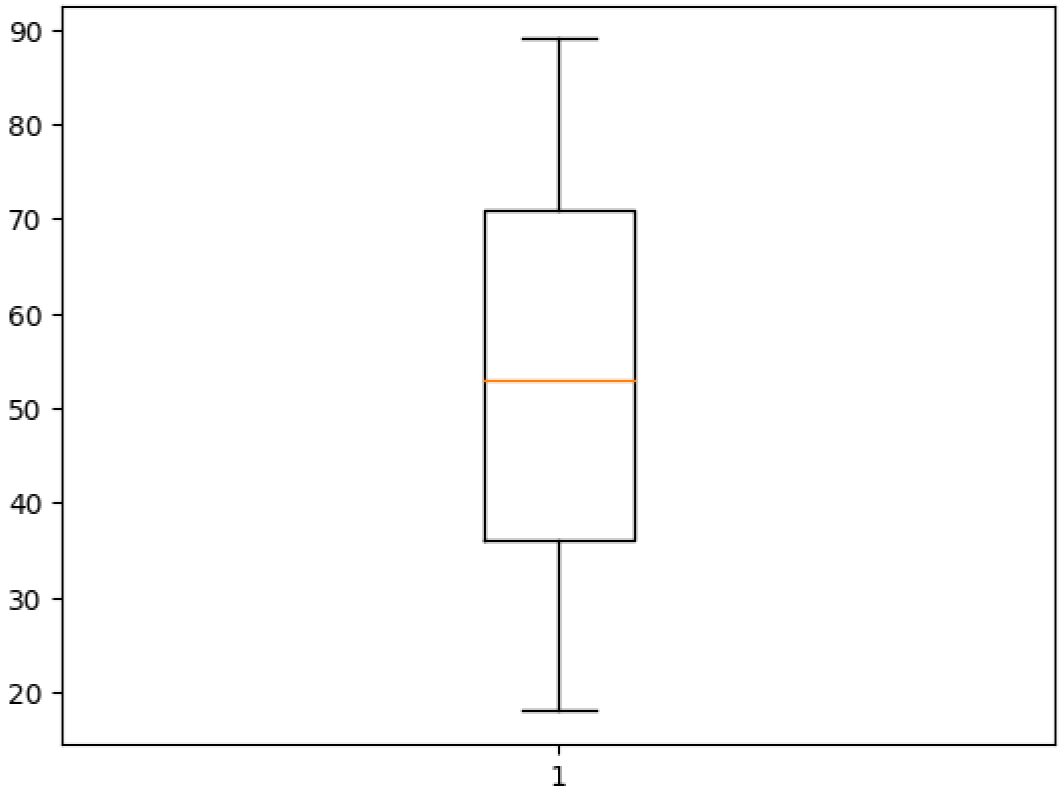


In [10]:
```
# Treat outliers with imputation - Finding the maximuim value for the box plot (upper
Q3_children = np.percentile(medical_data['Children'], 75)
Q1_children = np.percentile(medical_data['Children'], 25)
IQR_children = Q3_children - Q1_children
Max_children = Q3_children + (1.5 * IQR_children)
print(Max_children)
```

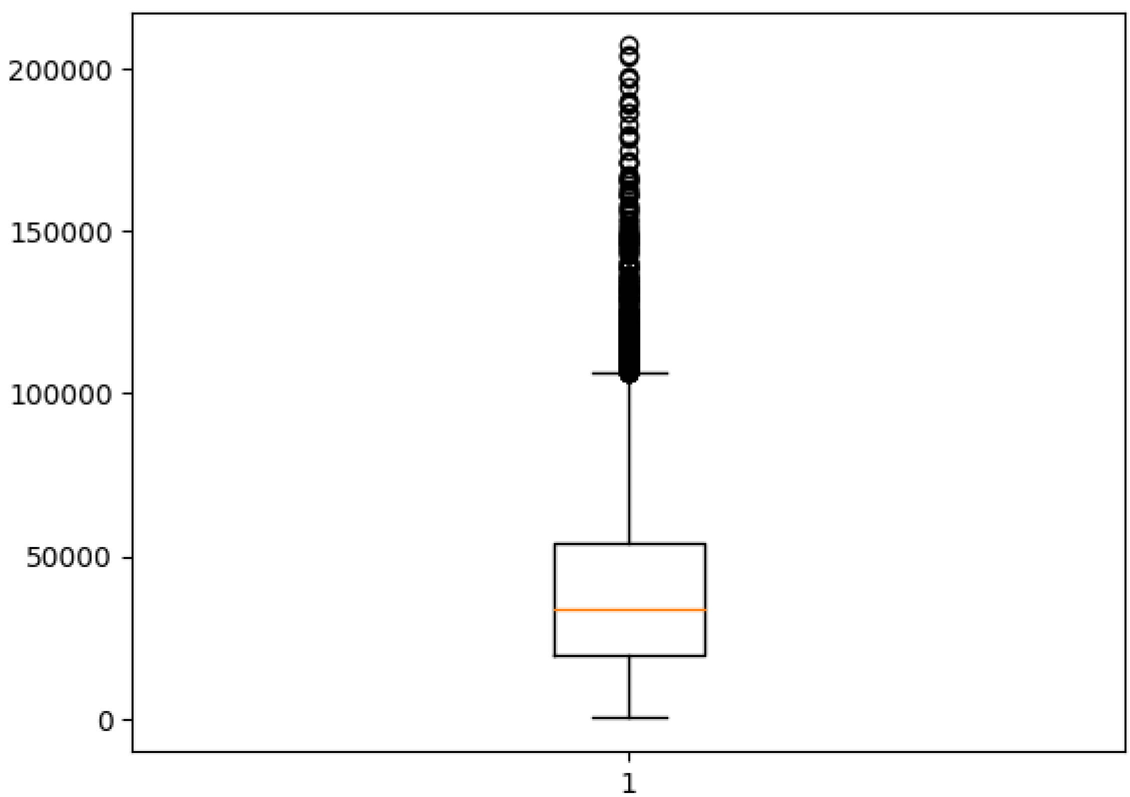
```
7.5
```

In [11]:
```
# Replacing with the median
median = float(medical_data['Children'].median())
medical_data['Children'] = np.where(medical_data['Children'] > Max_children, median, r
```

