In [1]:
```
# Import packages that will be used for the logistics regression analysis
import pylab
import seaborn as sb
sb.set(style="white")
sb.set(style="whitegrid", color_codes=True)
import sklearn
from sklearn.metrics import confusion_matrix
from sklearn import preprocessing
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.metrics import classification_report
from sklearn import metrics
import matplotlib.pyplot as plt
plt.rc("font", size=14)
import numpy as np
import scipy.stats as stats
import statsmodels.api as sm
import statsmodels.formula.api as smf
from statsmodels.graphics.mosaicplot import mosaic
from statsmodels.stats.outliers_influence import variance_inflation_factor
from IPython.core.display import HTML
from IPython.display import display
import pandas as pd
from pandas.api.types import CategoricalDtype
from pandas import Series, DataFrame
from sklearn.metrics import classification_report, confusion_matrix
from imblearn.over_sampling import SMOTE

# Import data set that will be used for the logistics regression analysis
pd.set_option('display.max_columns', None)
df = pd.read_csv (r'C:\Users\fahim\Documents\0_WGUDocuments\d208\1medical_clean.csv')
# Check data types and number of values, as well as overall size of dataframe
df.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 [2]:

```
# Visually inspect dataframe to facilitate exploration, spot problems
pd.set_option("display.max_columns", None)
df.head(5)
```

Out[2]:

	CaseOrder	Customer_id	Interaction	UID	City	State	County	Zip	Lat	Lng
0	1	C412403	8cd49b13-f45a-4b47-a2bd-173ffa932c2f	3a83ddb66e2ae73798bdf1d705dc0932	Eva	AL	Morgan	35621	34.34960	-86.72508
1	2	Z919181	d2450b70-0337-4406-bdbb-bc1037f1734c	176354c5eef714957d486009feabf195	Marianna	FL	Jackson	32446	30.84513	-85.22907
2	3	F995323	a2057123-abf5-4a2c-abad-8ffe33512562	e19a0fa00aeda885b8a436757e889bc9	Sioux Falls	SD	Minnehaha	57110	43.54321	-96.63772
3	4	A879973	1dec528d-eb34-4079-adce-0d7a40e82205	cd17d7b6d152cb6f23957346d11c3f07	New Richland	MN	Waseca	56072	43.89744	-93.51479
4	5	C544523	5885f56b-d6da-43a3-8760-83583af94266	d2f0425877b10ed6bb381f3e2579424a	West Point	VA	King William	23181	37.59894	-76.88958

In [3]:
```
#check if there is any duplicate data entries present in columns
df[df.duplicated()]
```

Out[3]:

CaseOrder	Customer_id	Interaction	UID	City	State	County	Zip	Lat	Lng	Population	Area	TimeZone	Job	Children	Age	Incor

In [4]:
```
# check if there are any duplicated columns in the data set - if there are none then the output should be Fals
df.columns.duplicated().any()
```

Out[4]:
```
False
```

In [5]:
```
# check if there are any duplicated rows in the data set - if there are none then the output should be False
df.duplicated().any()
```

Out[5]:
```
False
```

In [6]:
```
#Summary Statistics
df.Age.describe()
```

Out[6]:
```
count    10000.000000
mean        53.511700
std         20.638538
min         18.000000
25%         36.000000
50%         53.000000
75%         71.000000
max         89.000000
Name: Age, dtype: float64
```

In [7]:
```
df.Gender.value_counts()
```

Out[7]:
```
Female       5018
Male         4768
Nonbinary     214
Name: Gender, dtype: int64
```

In [8]:
```
df.VitD_levels.describe()
```

Out[8]:
```
count    10000.000000
mean        17.964262
std          2.017231
min          9.806483
25%         16.626439
50%         17.951122
75%         19.347963
max         26.394449
Name: VitD_levels, dtype: float64
```

In [9]:
```
df.Initial_admin.value_counts().sort_index()
```

Out[9]:
```
Elective Admission       2504
Emergency Admission      5060
Observation Admission    2436
Name: Initial_admin, dtype: int64
```

In [10]:
```
df.HighBlood.value_counts()
```

Out[10]:
```
No     5910
Yes    4090
Name: HighBlood, dtype: int64
```

In [11]:
```
df.Complication_risk.value_counts().sort_index()
```

Out[11]:
```
High      3358
Low       2125
Medium    4517
Name: Complication_risk, dtype: int64
```

In [12]:
```
df.Overweight.value_counts()
```

Out[12]:
```
Yes    7094
No     2906
Name: Overweight, dtype: int64
```

In [13]:
```
df.BackPain.value_counts()
```

Out[13]:
```
No     5886
Yes    4114
Name: BackPain, dtype: int64
```

In [14]:
```
df.Stroke.value_counts()
```

Out[14]:
```
No     8007
Yes    1993
Name: Stroke, dtype: int64
```

In [15]:
```
df.Diabetes.value_counts()
```

Out[15]:
```
No     7262
Yes    2738
Name: Diabetes, dtype: int64
```

In [16]:
```
df.Asthma.value_counts()
```

Out[16]:
```
No     7107
Yes    2893
Name: Asthma, dtype: int64
```

In [17]:
```
df.Initial_days.describe()
```

Out[17]:
```
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 [18]:
```
df.Initial_days.nlargest(n=20)
```

Out[18]:
```
7968    71.98149
5326    71.96869
7479    71.96546
6166    71.96415
8066    71.96342
5874    71.96164
5829    71.96134
9159    71.95813
8817    71.95472
7524    71.94732
9074    71.94459
7839    71.92930
9677    71.92647
9221    71.92413
5162    71.92171
9101    71.90712
9766    71.90694
5374    71.90056
6601    71.89863
7214    71.89805
Name: Initial_days, dtype: float64
```

In [19]:
```
df.Arthritis.value_counts()
```

Out[19]:
```
No     6426
Yes    3574
Name: Arthritis, dtype: int64
```

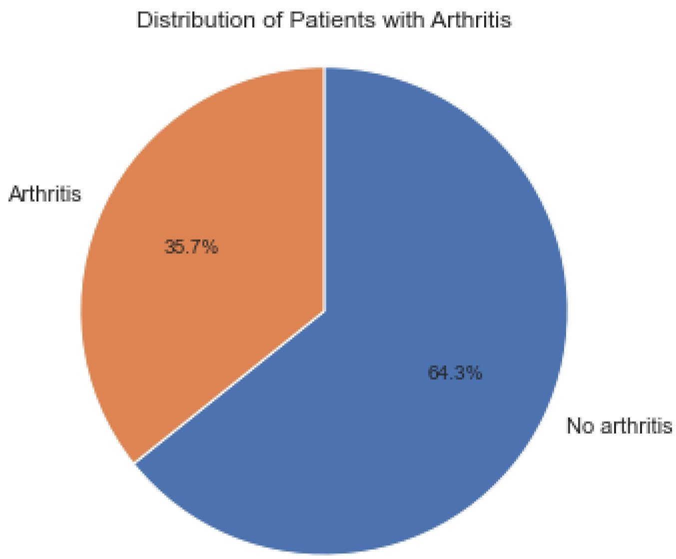
In [20]:
```
# Convert column to category from string
df["TimeZone"] = df["TimeZone"].astype("category")
# Reformat column representing currency in USD to 3 decimal places from 6
df["Income"] = df["Income"].astype(int)
# Convert column to category from string
df["Marital"] = df["Marital"].astype("category")
# Convert column to category from string
df["Gender"] = df["Gender"].astype("category")

# Convert categorical yes/no values to numeric 1/0 values
df = df.replace(to_replace = ['Yes','No'],value = [1,0])

# Perform one-hot encoding
# Generate columns of dummy values for dataframe's Gender column
gender_temp_df = pd.get_dummies(data=df["Gender"], drop_first=True)
# Generate columns of dummy values for dataframe's Initial_admin column
initial_admit_temp_df = pd.get_dummies(data=df["Initial_admin"], drop_first=True)
# Generate columns of dummy values for dataframe's Complication_risk column
comp_risk_temp_df = pd.get_dummies(data=df["Complication_risk"], drop_first=True)
# Create the new df with the variables used for this analysis
regress_df = df[["Age", "VitD_levels", "HighBlood", "Overweight", "Arthritis", "Diabetes", "BackPain", "Asthma
# Generate and apply new Pythonic names for ease of use
pythonic_columns = ["age", "vit_d_level", "high_bp", "overweight", "arthritis", "diabetes", "back_pain", "asth
regress_df.set_axis(pythonic_columns, axis=1, inplace=True)
# Insert the generated dummy variables to new dataframe, placing them in the same order as the original datafr
# Dummies for Complication Risk
regress_df.insert(4, "comp_risk_medium", comp_risk_temp_df.Medium)
regress_df.insert(4, "comp_risk_low", comp_risk_temp_df.Low)
# Dummies for Initial Admit
regress_df.insert(3, "initial_admit_emerg", initial_admit_temp_df["Emergency Admission"])
regress_df.insert(3, "initial_admit_observ", initial_admit_temp_df["Observation Admission"])
# Dummies for Gender
regress_df.insert(2, "gender_nonbinary", gender_temp_df.Male)
regress_df.insert(2, "gender_male", gender_temp_df.Male)
# Check resulting dataframe
regress_df
```

Out[20]:

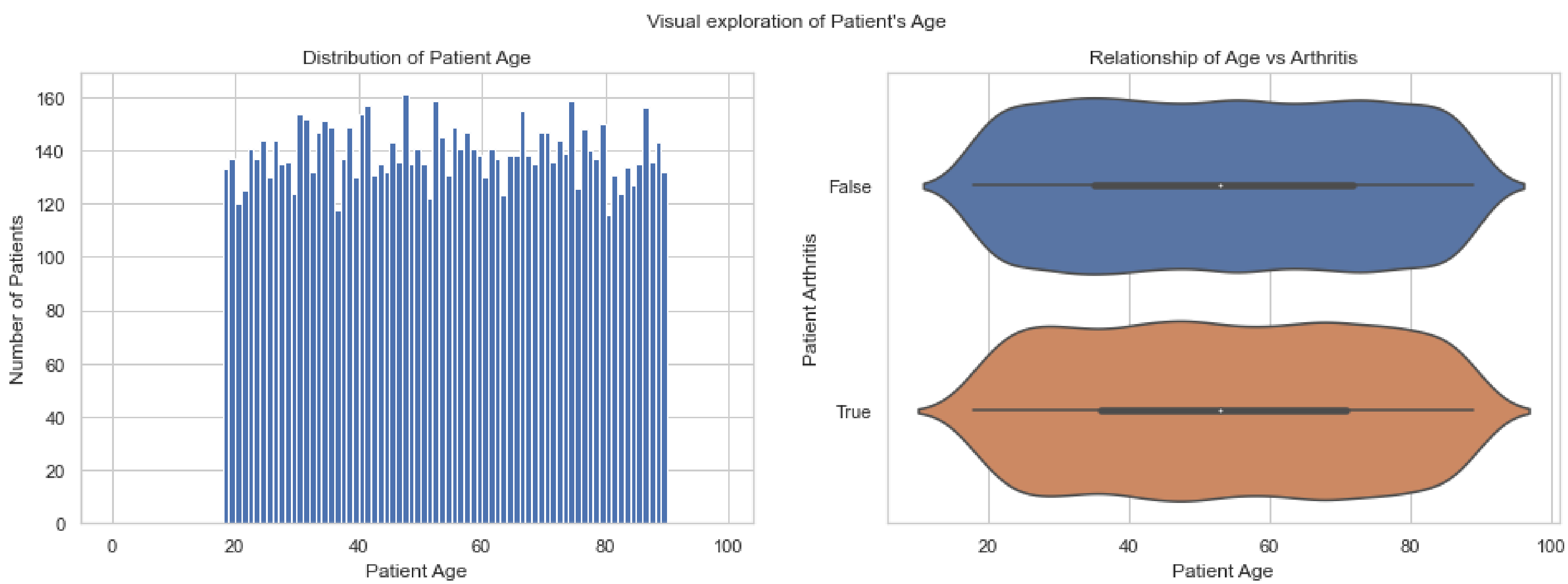
	age	vit_d_level	gender_male	gender_nonbinary	high_bp	initial_admit_observ	initial_admit_emerg	overweight	comp_risk_low	c
0	53	19.141466	1	1	1	0	1	0	0	
1	51	18.940352	0	0	1	0	1	1	0	
2	53	18.057507	0	0	1	0	0	1	0	
3	78	16.576858	1	1	0	0	0	0	0	
4	22	17.439069	0	0	0	0	0	0	1	
...	...	...	...	...	...	...	...	...	...	
9995	25	16.980860	1	1	1	0	1	0	0	
9996	87	18.177020	1	1	1	0	0	1	0	
9997	45	17.129070	0	0	1	0	0	1	0	
9998	43	19.910430	1	1	0	0	1	1	0	
9999	70	18.388620	0	0	0	1	0	1	1	

10000 rows × 15 columns

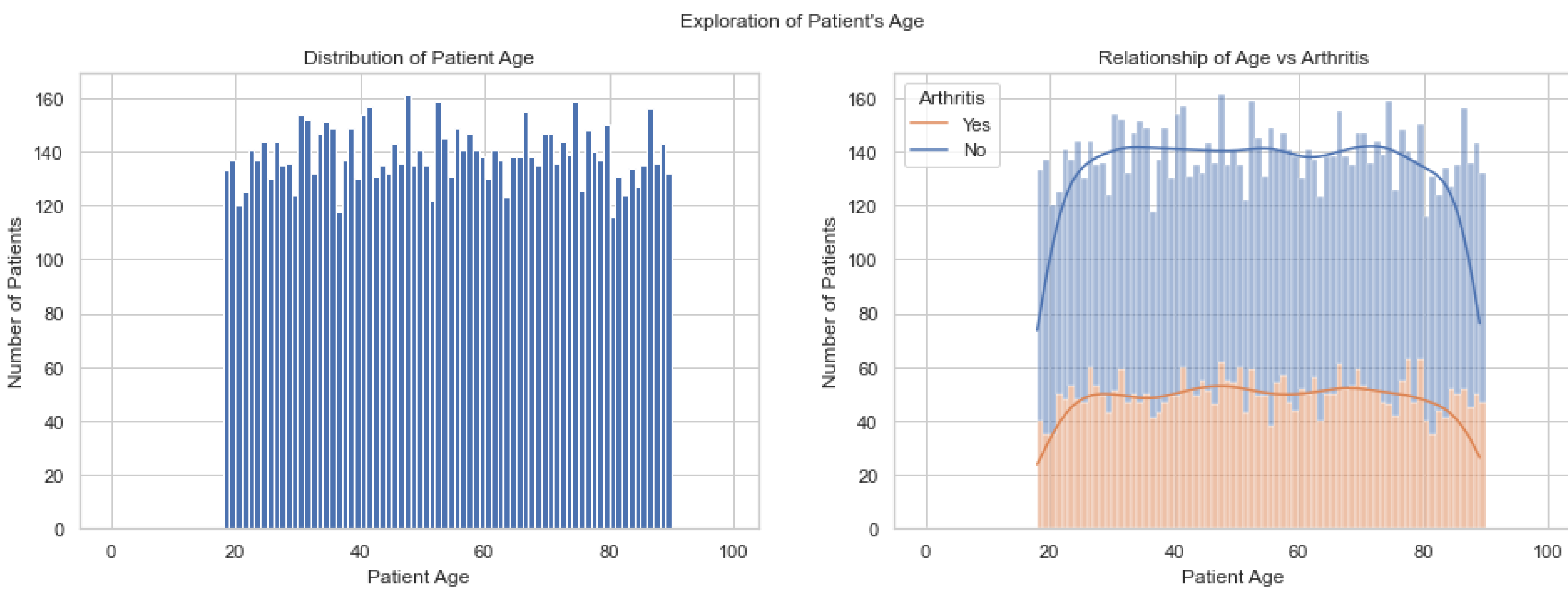
In [21]:
```
plt.figure(figsize = [16,5])
plt.title('Distribution of Patients with Arthritis')
arthritis_counts = regress_df.arthritis.value_counts()
arthritis_labels = ["No arthritis", "Arthritis"]
plt.pie(arthritis_counts, labels=arthritis_labels, autopct='%1.1f%%', startangle=90, counterclock=False)
plt.axis('square');
```