In [12]:
```
AgePlot = plt.boxplot(x='Age', data = medical_data)
```



In [13]:
```
IncomePlot = plt.boxplot(x='Income', data = medical_data)
```



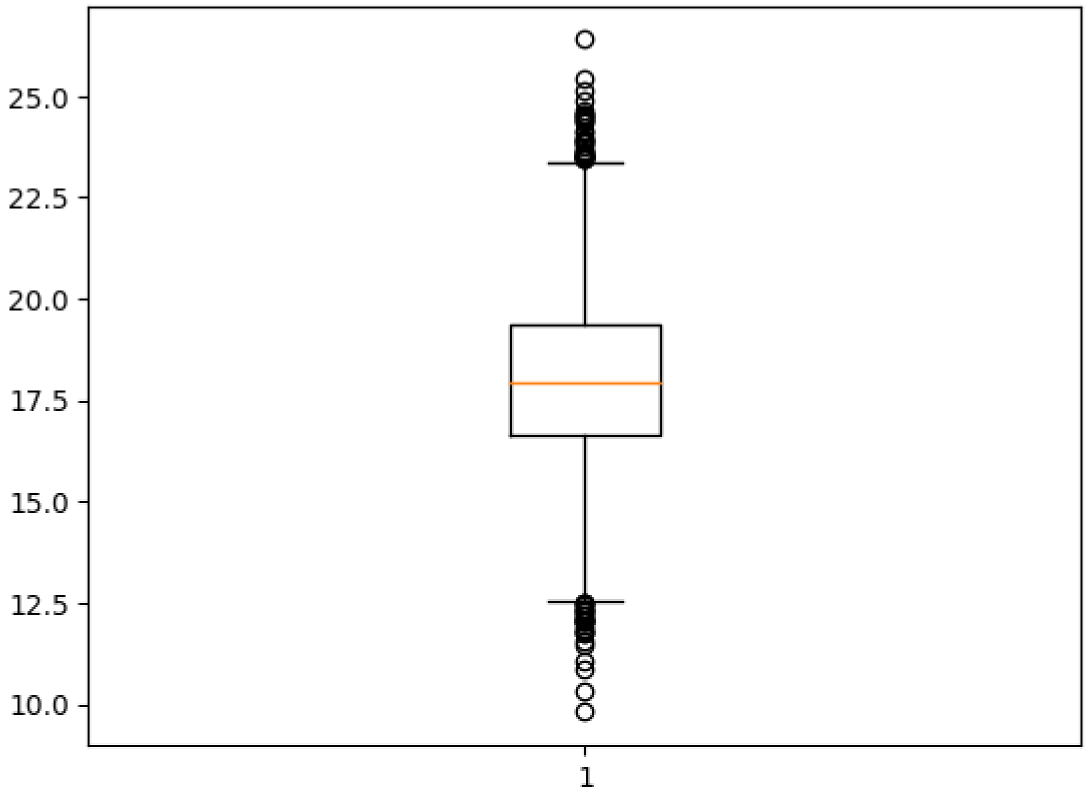
In [14]:
```
# Treat outliers with imputation - Finding the maximuim value for the box plot (upper
Q3_income = np.percentile(medical_data['Income'], 75)
Q1_income = np.percentile(medical_data['Income'], 25)
IQR_income = Q3_income - Q1_income
```

```
Max_income = Q3_income + (1.5 * IQR_income)
print(Max_income)
```

106342.84374999999

In [15]:
```
# Replacing with the median
median = float(medical_data['Income'].median())
medical_data['Income'] = np.where(medical_data['Income'] > Max_income, median, medical
```

In [16]:
```
VitDlevelsplot = plt.boxplot(x='VitD_levels', data = medical_data)
```



In [17]:
```
# Treat outliers with imputation - Finding the maximuim value for the box plot (upper
Q3_vitd = np.percentile(medical_data['VitD_levels'], 75)
Q1_vitd = np.percentile(medical_data['VitD_levels'], 25)
IQR_vitd = Q3_vitd - Q1_vitd
Max_vitd = Q3_vitd + (1.5 * IQR_vitd)
rounded_max_vitd = round(Max_vitd,1)
print(rounded_max_vitd)
```

23.4

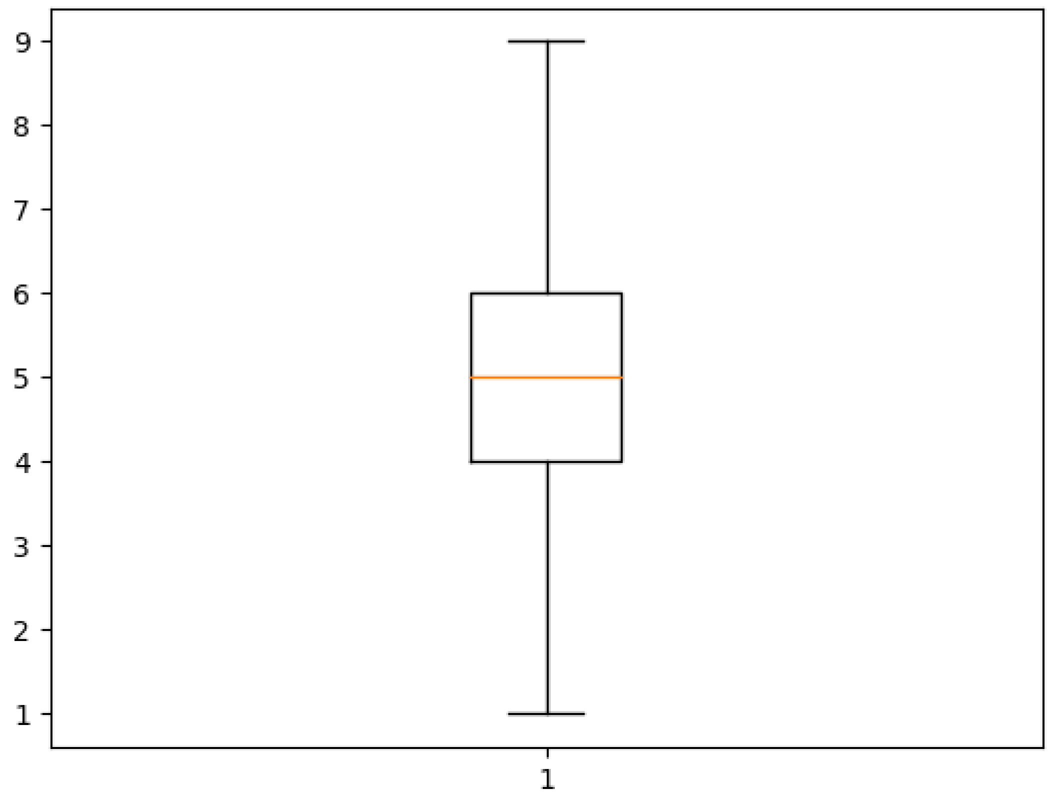
In [18]:
```
# Treat outliers with imputation - Finding the maximuim value for the box plot (lower
Q3_vitd = np.percentile(medical_data['VitD_levels'], 75)
Q1_vitd = np.percentile(medical_data['VitD_levels'], 25)
IQR_vitd = Q3_vitd - Q1_vitd
Min_vitd = Q1_vitd - (1.5 * IQR_vitd)
rounded_min_vitd = round(Min_vitd,1)
print(rounded_min_vitd)
```