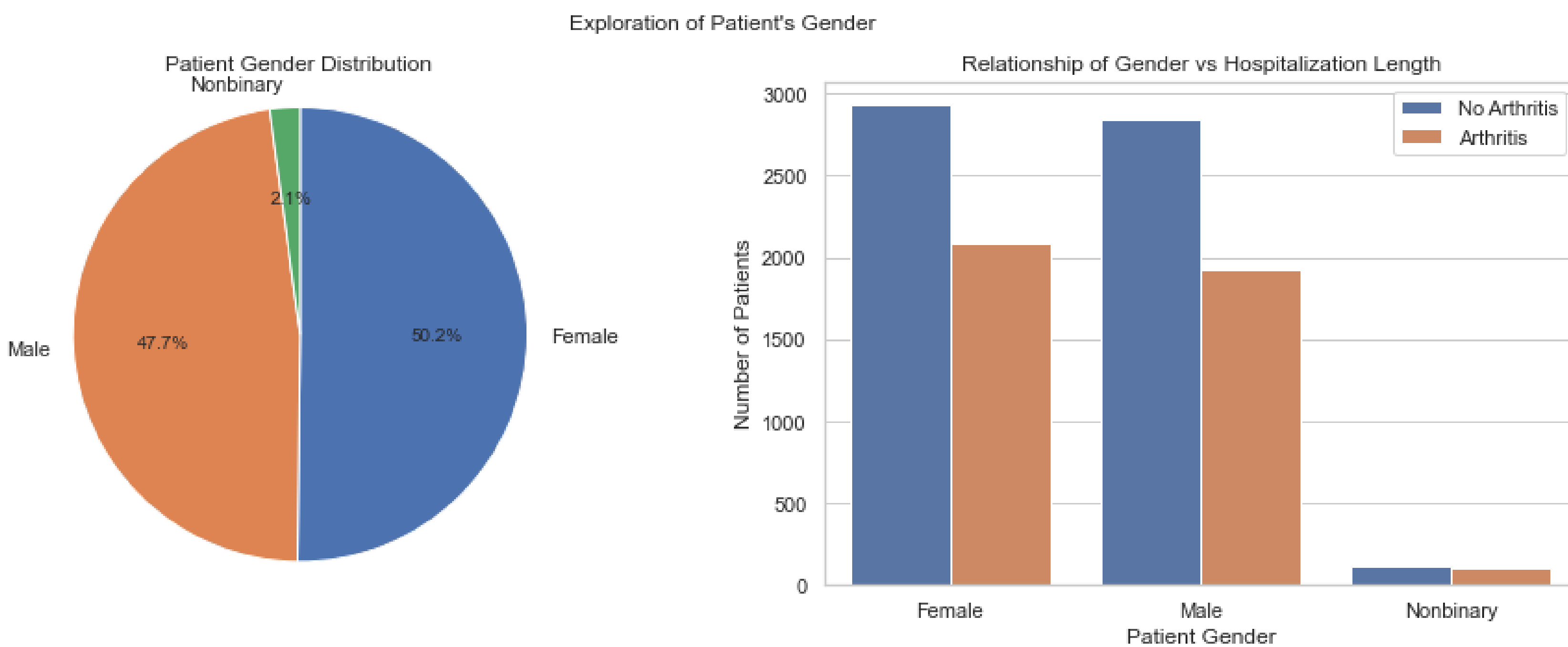
In [22]:
```
#Age
plt.figure(figsize = [16,5])
plt.suptitle("Visual exploration of Patient's Age")

# LEFT plot: Univariate exploration of age
plt.subplot(1, 2, 1)
plt.title('Distribution of Patient Age')
bins = np.arange(0, 100, 1)
plt.hist(data=regress_df, x="age", bins=bins)
plt.xlabel('Patient Age')
plt.ylabel("Number of Patients");

# RIGHT plot: Bivariate exploration of age vs back_pain
plt.subplot(1, 2, 2)
plt.title("Relationship of Age vs Arthritis")
sb.violinplot(data = regress_df, x="age", y="arthritis", orient='h')
plt.xlabel("Patient Age")
plt.ylabel("Patient Arthritis")
plt.yticks([0,1], ["False", "True"]);
```



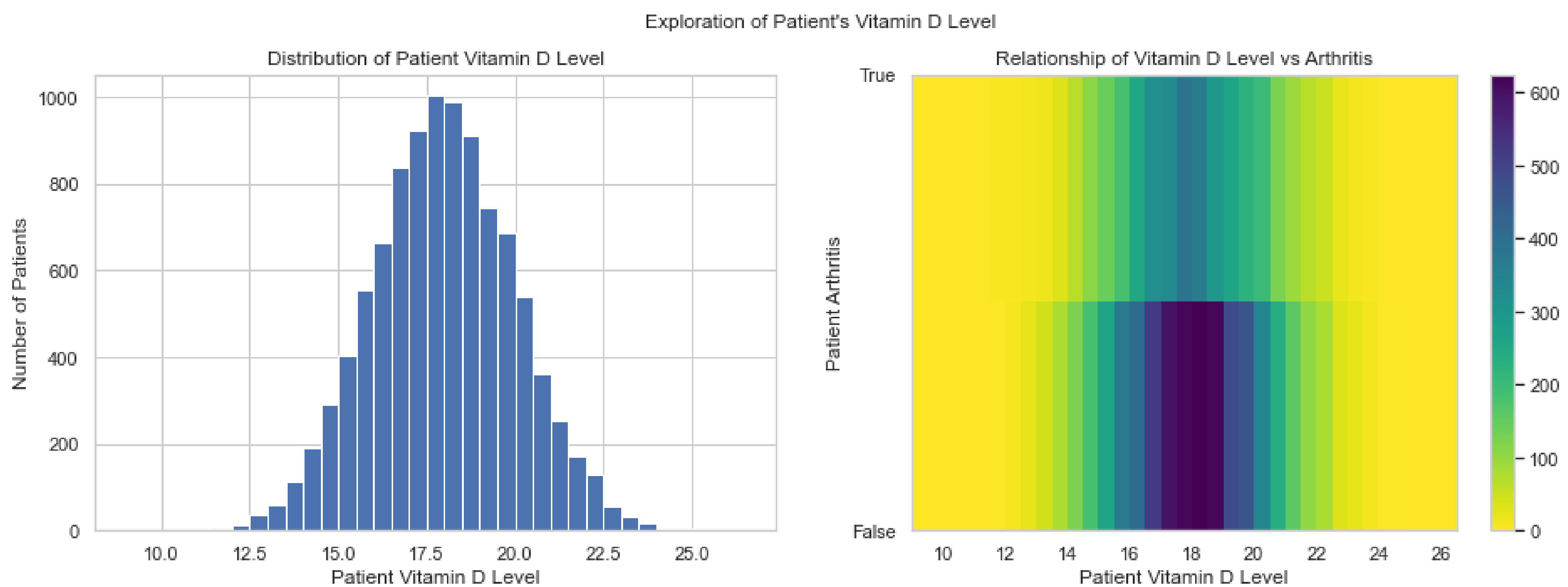
In [23]:
```
plt.figure(figsize = [16,5])
plt.suptitle("Exploration of Patient's Age")

# LEFT plot: Univariate exploration of age
plt.subplot(1, 2, 1)
plt.title('Distribution of Patient Age')
bins = np.arange(0, 100, 1)
plt.hist(data=regress_df, x="age", bins=bins)
plt.xlabel('Patient Age')
plt.ylabel("Number of Patients");

# RIGHT plot: Bivariate exploration of age vs arthritis
plt.subplot(1, 2, 2)
plt.title("Relationship of Age vs Arthritis")
sb.histplot(data = regress_df, x="age", hue="arthritis", bins=bins, kde=True, multiple="stack")
plt.legend(title="Arthritis", labels=["Yes", "No"])
plt.xlabel("Patient Age")
plt.ylabel("Number of Patients");
```



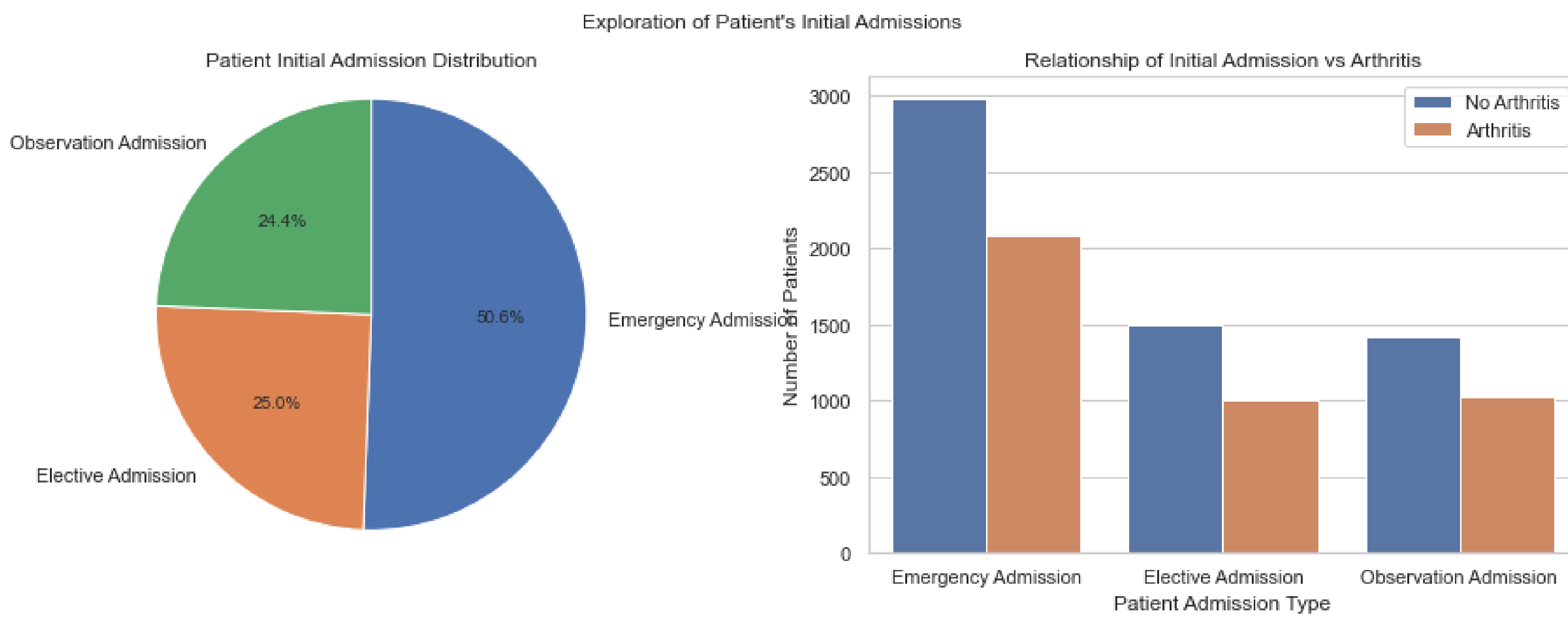
In [24]:
```
plt.figure(figsize = [16,5])
plt.suptitle("Exploration of Patient's Gender")

# LEFT plot: Univariate exploration of num_children
plt.subplot(1, 2, 1)
plt.title("Patient Gender Distribution")
gender_counts = df["Gender"].value_counts()
plt.pie(gender_counts, labels=gender_counts.index, autopct='%1.1f%%', startangle=90, counterclock = False)
plt.axis('square');

# RIGHT plot: Bivariate exploration of num_children vs arthritis
plt.subplot(1, 2, 2)
plt.title("Relationship of Gender vs Hospitalization Length")
sb.countplot(data = df, x="Gender", hue="BackPain")
plt.legend(["No Arthritis", "Arthritis"])
plt.xlabel("Patient Gender")
plt.ylabel("Number of Patients");
```



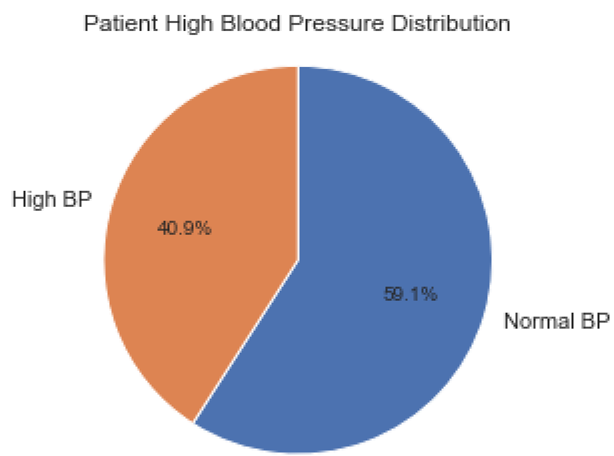
In [25]:
```
plt.figure(figsize = [16,5])
plt.suptitle("Exploration of Patient's Vitamin D Level")

# LEFT plot: Univariate exploration of vit_d_level
plt.subplot(1, 2, 1)
plt.title('Distribution of Patient Vitamin D Level')
bins = np.arange(9, 27, 0.5)
plt.hist(data=regress_df, x="vit_d_level", bins=bins)
plt.xlabel('Patient Vitamin D Level')
plt.ylabel("Number of Patients");

# RIGHT plot: Bivariate exploration of vit_d_level vs arthritis
plt.subplot(1, 2, 2)
plt.title("Relationship of Vitamin D Level vs Arthritis")
bins_y = np.arange(0, 1.25, 0.5)
plt.hist2d(data= regress_df, x="vit_d_level", y="arthritis", bins=[bins, bins_y], cmap= "viridis_r")
plt.colorbar()
plt.xlabel("Patient Vitamin D Level")
plt.ylabel("Patient Arthritis")
plt.yticks([0,1], ["False", "True"]);
```

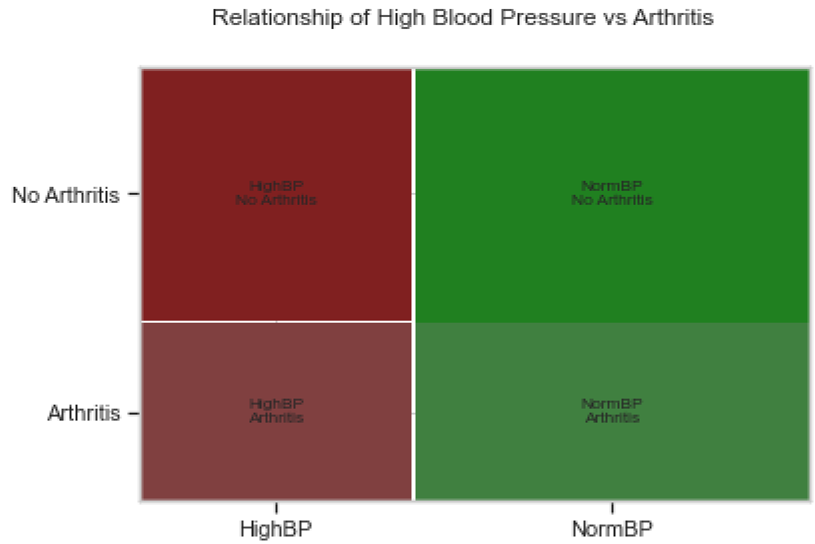


In [26]:
```
plt.figure(figsize = [16,5])
plt.suptitle("Exploration of Patient's Initial Admissions")

# LEFT plot: Univariate exploration of initial_admin
plt.subplot(1, 2, 1)
plt.title("Patient Initial Admission Distribution")
init_admit_counts = df["Initial_admin"].value_counts()
plt.pie(init_admit_counts, labels=init_admit_counts.index, autopct='%1.1f%%', startangle=90, counterclock = Fa
plt.axis('square');

# RIGHT plot: Bivariate exploration of Initial_admin vs arthritis
plt.subplot(1, 2, 2)
plt.title("Relationship of Initial Admission vs Arthritis")
sb.countplot(data = df, x="Initial_admin", hue="BackPain")
plt.legend(["No Arthritis", "Arthritis"])
plt.xlabel("Patient Admission Type")
plt.ylabel("Number of Patients");
```

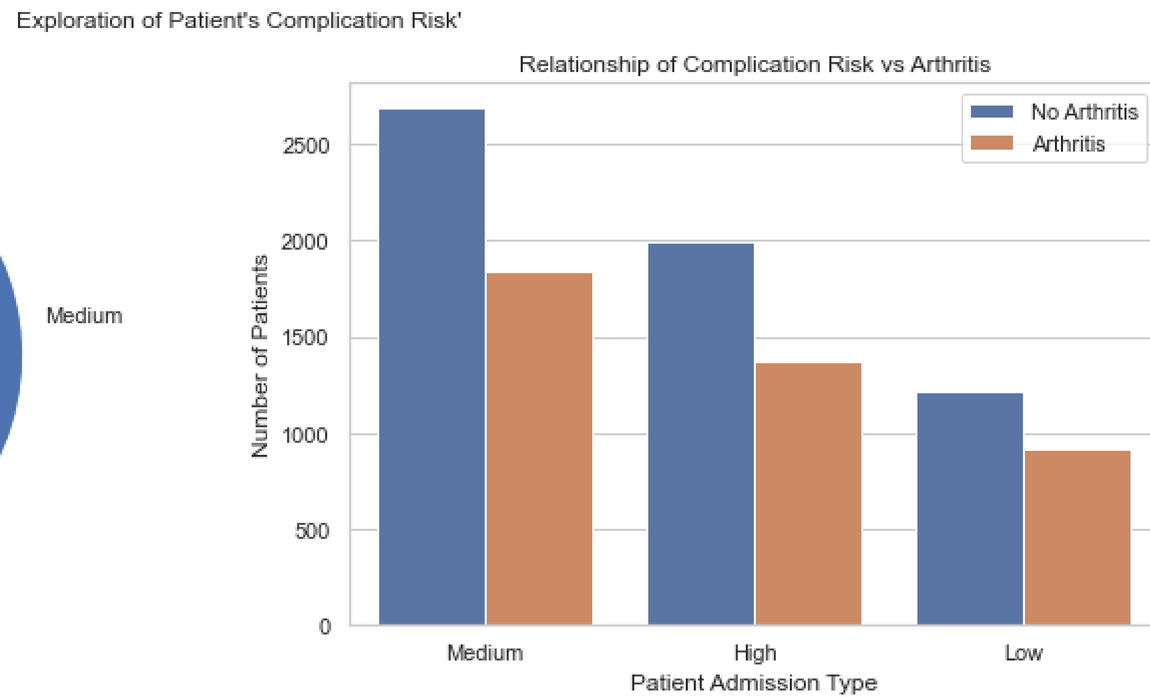


In [27]:
```
# TOP plot: Univariate exploration of high bp
plt.title("Patient High Blood Pressure Distribution")
high_bp_counts = df["HighBlood"].value_counts()
plt.pie(high_bp_counts, labels=["Normal BP", "High BP"], autopct='%1.1f%%', startangle=90, counterclock = Fals
plt.axis('square');

# BOTTOM plot: Bivariate exploration of high bp vs arthritis
temp_df = df[["HighBlood", "BackPain"]].copy()
high_bp_map = {1 : "HighBP", 0: "NormBP"}
arthritis_map = {1 : "Arthritis", 0: "No Arthritis"}
temp_df["HighBlood"] = temp_df["HighBlood"].map(high_bp_map)
temp_df["BackPain"] = temp_df["BackPain"].map(arthritis_map)
mosaic(temp_df, ["HighBlood", "BackPain"])
plt.suptitle("Relationship of High Blood Pressure vs Arthritis");
```