12.5

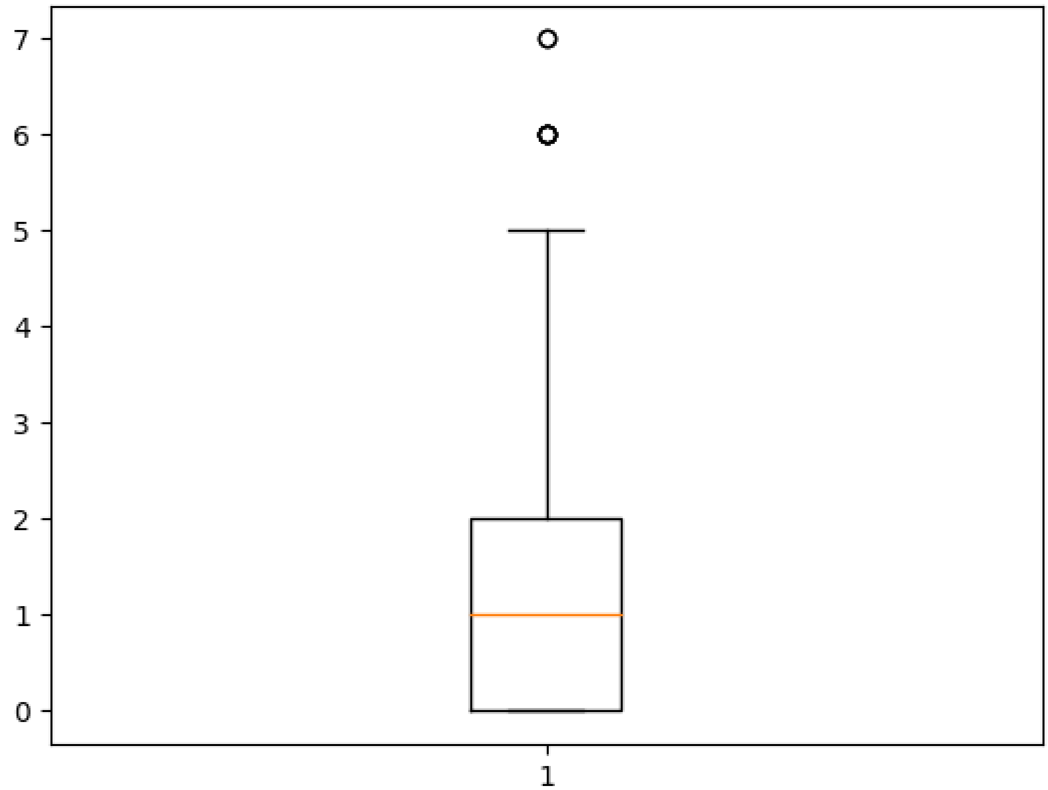
In [19]:
```
# Replacing with the median
median = float(medical_data['VitD_levels'].median())
medical_data['VitD_levels'] = np.where(medical_data['VitD_levels'] > rounded_max_vitd,
```

In [20]:
```
# Replacing with the median
median = float(medical_data['VitD_levels'].median())
medical_data['VitD_levels'] = np.where(medical_data['VitD_levels'] < rounded_min_vitd,
```

In [21]:
```
Docvisitsplot = plt.boxplot(x='Doc_visits', data = medical_data)
```



In [22]:
```
Fullsmealseatenplot = plt.boxplot(x='Full_meals_eaten', data = medical_data)
```

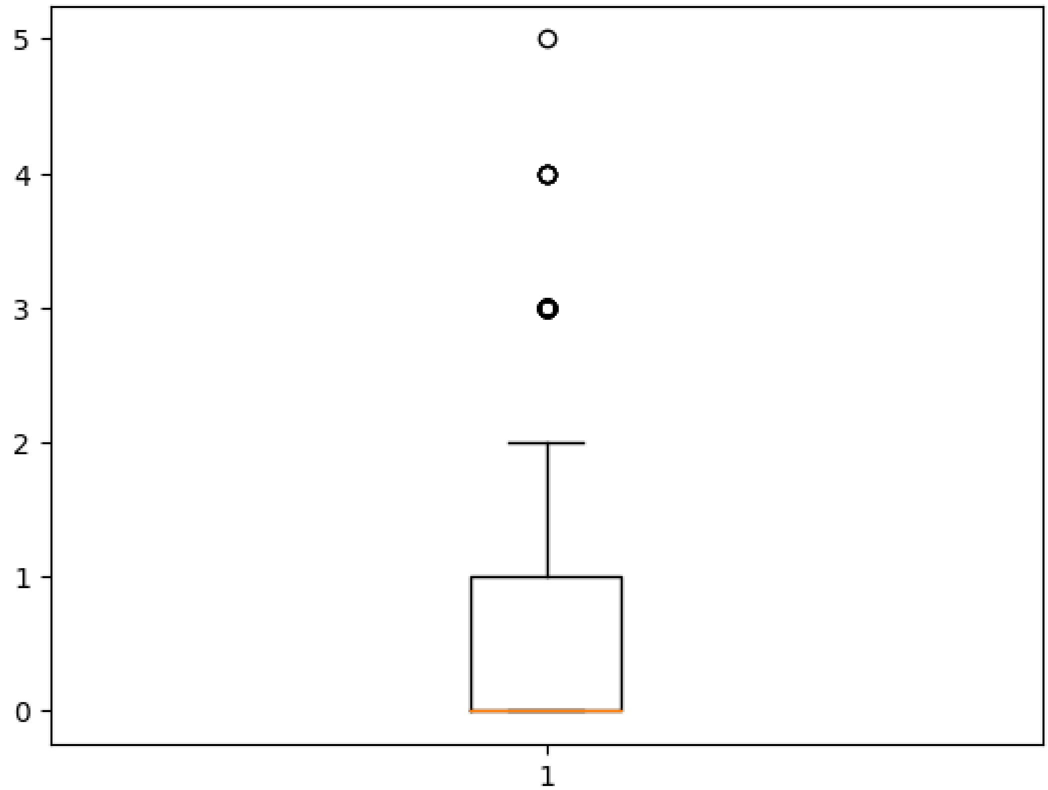


In [23]:
```
# Treat outliers with imputation - Finding the maximuim value for the box plot (upper
Q3_meals = np.percentile(medical_data['Full_meals_eaten'], 75)
Q1_meals = np.percentile(medical_data['Full_meals_eaten'], 25)
IQR_meals = Q3_vitd - Q1_vitd
Max_meals = Q3_vitd + (1.5 * IQR_vitd)
rounded_max_meals = round(Max_meals,1)
print(rounded_max_meals)
```

```
23.4
```

In [24]:
```
# Replacing with the median
median = float(medical_data['Full_meals_eaten'].median())
medical_data['Full_meals_eaten'] = np.where(medical_data['Full_meals_eaten'] > roundec
```

In [25]:
```
VitDSuppplot = plt.boxplot(x='vitD_supp', data = medical_data)
```

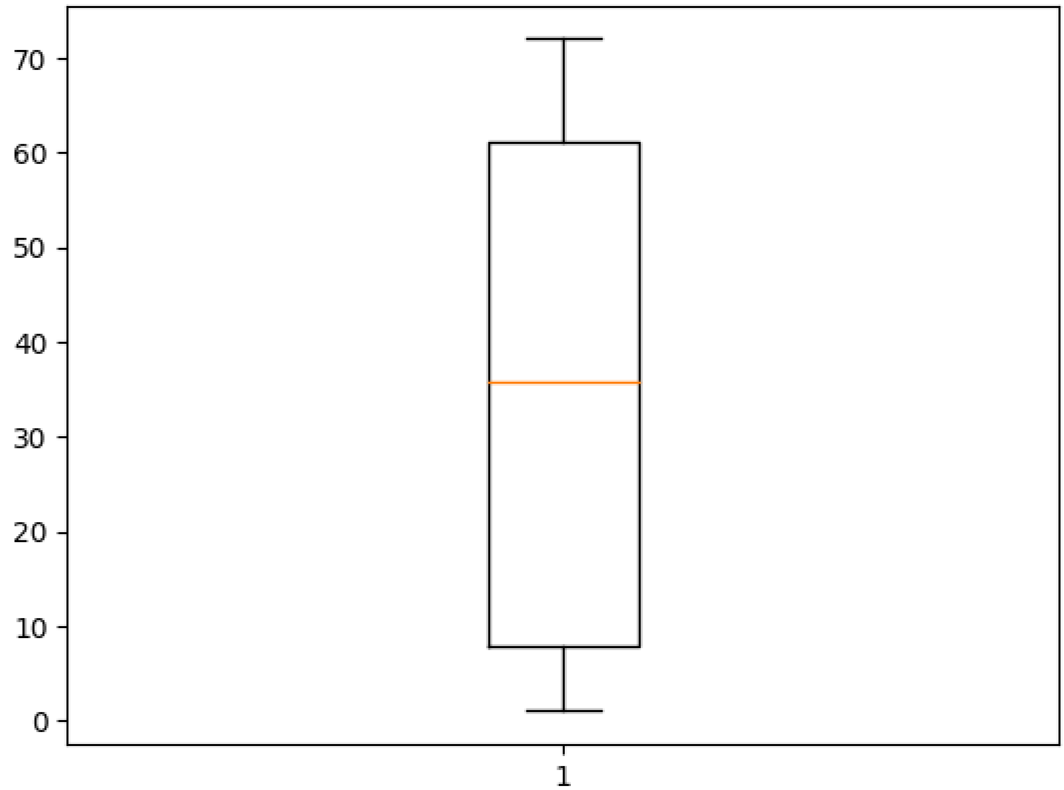


In [26]:
```
# Treat outliers with imputation - Finding the maximuim value for the box plot (upper
Q3_supp = np.percentile(medical_data['vitD_supp'], 75)
Q1_supp = np.percentile(medical_data['vitD_supp'], 25)
IQR_supp = Q3_supp - Q1_supp
Max_supp = Q3_supp + (1.5 * IQR_supp)
rounded_max_supp = round(Max_supp,1)
print(rounded_max_supp)
```

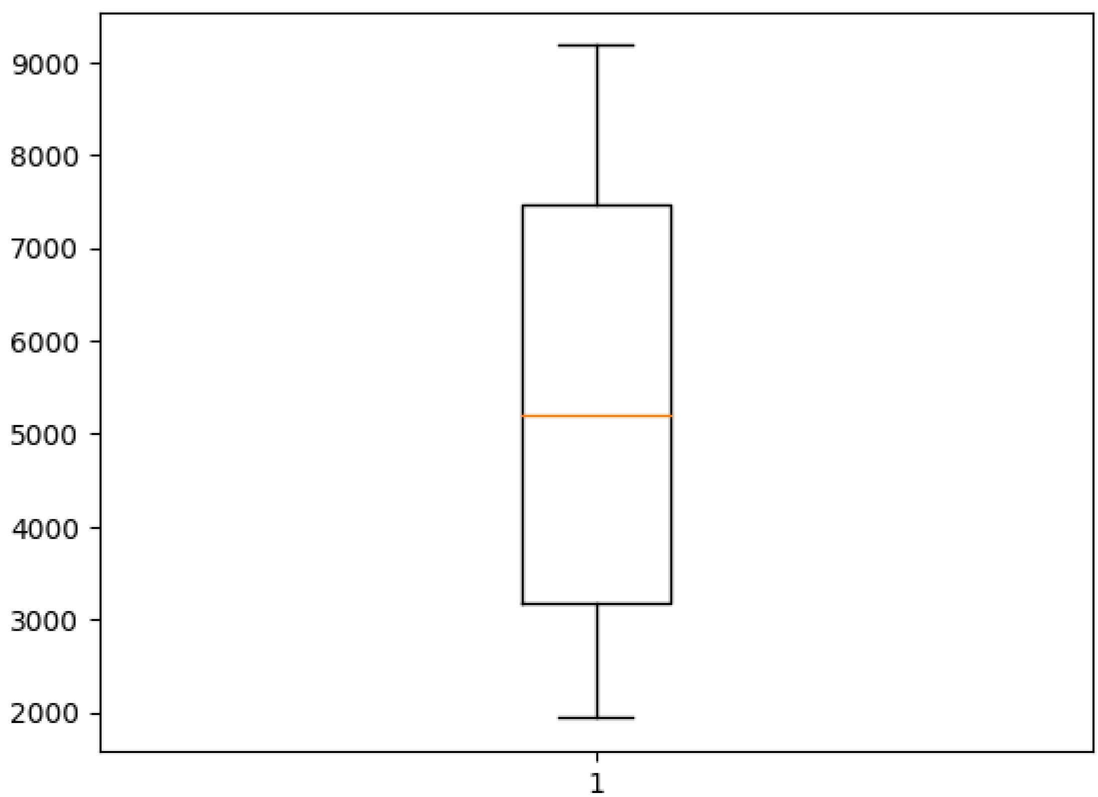
```
2.5
```

In [27]:
```
# Replacing with the median
median = float(medical_data['vitD_supp'].median())
medical_data['vitD_supp'] = np.where(medical_data['vitD_supp'] > rounded_max_supp, mec
```

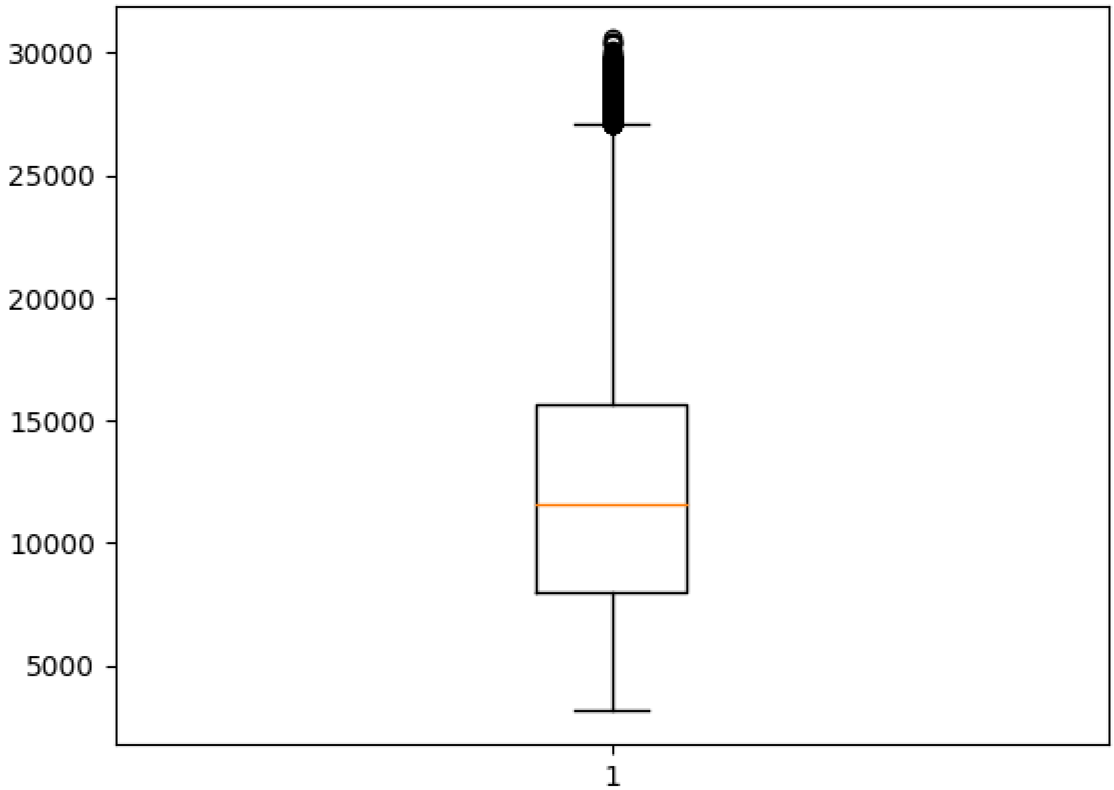
In [28]:
```
Initialdaysplot = plt.boxplot(x='Initial_days', data = medical_data)
```



In [29]:
```
TotalChargePlot = plt.boxplot(x='TotalCharge', data = medical_data)
```



In [30]:
```
AddPlot = plt.boxplot(x='Additional_charges', data = medical_data)
```