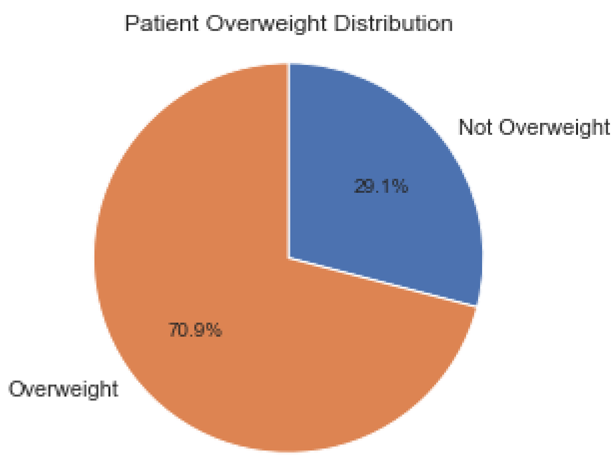


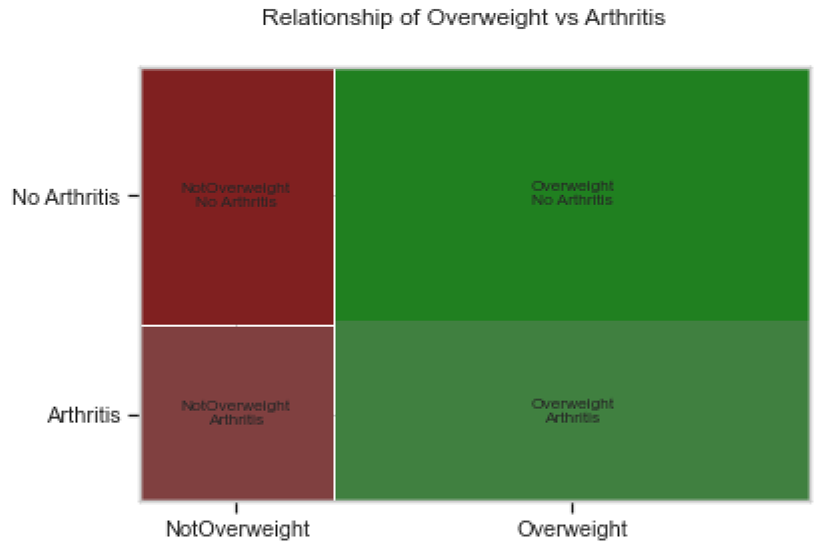

Relationship of High Blood Pressure vs Arthritis
No Arthritis
Arthritis
HighBP
No Arthritis
NormBP
No Arthritis
HighBP
Arthritis
NormBP
Arthritis
HighBP
NormBP

In [28]:
```
plt.figure(figsize = [16,5])
plt.suptitle("Exploration of Patient's Complication Risk'")

# LEFT plot: Univariate exploration of complication_risk
plt.subplot(1, 2, 1)
plt.title("Patient Complication Risk Distribution")
comp_risk_counts = df["Complication_risk"].value_counts()
comp_risk_labels = ["Medium", "High", "Low"]
plt.pie(comp_risk_counts, labels=comp_risk_counts.index, autopct='%1.1f%%', startangle=90, counterclock = Fals
plt.axis('square');

# RIGHT plot: Bivariate exploration of complication_risk vs arthritis
plt.subplot(1, 2, 2)
plt.title("Relationship of Complication Risk vs Arthritis")
sb.countplot(data = df, x="Complication_risk", hue="BackPain")
plt.legend(["No Arthritis", "Arthritis"])
plt.xlabel("Patient Admission Type")
plt.ylabel("Number of Patients");
```

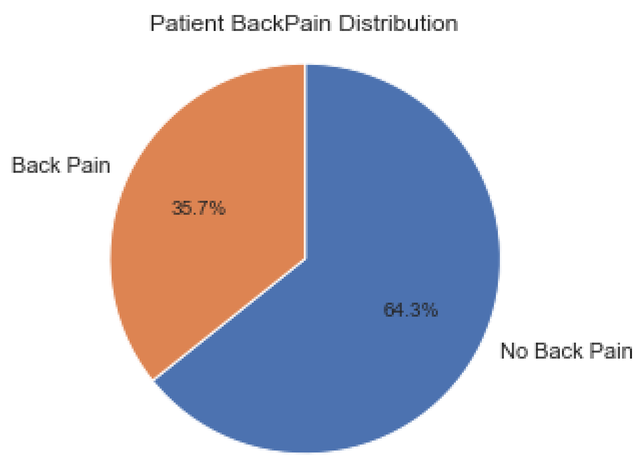


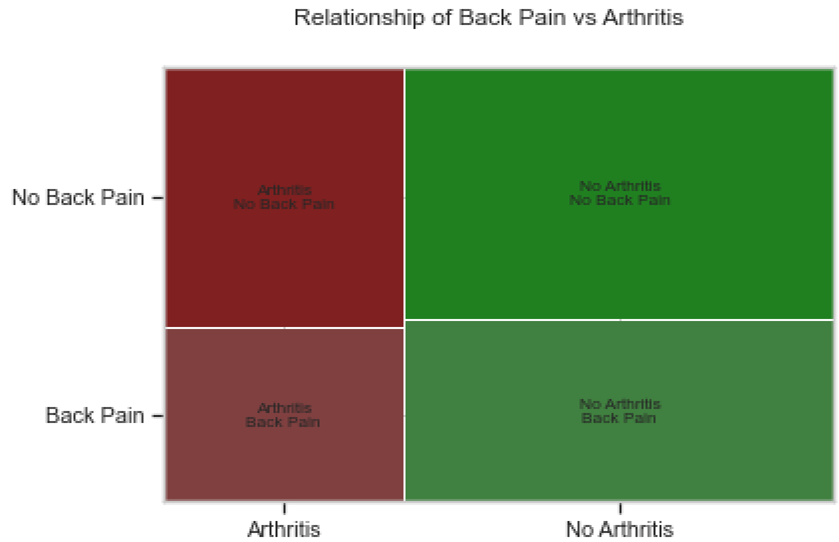
In [29]:
```
# TOP plot: Univariate exploration of overweight
plt.title("Patient Overweight Distribution")
overweight_counts = df["Overweight"].value_counts().sort_index()
plt.pie(overweight_counts, labels=["Not Overweight", "Overweight"], autopct='%1.1f%%', startangle=90, counterc
plt.axis('square');

# BOTTOM plot: Bivariate exploration of overweight vs arthritis
temp_df = df[["Overweight", "BackPain"]].copy()
overweight_map = {1 : "Overweight", 0: "NotOverweight"}
arthritis_map = {1 : "Arthritis", 0: "No Arthritis"}
temp_df["Overweight"] = temp_df["Overweight"].map(overweight_map)
temp_df["BackPain"] = temp_df["BackPain"].map(arthritis_map)
mosaic(temp_df, ["Overweight", "BackPain"])
plt.suptitle("Relationship of Overweight vs Arthritis");
```



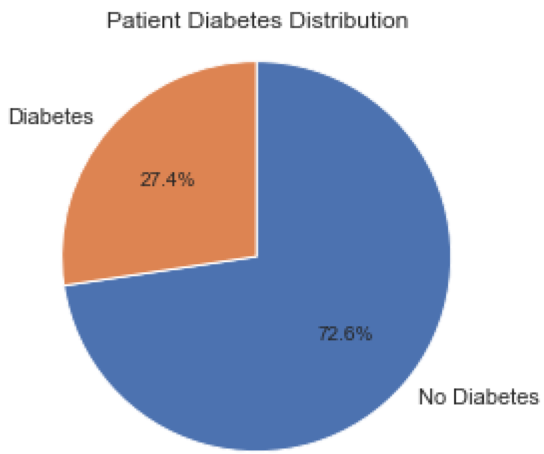

Relationship of Overweight vs Arthritis
No Arthritis
Arthritis
NotOverweight
No Arthritis
Overweight
No Arthritis
NotOverweight
Arthritis
Overweight
Arthritis
NotOverweight
Overweight