In [31]:
```
# Treat outliers with imputation - Finding the maximuim value for the box plot (upper
Q3_add = np.percentile(medical_data['Additional_charges'], 75)
Q1_add = np.percentile(medical_data['Additional_charges'], 25)
IQR_add = Q3_add - Q1_add
Max_add = Q3_add + (1.5 * IQR_add)
rounded_max_add = round(Max_add,1)
print(rounded_max_add)
```

```
27086.5
```

In [32]:
```
# Replacing with the median
median = float(medical_data['Additional_charges'].median())
medical_data['Additional_charges'] = np.where(medical_data['Additional_charges'] > rou
```

In [33]:
```
# Exploratory
# EDA - Looking at descriptive statistics
medical_data.describe()
```

Out[33]:

	Children	Age	Income	VitD_levels	Doc_visits	Full_meals_eaten	vi
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000	1000
mean	1.779900	53.511700	37355.193095	17.958778	5.012200	1.001400	
std	1.673361	20.638538	22986.930317	1.962375	1.045734	1.008117	
min	0.000000	18.000000	154.080000	12.507730	1.000000	0.000000	
25%	0.000000	36.000000	19598.775000	16.642449	4.000000	0.000000	
50%	1.000000	53.000000	33766.005000	17.951074	5.000000	1.000000	
75%	3.000000	71.000000	51024.942500	19.325515	6.000000	2.000000	
max	7.000000	89.000000	106220.500000	23.363658	9.000000	7.000000	

In [34]:
```
# Qualitative/categorical descriptive data
medical_data.describe(include='object')
```

Out[34]:

	Gender	ReAdmis	Soft_drink	Initial_admin	HighBlood	Stroke	Complication_risk	Overweigh
count	10000	10000	10000	10000	10000	10000	10000	1000
unique	3	2	2	3	2	2	3	
top	Female	No	No	Emergency Admission	No	No	Medium	Ye
freq	5018	6331	7425	5060	5910	8007	4517	709

In [35]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['ReAdmis_numeric'] = medical_data['ReAdmis']
# 2. Create dictionary for the values
dict_readmis = {"ReAdmis_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dict_readmis, inplace = True)
```

In [36]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['HighBlood_numeric'] = medical_data['HighBlood']
# 2. Create dictionary for the values
dict_highblood = {"HighBlood_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dict_highblood, inplace = True)
```

In [37]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Soft_drink_numeric'] = medical_data['Soft_drink']
# 2. Create dictionary for the values
dict_soft = {"Soft_drink_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dict_soft, inplace = True)
```

In [38]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Stroke_numeric'] = medical_data['Stroke']
# 2. Create dictionary for the values
```

```
dictstroke = {"Stroke_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictstroke, inplace = True)
```

In [39]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Overweight_numeric'] = medical_data['Overweight']
# 2. Create dictionary for the values
dictover = {"Overweight_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictover, inplace = True)
```

In [40]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Arthritis_numeric'] = medical_data['Arthritis']
# 2. Create dictionary for the values
dictarth = {"Arthritis_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictarth, inplace = True)
```

In [41]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Diabetes_numeric'] = medical_data['Diabetes']
# 2. Create dictionary for the values
dictdib = {"Diabetes_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictdib, inplace = True)
```

In [42]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Hyperlipidemia_numeric'] = medical_data['Hyperlipidemia']
# 2. Create dictionary for the values
dicthyp = {"Hyperlipidemia_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dicthyp, inplace = True)
```

In [43]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['BackPain_numeric'] = medical_data['BackPain']
# 2. Create dictionary for the values
dictback = {"BackPain_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictback, inplace = True)
```

In [44]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Anxiety_numeric'] = medical_data['Anxiety']
# 2. Create dictionary for the values
dictanx = {"Anxiety_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictanx, inplace = True)
```

In [45]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Allergic_rhinitis_numeric'] = medical_data['Allergic_rhinitis']
# 2. Create dictionary for the values
dictallerg = {"Allergic_rhinitis_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictallerg, inplace = True)
```

In [46]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Reflux_esophagitis_numeric'] = medical_data['Reflux_esophagitis']
# 2. Create dictionary for the values
```

```
dictreflux = {"Reflux_esophagitis_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictreflux, inplace = True)
```

In [47]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Asthma_numeric'] = medical_data['Asthma']
# 2. Create dictionary for the values
dictasthma = {"Asthma_numeric": {"Yes": 1, "No": 0}}
medical_data.replace(dictasthma, inplace = True)
```

In [48]:
```
# Data Wrangling
# 1. Create new column to input into
medical_data['Complication_risk_numeric'] = medical_data['Complication_risk']
# 2. Create dictionary for the values
dictcompl = {"Complication_risk_numeric": {"High": 2, "Medium": 1, "Low": 0}}
medical_data.replace(dictcompl, inplace = True)
```

In [49]:
```
medical_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 41 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   Children                    10000 non-null  float64
 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  float64
 8   vitD_supp                   10000 non-null  float64
 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
 27  ReAdmis_numeric             10000 non-null  int64  
 28  HighBlood_numeric           10000 non-null  int64  
 29  Soft_drink_numeric          10000 non-null  int64  
 30  Stroke_numeric              10000 non-null  int64  
 31  Overweight_numeric          10000 non-null  int64  
 32  Arthritis_numeric           10000 non-null  int64  
 33  Diabetes_numeric            10000 non-null  int64  
 34  Hyperlipidemia_numeric      10000 non-null  int64  
 35  BackPain_numeric            10000 non-null  int64  
 36  Anxiety_numeric             10000 non-null  int64  
 37  Allergic_rhinitis_numeric   10000 non-null  int64  
 38  Reflux_esophagitis_numeric  10000 non-null  int64  
 39  Asthma_numeric              10000 non-null  int64  
 40  Complication_risk_numeric   10000 non-null  int64  
dtypes: float64(8), int64(16), object(17)
memory usage: 3.1+ MB
```

In [50]:
```
# Drop all categorical variables that were re-expressed
medical_data = medical_data.drop(columns=['HighBlood','Stroke','Complication_risk','Ov
```

In [51]:
```
medical_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  float64
 1   Age                          10000 non-null  int64  
 2   Income                       10000 non-null  float64
 3   Gender                       10000 non-null  object 
 4   VitD_levels                  10000 non-null  float64
 5   Doc_visits                   10000 non-null  int64  
 6   Full_meals_eaten             10000 non-null  float64
 7   vitD_supp                    10000 non-null  float64
 8   Initial_admin                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  ReAdmis_numeric              10000 non-null  int64  
 14  HighBlood_numeric            10000 non-null  int64  
 15  Soft_drink_numeric           10000 non-null  int64  
 16  Stroke_numeric               10000 non-null  int64  
 17  Overweight_numeric           10000 non-null  int64  
 18  Arthritis_numeric            10000 non-null  int64  
 19  Diabetes_numeric             10000 non-null  int64  
 20  Hyperlipidemia_numeric       10000 non-null  int64  
 21  BackPain_numeric             10000 non-null  int64  
 22  Anxiety_numeric              10000 non-null  int64  
 23  Allergic_rhinitis_numeric    10000 non-null  int64  
 24  Reflux_esophagitis_numeric   10000 non-null  int64  
 25  Asthma_numeric               10000 non-null  int64  
 26  Complication_risk_numeric    10000 non-null  int64  
dtypes: float64(8), int64(16), object(3)
memory usage: 2.1+ MB
```

In [52]:

```
# Using get dummies pandas function to get numerical values for the 3 nominal categori
medical_data = pd.get_dummies(medical_data, columns=['Services', 'Gender', 'Initial_ad
medical_data.head()
```

Out[52]:

	Children	Age	Income	VitD_levels	Doc_visits	Full_meals_eaten	vitD_supp	Initial_days	TotalCha
0	1.0	53	86575.93	19.141466	6	0.0	0.0	10.585770	3726.702
1	3.0	51	46805.99	18.940352	4	2.0	1.0	15.129562	4193.190
2	3.0	53	14370.14	18.057507	4	1.0	0.0	4.772177	2434.234
3	0.0	78	39741.49	16.576858	4	1.0	0.0	1.714879	2127.830
4	1.0	22	1209.56	17.439069	5	0.0	2.0	1.254807	2113.073

5 rows × 34 columns

In [53]:

```
medical_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 34 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   Children                    10000 non-null  float64
 1   Age                         10000 non-null  int64  
 2   Income                      10000 non-null  float64
 3   VitD_levels                 10000 non-null  float64
 4   Doc_visits                  10000 non-null  int64  
 5   Full_meals_eaten            10000 non-null  float64
 6   vitD_supp                   10000 non-null  float64
 7   Initial_days                10000 non-null  float64
 8   TotalCharge                 10000 non-null  float64
 9   Additional_charges          10000 non-null  float64
 10  ReAdmis_numeric             10000 non-null  int64  
 11  HighBlood_numeric           10000 non-null  int64  
 12  Soft_drink_numeric          10000 non-null  int64  
 13  Stroke_numeric              10000 non-null  int64  
 14  Overweight_numeric          10000 non-null  int64  
 15  Arthritis_numeric           10000 non-null  int64  
 16  Diabetes_numeric            10000 non-null  int64  
 17  Hyperlipidemia_numeric      10000 non-null  int64  
 18  BackPain_numeric            10000 non-null  int64  
 19  Anxiety_numeric             10000 non-null  int64  
 20  Allergic_rhinitis_numeric   10000 non-null  int64  
 21  Reflux_esophagitis_numeric  10000 non-null  int64  
 22  Asthma_numeric              10000 non-null  int64  
 23  Complication_risk_numeric   10000 non-null  int64  
 24  New_Blood Work              10000 non-null  int32  
 25  New_CT Scan                 10000 non-null  int32  
 26  New_Intravenous             10000 non-null  int32  
 27  New_MRI                     10000 non-null  int32  
 28  New_Female                  10000 non-null  int32  
 29  New_Male                    10000 non-null  int32  
 30  New_Nonbinary               10000 non-null  int32  
 31  New_Elective Admission      10000 non-null  int32  
 32  New_Emergency Admission     10000 non-null  int32  
 33  New_Observation Admission   10000 non-null  int32  
dtypes: float64(8), int32(10), int64(16)
memory usage: 2.2 MB
```

In [54]:
```
# Exploratory Data Analysis
```

In [55]:
```
# Define variables
X = medical_data.drop('ReAdmis_numeric',axis=1)
y = medical_data['ReAdmis_numeric']
```

In [56]:
```
feature_names = X.columns
```

In [57]:
```
from sklearn.feature_selection import SelectKBest, f_classif
skbest = SelectKBest(score_func=f_classif, k='all')
X_new = skbest.fit_transform(X, y)
selected_feature_names = X.columns[skbest.get_support()]
print(X_new.shape)
```

```
(10000, 33)
```

In [58]:
```
p_values = pd.DataFrame({'Feature': X.columns, 'p-value': skbest.pvalues_})
significant_features = p_values[p_values['p-value'] < 0.05]