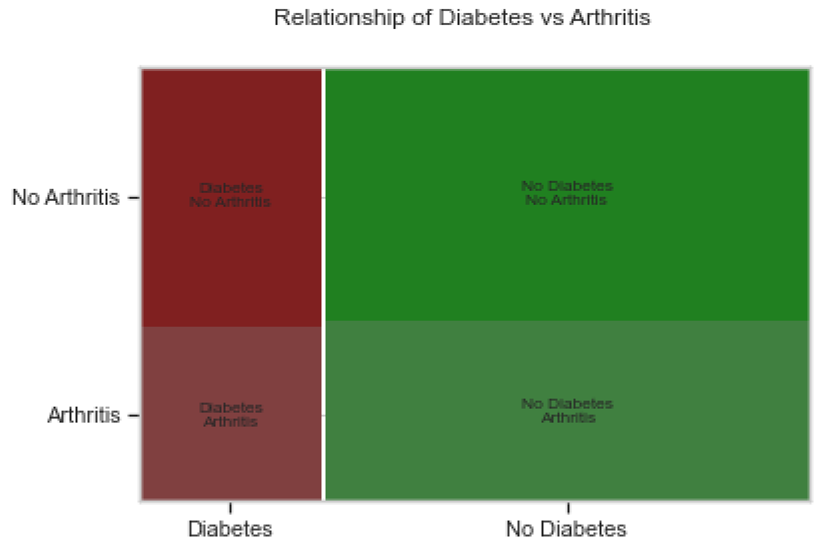
In [30]:
```
# TOP plot: Univariate exploration of arthritis
plt.title("Patient BackPain Distribution")
back_pain_counts = df["BackPain"].value_counts().sort_index()
plt.pie(arthritis_counts, labels=["No Back Pain", "Back Pain"], autopct='%1.1f%%', startangle=90, counterclock
plt.axis('square');

# BOTTOM plot: Bivariate exploration of arthritis vs back_pain
temp_df = df[["Arthritis", "BackPain"]].copy()
back_pain_map = {1 : "Back Pain", 0: "No Back Pain"}
arthritis_map = {1 : "Arthritis", 0: "No Arthritis"}
temp_df["BackPain"] = temp_df["BackPain"].map(back_pain_map)
temp_df["Arthritis"] = temp_df["Arthritis"].map(arthritis_map)
mosaic(temp_df, ["Arthritis", "BackPain"])
plt.suptitle("Relationship of Back Pain vs Arthritis");
```



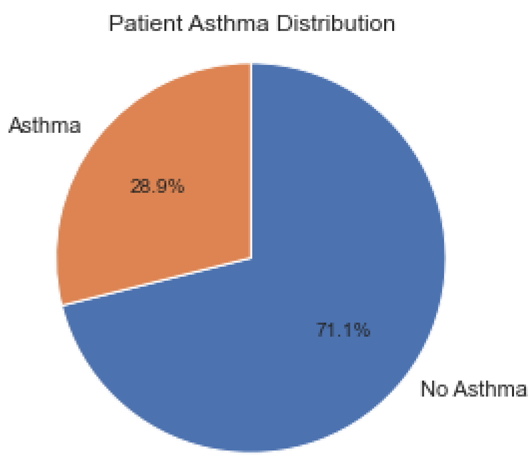

Relationship of Back Pain vs Arthritis
No Back Pain
Back Pain
Arthritis
No Back Pain
No Arthritis
No Back Pain
Arthritis
Back Pain
No Arthritis
Back Pain
Arthritis
No Arthritis

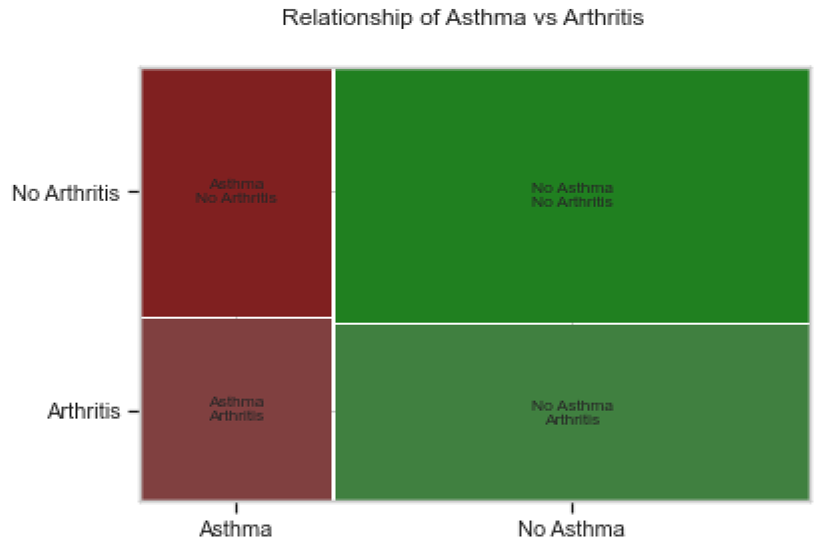
In [31]:
```
# TOP plot: Univariate exploration of diabetes
plt.title("Patient Diabetes Distribution")
diabetes_counts = df["Diabetes"].value_counts().sort_index()
plt.pie(diabetes_counts, labels=["No Diabetes", "Diabetes"], autopct='%1.1f%%', startangle=90, counterclock =
plt.axis('square');

# BOTTOM plot: Bivariate exploration of diabetes vs arthritis
temp_df = df[["Diabetes", "BackPain"]].copy()
diabetes_map = {1 : "Diabetes", 0: "No Diabetes"}
arthritis_map = {1 : "Arthritis", 0: "No Arthritis"}
temp_df["Diabetes"] = temp_df["Diabetes"].map(diabetes_map)
temp_df["BackPain"] = temp_df["BackPain"].map(arthritis_map)
mosaic(temp_df, ["Diabetes", "BackPain"])
plt.suptitle("Relationship of Diabetes vs Arthritis");
```



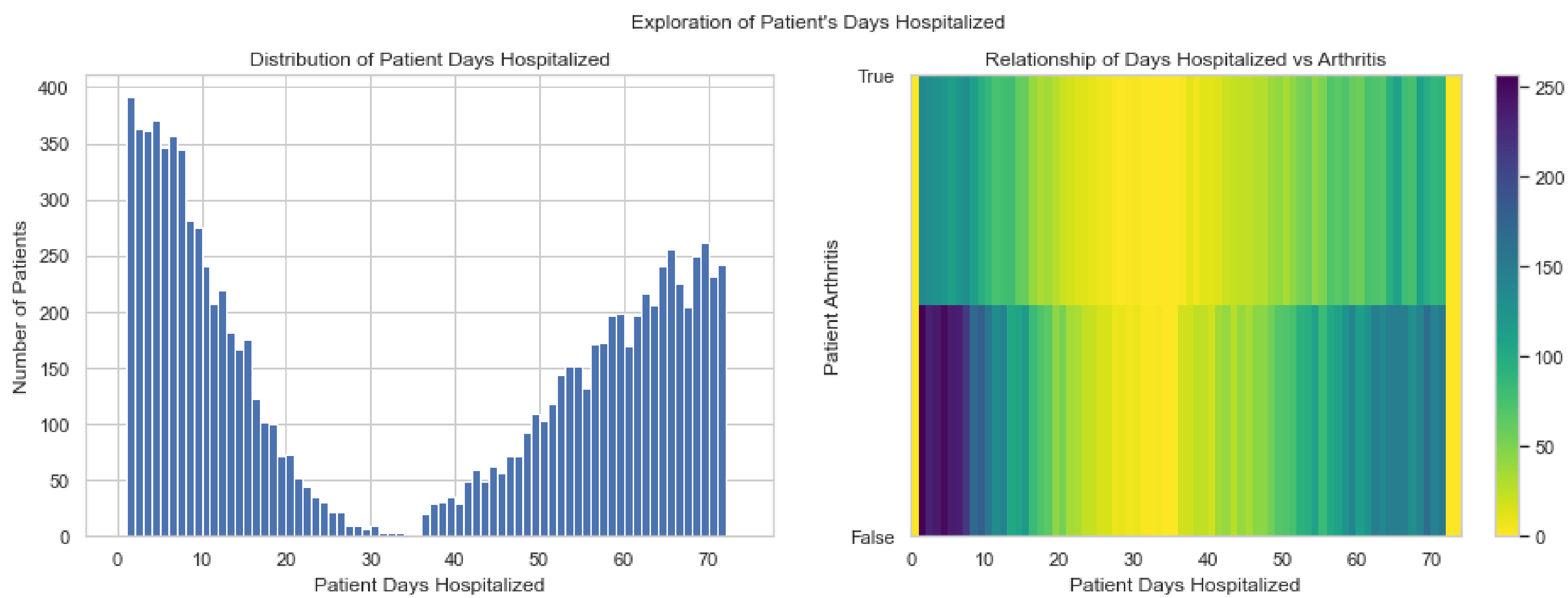

Relationship of Diabetes vs Arthritis
No Arthritis
Arthritis
Diabetes
No Arthritis
No Diabetes
No Arthritis
Diabetes
Arthritis
No Diabetes
Arthritis
Diabetes
No Diabetes

In [32]:
```
# TOP plot: Univariate exploration of asthma
plt.title("Patient Asthma Distribution")
asthma_counts = df["Asthma"].value_counts()
plt.pie(asthma_counts, labels=["No Asthma", "Asthma"], autopct='%1.1f%%', startangle=90, counterclock = False)
plt.axis('square');

# BOTTOM plot: Bivariate exploration of asthma vs arthritis
temp_df = df[["Asthma", "BackPain"]].copy()
asthma_map = {1 : "Asthma", 0: "No Asthma"}
arthritis_map = {1 : "Arthritis", 0: "No Arthritis"}
temp_df["Asthma"] = temp_df["Asthma"].map(asthma_map)
temp_df["BackPain"] = temp_df["BackPain"].map(arthritis_map)
mosaic(temp_df, ["Asthma", "BackPain"])
plt.suptitle("Relationship of Asthma vs Arthritis");
```