print(significant_features)
```

```
                   Feature   p-value
0                 Children  0.032390
6                vitD_supp  0.013164
7             Initial_days  0.000000
8              TotalCharge  0.000000
24             New_CT Scan  0.014707
25         New_Intravenous  0.042233
31  New_Emergency Admission  0.048766
```

In [59]:
```
medical_data = medical_data.drop(columns=['Age','Income','VitD_levels','Doc_visits','F
```

In [60]:
```
medical_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 8 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Children                 10000 non-null  float64
 1   vitD_supp                10000 non-null  float64
 2   Initial_days             10000 non-null  float64
 3   TotalCharge              10000 non-null  float64
 4   ReAdmis_numeric          10000 non-null  int64
 5   New_CT Scan              10000 non-null  int32
 6   New_Intravenous          10000 non-null  int32
 7   New_Emergency Admission  10000 non-null  int32
dtypes: float64(4), int32(3), int64(1)
memory usage: 507.9 KB
```

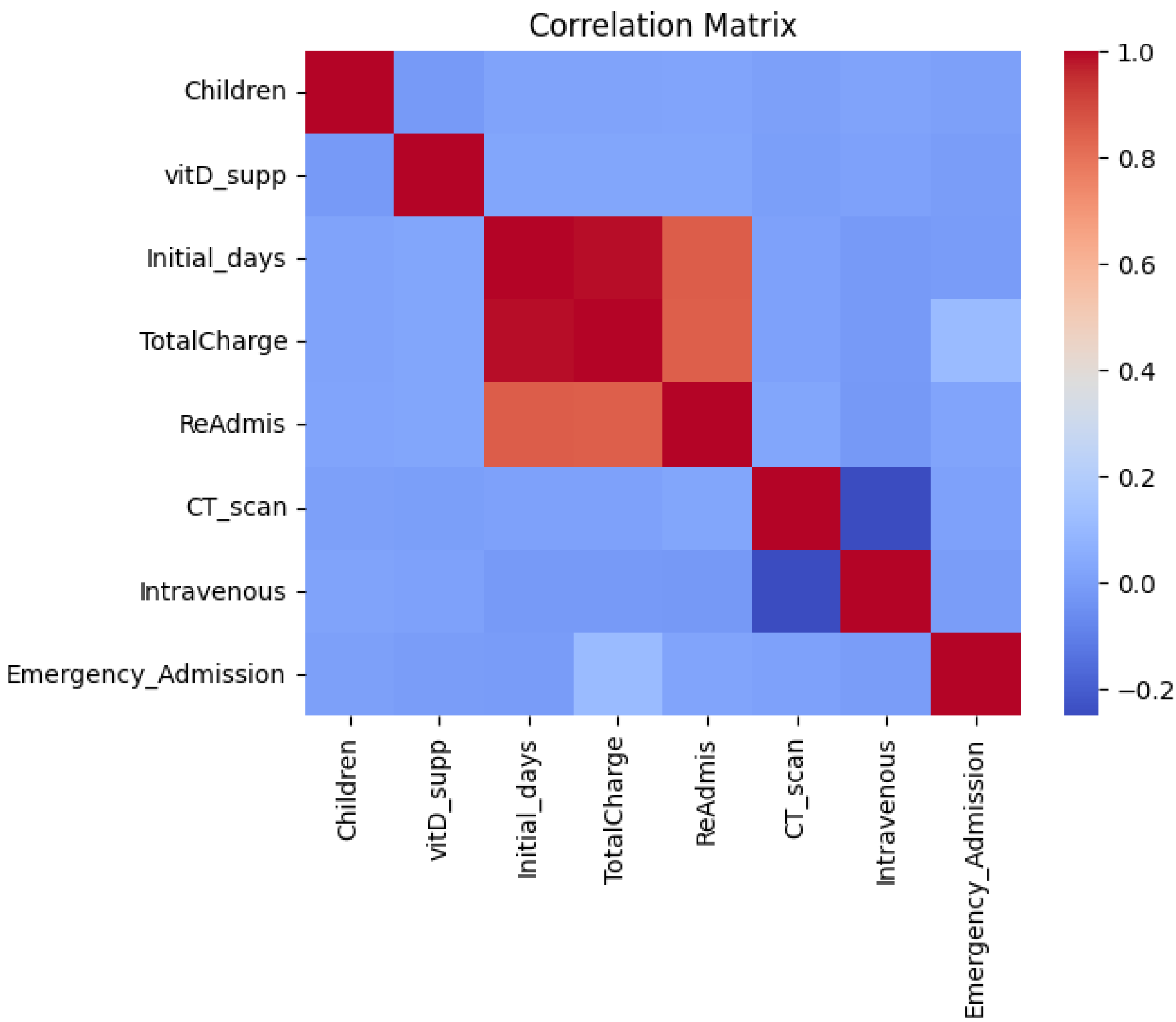
In [61]:
```
# Rename columns
medical_data.rename(columns = {'New_CT Scan':'CT_scan','New_Intravenous':'Intravenous'
```

In [62]:
```
# Look at new column names
medical_data.info()
```

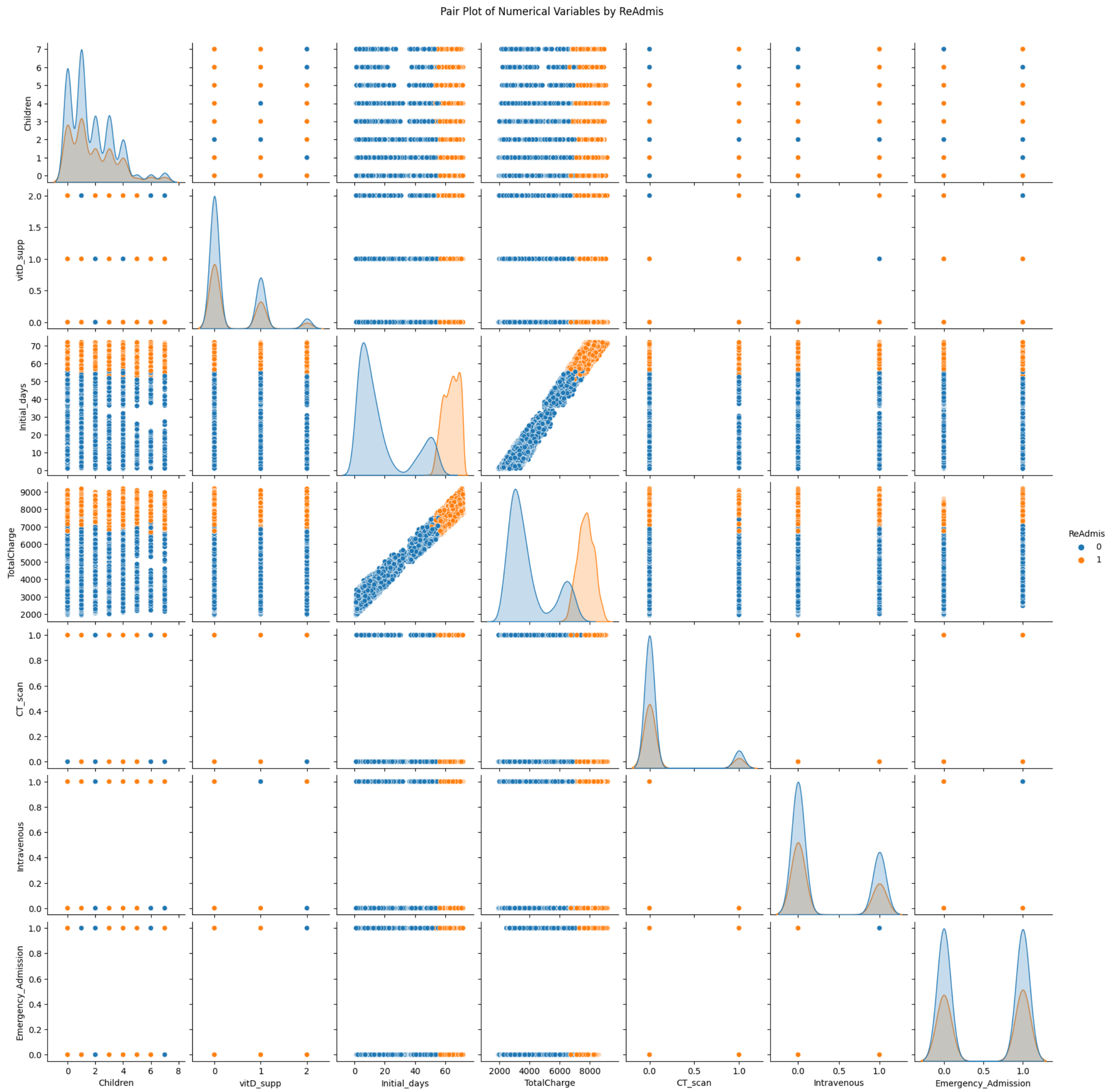
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 8 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Children             10000 non-null  float64
 1   vitD_supp            10000 non-null  float64
 2   Initial_days         10000 non-null  float64
 3   TotalCharge          10000 non-null  float64
 4   ReAdmis              10000 non-null  int64
 5   CT_scan              10000 non-null  int32
 6   Intravenous          10000 non-null  int32
 7   Emergency_Admission  10000 non-null  int32
dtypes: float64(4), int32(3), int64(1)
memory usage: 507.9 KB
```

In [63]:
```
# Export CSV file
medical_data.to_csv("C:/Users/Makayla Avendano/Desktop/new_med_data_209_task1.csv")
```

In [64]:
```
# Correlation matrix
corr_matrix = medical_data.corr()
sns.heatmap(corr_matrix, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



In [65]:
```
# Pairplot
sns.pairplot(data=medical_data, vars=['Children', 'vitD_supp', 'Initial_days', 'TotalC
plt.suptitle("Pair Plot of Numerical Variables by ReAdmis", y=1.02)
plt.show()
```



In [66]:
```
# Splitting the data into test and train sets
X = medical_data.drop('ReAdmis',axis=1)
y = medical_data['ReAdmis']

from sklearn.model_selection import train_test_split
X_train,X_test, y_train, y_test = train_test_split(X,y, test_size=0.2, random_state=2
```

In [67]:
```
# Export train/test sets
X_train.to_csv("C:/Users/Makayla Avendano/Desktop/X_train.csv")
X_test.to_csv("C:/Users/Makayla Avendano/Desktop/X_test.csv")
y_train.to_csv("C:/Users/Makayla Avendano/Desktop/y_train.csv")
y_test.to_csv("C:/Users/Makayla Avendano/Desktop/y_test.csv")
```

In [68]:
```
# Grid Search Cross Validation and Scaling a Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
from sklearn.pipeline import Pipeline
from sklearn.metrics import confusion_matrix
```

```
from sklearn.metrics import roc_auc_score

# Define variables
X = medical_data.drop('ReAdmis',axis=1)
y = medical_data['ReAdmis']

# Setup the pipeline
steps = [('scaler', StandardScaler()),
         ('knn', KNeighborsClassifier())]
pipeline = Pipeline(steps)

# Define train and test sets (80/20)
X_train,X_test, y_train, y_test = train_test_split(X,y, test_size=0.2, random_state=2