Relationship of Asthma vs Arthritis
No Arthritis
Arthritis
Asthma
No Asthma
Asthma
No Arthritis
No Asthma
No Arthritis
Asthma
Arthritis
No Asthma
Arthritis

In [33]:
```
plt.figure(figsize = [16,5])
plt.suptitle("Exploration of Patient's Days Hospitalized")

# LEFT plot: Univariate exploration of days_hospitalized
plt.subplot(1, 2, 1)
plt.title('Distribution of Patient Days Hospitalized')
bins = np.arange(0, 75, 1)
plt.hist(data=regress_df, x="days_hospitalized", bins=bins)
plt.xlabel('Patient Days Hospitalized')
plt.ylabel("Number of Patients");

# RIGHT plot: Bivariate exploration of days_hospitalized vs arthritis
plt.subplot(1, 2, 2)
plt.title("Relationship of Days Hospitalized vs Arthritis")
bins_y = np.arange(0, 1.25, 0.5)
plt.hist2d(data= regress_df, x="days_hospitalized", y="arthritis", bins=[bins, bins_y], cmap= "viridis_r")
plt.colorbar()
plt.xlabel("Patient Days Hospitalized")
plt.ylabel("Patient Arthritis")
plt.yticks([0,1], ["False", "True"]);
```



In [34]:
```
# Save dataframe to CSV
df.to_csv('d208task2_full_clean.csv', index=False)

# Save dataframe to CSV
regress_df.to_csv('d208task2_red_clean.csv', index=False)
```

In [35]:
```
#D1
# Check for VIF to determine if variables should be eliminated due to high multicolinearity
# Selecting the features for VIF calculation
X = regress_df[["age", "gender_male", "gender_nonbinary", "vit_d_level", "initial_admit_observ", "initial_admi

# Calculating VIF for each feature
vif_df = pd.DataFrame()
vif_df["feature"] = X.columns
vif_df["vif"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]

print(vif_df)
```

```
                 feature        vif
0                    age   7.241636
1            gender_male        inf
2       gender_nonbinary        inf
3            vit_d_level  16.219844
4   initial_admit_observ   1.937223
5    initial_admit_emerg   2.958292
6                high_bp   1.685677
7          comp_risk_low   1.616196
8       comp_risk_medium   2.314027
9             overweight   3.371327
10             back_pain   1.691008
11              diabetes   1.368503
12                asthma   1.404771
13     days_hospitalized   2.671579

C:\Users\fahim\AppData\Local\Programs\Python\Python310\lib\site-packages\statsmodels\stats\outliers_influenc
e.py:195: RuntimeWarning: divide by zero encountered in scalar divide
  vif = 1. / (1. - r_squared_i)
```

In [36]:

```
#Create the initial Logistic Regression model
y = regress_df.arthritis
X = regress_df[["age", "vit_d_level", "initial_admit_observ", "initial_admit_emerg", "high_bp", "comp_risk_low
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.651191
         Iterations 4
                           Logit Regression Results                           
==============================================================================
Dep. Variable:              arthritis   No. Observations:                10000
Model:                          Logit   Df Residuals:                     9987
Method:                           MLE   Df Model:                           12
Date:                Sat, 21 Oct 2023   Pseudo R-squ.:                0.001100
Time:                        17:32:35   Log-Likelihood:                -6511.9
converged:                       True   LL-Null:                       -6519.1
Covariance Type:            nonrobust   LLR p-value:                    0.2798
========================================================================================
                           coef    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------------
age                      0.0007      0.001      0.734      0.463      -0.001       0.003
vit_d_level            -2.5e-05      0.010     -0.002      0.998      -0.020       0.020
initial_admit_observ    -0.0023      0.059     -0.039      0.969      -0.119       0.114
initial_admit_emerg     -0.0017      0.051     -0.034      0.973      -0.102       0.098
high_bp                  0.0318      0.042      0.748      0.455      -0.051       0.115
comp_risk_low            0.0743      0.058      1.280      0.201      -0.040       0.188
comp_risk_medium         0.1019      0.048      2.134      0.033       0.008       0.195
overweight               0.0188      0.046      0.407      0.684      -0.072       0.109
back_pain               -0.0816      0.043     -1.918      0.055      -0.165       0.002
diabetes                 0.0420      0.047      0.898      0.369      -0.050       0.134
asthma                  -0.0297      0.046     -0.643      0.520      -0.120       0.061
days_hospitalized        0.0015      0.001      1.912      0.056   -3.84e-05       0.003
const                   -0.7352      0.206     -3.568      0.000      -1.139      -0.331
========================================================================================
```

In [37]:
```
#D2
# Check for VIF to see if variables should be eliminated due to high multicolinearity
X = regress_df[["age", "vit_d_level", "initial_admit_observ", "initial_admit_emerg", "high_bp", "comp_risk_low

vif_df = pd.DataFrame()
vif_df["feature"] = X.columns

vif_df["VIF"] = [variance_inflation_factor(X.values, i)
for i in range(len(X.columns))]

print(vif_df)
```

```
                 feature        VIF
0                    age   7.240313
1            vit_d_level  15.545766
2   initial_admit_observ   1.937083
3    initial_admit_emerg   2.958200
4                high_bp   1.685371
5          comp_risk_low   1.615953
6       comp_risk_medium   2.312916
7             overweight   3.370614
8              back_pain   1.690952
9               diabetes   1.368418
10                asthma   1.404604
11     days_hospitalized   2.670182
```

In [38]:
```
# Eliminated vit_d_level (VIF = 15.545766), rerunning analysis to see if any VIF still above 10
X = regress_df[["age", "initial_admit_observ", "initial_admit_emerg", "high_bp", "comp_risk_low", "comp_risk_m

vif_df = pd.DataFrame()
vif_df["feature"] = X.columns

vif_df["VIF"] = [variance_inflation_factor(X.values, i)
for i in range(len(X.columns))]

print(vif_df)
```

```
                 feature       VIF
0                    age  4.980023
1   initial_admit_observ  1.772019
2    initial_admit_emerg  2.573046
3                high_bp  1.639583
4          comp_risk_low  1.543146
5       comp_risk_medium  2.148722
6             overweight  3.003566
7              back_pain  1.655807
8               diabetes  1.348573
9                 asthma  1.383555
10     days_hospitalized  2.475831
```

In [39]:

```
# BACKWARD ELIMINATION # 1: Seek highest p-value above 0.10
y = regress_df.arthritis
X = regress_df[["age", "initial_admit_observ", "initial_admit_emerg", "high_bp", "comp_risk_low", "comp_risk_m
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.651191
         Iterations 4
                           Logit Regression Results
==============================================================================
Dep. Variable:              arthritis   No. Observations:                10000
Model:                          Logit   Df Residuals:                     9988
Method:                           MLE   Df Model:                           11
Date:                Sat, 21 Oct 2023   Pseudo R-squ.:                0.001100
Time:                        17:32:36   Log-Likelihood:                -6511.9
converged:                       True   LL-Null:                       -6519.1
Covariance Type:            nonrobust   LLR p-value:                    0.2149
========================================================================================
                           coef    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------------
age                      0.0007      0.001      0.734      0.463      -0.001       0.003
initial_admit_observ    -0.0023      0.059     -0.039      0.969      -0.119       0.114
initial_admit_emerg     -0.0017      0.051     -0.034      0.973      -0.102       0.098
high_bp                  0.0318      0.042      0.748      0.455      -0.051       0.115
comp_risk_low            0.0743      0.058      1.280      0.201      -0.039       0.188
comp_risk_medium         0.1019      0.048      2.134      0.033       0.008       0.195
overweight               0.0188      0.046      0.407      0.684      -0.072       0.109
back_pain               -0.0816      0.043     -1.918      0.055      -0.165       0.002
diabetes                 0.0420      0.047      0.899      0.369      -0.050       0.134
asthma                  -0.0297      0.046     -0.643      0.520      -0.120       0.061
days_hospitalized        0.0015      0.001      1.912      0.056   -3.84e-05       0.003
const                   -0.7356      0.091     -8.102      0.000      -0.914      -0.558
========================================================================================
```

In [46]:

```
# BACKWARD ELIMINATION # 2: Seek highest p-value above 0.10 (eliminated initial_admit_emerg, p-value of 0.973)
y = regress_df.arthritis
X = regress_df[["age", "initial_admit_observ", "high_bp", "comp_risk_low", "comp_risk_medium", "overweight", '
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.651191
         Iterations 4
                           Logit Regression Results
==============================================================================
Dep. Variable:              arthritis   No. Observations:                10000
Model:                          Logit   Df Residuals:                     9989
Method:                           MLE   Df Model:                           10
Date:                Sat, 21 Oct 2023   Pseudo R-squ.:                0.001099
Time:                        17:37:56   Log-Likelihood:                -6511.9
converged:                       True   LL-Null:                       -6519.1
Covariance Type:            nonrobust   LLR p-value:                    0.1583
========================================================================================
                           coef    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------------
age                      0.0007      0.001      0.735      0.462      -0.001       0.003
initial_admit_observ    -0.0011      0.049     -0.023      0.981      -0.097       0.094
high_bp                  0.0318      0.042      0.748      0.455      -0.051       0.115
comp_risk_low            0.0743      0.058      1.279      0.201      -0.040       0.188
comp_risk_medium         0.1019      0.048      2.134      0.033       0.008       0.195
overweight               0.0188      0.046      0.407      0.684      -0.072       0.109
back_pain               -0.0816      0.043     -1.918      0.055      -0.165       0.002
diabetes                 0.0420      0.047      0.899      0.369      -0.050       0.134
asthma                  -0.0297      0.046     -0.643      0.520      -0.120       0.061
days_hospitalized        0.0015      0.001      1.912      0.056    -3.8e-05       0.003
const                   -0.7368      0.084     -8.790      0.000      -0.901      -0.573
========================================================================================
```