# Define parameters for KNN n_neighbors
parameters = {'knn__n_neighbors': np.arange(1,30)}

# Apply hyperparameter tuning (grid search cross validation)
cv = GridSearchCV(pipeline, param_grid=parameters)

# Fit the model
cv.fit(X_train,y_train)

# Predict from the model
y_pred = cv.predict(X_test)
```

In [69]:

```
# Best performing n_neighbors value (k)
print("Best parameters:", cv.best_params_)
# Mean score for the top performing value of n_neighbors
print("Score:", cv.best_score_)
```

```
Best parameters: {'knn__n_neighbors': 4}
Score: 0.97075
```

In [70]:

```
# Accuracy score on the training model
print("The training accuracy is: ", cv.score(X_train,y_train))
# Accuracy score on the test model
print("The testing accuracy is: ", cv.score(X_test, y_test))
```

```
The training accuracy is:  0.980375
The testing accuracy is:  0.9705
```

In [71]:

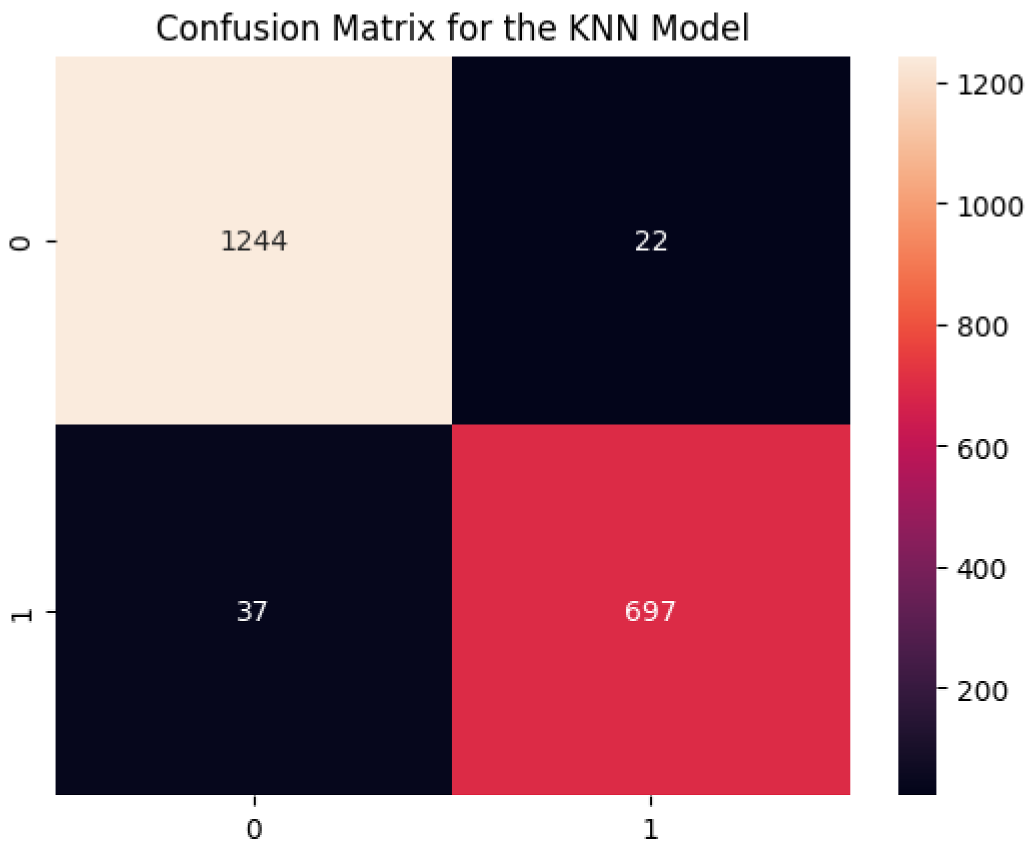
```
# Classification Report for the KNN model
print("Classification Report:")
print(classification_report(y_test,y_pred))
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.98      0.98      1266
           1       0.97      0.95      0.96       734

    accuracy                           0.97      2000
   macro avg       0.97      0.97      0.97      2000
weighted avg       0.97      0.97      0.97      2000
```

In [72]:

```
# Confusion Matrix and the plot
cm = confusion_matrix(y_test,y_pred)
```

```
conf_matrix = sns.heatmap(cm, annot=True, fmt='d')
conf_matrix = plt.title("Confusion Matrix for the KNN Model")
```



In [73]:

```
# Area under the curve (AUC) for the KNN Model
print("The Area under the curve (AUC) for the KNN model:")
print(roc_auc_score(y_test, y_pred))
```

```
The Area under the curve (AUC) for the KNN model:
0.9661068567566754
```

Results

The analysis technique that was used to analyze the data was the K-Nearest Neighbors. The first calculation performed to prepare the model was the imputation of outliers using the median. The maximum value was calculated using the equation Q3 + (1.5 *IQR) and the minimum was calculated using the equation Q1 – (1.5* IQR). These calculations were performed and then the where function was used to replace all values above the maximum and below the minimum with the median.

The next calculation performed was using SelectKBest to determine the best variables for the model. SelectKBest was used and then p-values were calculated and compared to indicate those with p-values below 0.05.

The next calculation performed was using the KNeighborsClassifier to determine best parameters and the best score with the given parameters. The parameters that are being input into KNeighborsClassifier include the knn classifier, the number of neighbors, and the range of neighbors from 1 to 30. The best parameter and score was calculated using the GridSearchCV hyperparameter tuning.

The accuracy score of the training and testing models were calculated along with the classification report, confusion matrix, and area under the curve for the KNN model.

Data Summary and Implications

Accuracy and AUC
The accuracy of the training model is 0.98 and the accuracy of the testing model is 0.97. Accuracy is, “the number of correct predictions made as a ration of all the predictions.” (Elleh, 2022) Given this definition, we can conclude that both the training and testing model are performing well and predicting data 98 to 97 percent accurate. Although this metric is useful, we can also look at the area under the curve (AUC) metric. “AUC is the measure of a classifier’s ability to distinguish between classes and is used as a summary of the ROC curve.”(Elleh, 2022) Essentially, we can look at the AUC metric as the metric that tells us how well our model is performing. This metric ranges from 0 to 1, with the values closer to 1 being a stronger model. The AUC was measured as 0.966 which is extremely high and indicates that our model is performing very well.

“The basic idea of k-NN is to predict the label of any data point by looking at the ‘k’ closest labeled data point and getting them to vote on what the unlabeled point should have.” (Elleh, 2022) With a model accuracy score of 98 for the training model and 97 for the testing model, we can assume that those predictions are highly accurate and dependable. For this model, the SelectKBest feature selection method was used to determine which variables are preferred. This feature selection method picks the best variables and picks the highest p-values that are below 0.05. My results included a total of 7 variables which were used in the final model.

GridSearchCV is the hyperparameter tuning method that was used to determine the best K value. The k that was determined was 4 and with this value of k the highest accuracy value would be 0.97 which is evident in the accuracy score of the testing model. Due to the accuracy being high, we can assume that hyperparameter tuning worked efficiently and reduced the risk of overfitting the model. (Bowne-Anderson, n.d)

One important limitation of this data analysis is the lack of equally distributed data. For the target variable readmission, the variable is not equally distributed and has 6331 that did not readmit to the hospital and the remaining 10,000 patients did readmit. It is important to note that this unequal distribution could affect the model and cause it to perform poorly.

Course of Action

Due to the positive results indicated in E2, we can use this model to recommend a course of action for the situation indicated in A1. Since this model performed well, this organization can use this model to predict readmission of patients. If this model can predict readmission of patients accurately, this organization can also use this information to potentially lower readmission of patients in the future.

```
In [ ]:
```