In [47]:
```python
# BACKWARD ELIMINATION # 3: Seek highest p-value above 0.10 (eliminated initial_admit_observ, p-value of 0.981
y = regress_df.arthritis
X = regress_df[["age", "high_bp", "comp_risk_low", "comp_risk_medium", "overweight", "back_pain", "diabetes",
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.651191
         Iterations 4
                           Logit Regression Results
==============================================================================
Dep. Variable:              arthritis   No. Observations:                10000
Model:                          Logit   Df Residuals:                     9990
Method:                           MLE   Df Model:                            9
Date:                Sat, 21 Oct 2023   Pseudo R-squ.:                0.001099
Time:                        17:38:34   Log-Likelihood:                -6511.9
converged:                       True   LL-Null:                       -6519.1
Covariance Type:            nonrobust   LLR p-value:                    0.1109
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
age                   0.0007      0.001      0.735      0.462      -0.001       0.003
high_bp               0.0317      0.042      0.747      0.455      -0.051       0.115
comp_risk_low         0.0743      0.058      1.279      0.201      -0.040       0.188
comp_risk_medium      0.1018      0.048      2.134      0.033       0.008       0.195
overweight            0.0188      0.046      0.407      0.684      -0.072       0.109
back_pain            -0.0816      0.043     -1.918      0.055      -0.165       0.002
diabetes              0.0420      0.047      0.899      0.369      -0.050       0.134
asthma               -0.0297      0.046     -0.643      0.520      -0.120       0.061
days_hospitalized     0.0015      0.001      1.912      0.056    -3.8e-05       0.003
const                -0.7371      0.083     -8.870      0.000      -0.900      -0.574
=====================================================================================
```

In [48]:
```
# BACKWARD ELIMINATION # 4: Seek highest p-value above 0.10 (eliminated overweight, p-value of 0.684)
y = regress_df.arthritis
X = regress_df[["age", "high_bp", "comp_risk_low", "comp_risk_medium", "back_pain", "diabetes", "asthma", "day
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.651199
         Iterations 4
                           Logit Regression Results
==============================================================================
Dep. Variable:              arthritis   No. Observations:                10000
Model:                          Logit   Df Residuals:                     9991
Method:                           MLE   Df Model:                            8
Date:                Sat, 21 Oct 2023   Pseudo R-squ.:                0.001087
Time:                        17:39:42   Log-Likelihood:                -6512.0
converged:                       True   LL-Null:                       -6519.1
Covariance Type:            nonrobust   LLR p-value:                   0.07748
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
age                   0.0007      0.001      0.732      0.464      -0.001       0.003
high_bp               0.0322      0.042      0.758      0.448      -0.051       0.115
comp_risk_low         0.0743      0.058      1.279      0.201      -0.040       0.188
comp_risk_medium      0.1021      0.048      2.141      0.032       0.009       0.196
back_pain            -0.0815      0.043     -1.914      0.056      -0.165       0.002
diabetes              0.0418      0.047      0.896      0.370      -0.050       0.133
asthma               -0.0294      0.046     -0.638      0.524      -0.120       0.061
days_hospitalized     0.0015      0.001      1.908      0.056   -4.14e-05       0.003
const                -0.7239      0.076     -9.464      0.000      -0.874      -0.574
=====================================================================================
```

In [49]:
```
# BACKWARD ELIMINATION # 5: Seek highest p-value above 0.10 (eliminated asthma, p-value of 0.524)
y = regress_df.arthritis
X = regress_df[["age", "high_bp", "comp_risk_low", "comp_risk_medium", "back_pain", "diabetes", "days_hospital
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.651219
         Iterations 4
                           Logit Regression Results
==============================================================================
Dep. Variable:              arthritis   No. Observations:                10000
Model:                          Logit   Df Residuals:                     9992
Method:                           MLE   Df Model:                            7
Date:                Sat, 21 Oct 2023   Pseudo R-squ.:                0.001055
Time:                        17:40:57   Log-Likelihood:                -6512.2
converged:                       True   LL-Null:                       -6519.1
Covariance Type:            nonrobust   LLR p-value:                   0.05559
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
age                   0.0007      0.001      0.726      0.468      -0.001       0.003
high_bp               0.0320      0.042      0.754      0.451      -0.051       0.115
comp_risk_low         0.0740      0.058      1.274      0.203      -0.040       0.188
comp_risk_medium      0.1019      0.048      2.135      0.033       0.008       0.195
back_pain            -0.0819      0.043     -1.924      0.054      -0.165       0.002
diabetes              0.0413      0.047      0.885      0.376      -0.050       0.133
days_hospitalized     0.0015      0.001      1.917      0.055   -3.41e-05       0.003
const                -0.7317      0.076     -9.692      0.000      -0.880      -0.584
=====================================================================================
```

In [50]:
```
# BACKWARD ELIMINATION # 6: Seek highest p-value above 0.10 (eliminated age, p-value of 0.468)
y = regress_df.arthritis
X = regress_df[["high_bp", "comp_risk_low", "comp_risk_medium", "back_pain", "diabetes", "days_hospitalized"]]
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.651246
         Iterations 4
                           Logit Regression Results
==============================================================================
Dep. Variable:              arthritis   No. Observations:                10000
Model:                          Logit   Df Residuals:                     9993
Method:                           MLE   Df Model:                            6
Date:                Sat, 21 Oct 2023   Pseudo R-squ.:                0.001015
Time:                        17:41:30   Log-Likelihood:                -6512.5
converged:                       True   LL-Null:                       -6519.1
Covariance Type:            nonrobust   LLR p-value:                   0.03945
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
high_bp               0.0322      0.042      0.759      0.448      -0.051       0.115
comp_risk_low         0.0738      0.058      1.272      0.203      -0.040       0.188
comp_risk_medium      0.1016      0.048      2.130      0.033       0.008       0.195
back_pain            -0.0812      0.043     -1.909      0.056      -0.165       0.002
diabetes              0.0415      0.047      0.888      0.375      -0.050       0.133
days_hospitalized     0.0015      0.001      1.929      0.054   -2.49e-05       0.003
const                -0.6930      0.053    -13.004      0.000      -0.797      -0.589
=====================================================================================
```

In [51]:
```
# BACKWARD ELIMINATION # 7: Seek highest p-value above 0.10 (eliminated high_bp, p-value of 0.448)
y = regress_df.arthritis
X = regress_df[["comp_risk_low", "comp_risk_medium", "back_pain", "diabetes", "days_hospitalized"]].assign(cor
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.651275
         Iterations 4
                           Logit Regression Results
==============================================================================
Dep. Variable:              arthritis   No. Observations:                10000
Model:                          Logit   Df Residuals:                     9994
Method:                           MLE   Df Model:                            5
Date:                Sat, 21 Oct 2023   Pseudo R-squ.:               0.0009709
Time:                        17:42:01   Log-Likelihood:                -6512.7
converged:                       True   LL-Null:                       -6519.1
Covariance Type:            nonrobust   LLR p-value:                   0.02680
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
comp_risk_low         0.0728      0.058      1.254      0.210      -0.041       0.187
comp_risk_medium      0.1017      0.048      2.131      0.033       0.008       0.195
back_pain            -0.0811      0.043     -1.906      0.057      -0.164       0.002
diabetes              0.0413      0.047      0.884      0.377      -0.050       0.133
days_hospitalized     0.0015      0.001      1.924      0.054   -2.84e-05       0.003
const                -0.6794      0.050    -13.535      0.000      -0.778      -0.581
=====================================================================================
```

In [52]:
```
# BACKWARD ELIMINATION # 8: Seek highest p-value above 0.10 (eliminated diabetes, p-value of 0.377)
y = regress_df.arthritis
X = regress_df[["comp_risk_low", "comp_risk_medium", "back_pain", "days_hospitalized"]].assign(const=1)
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.651314
         Iterations 4
                           Logit Regression Results
==============================================================================
Dep. Variable:              arthritis   No. Observations:                10000
Model:                          Logit   Df Residuals:                     9995
Method:                           MLE   Df Model:                            4
Date:                Sat, 21 Oct 2023   Pseudo R-squ.:               0.0009111
Time:                        17:42:39   Log-Likelihood:                -6513.1
converged:                       True   LL-Null:                       -6519.1
Covariance Type:            nonrobust   LLR p-value:                   0.01827
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
comp_risk_low         0.0732      0.058      1.261      0.207      -0.041       0.187
comp_risk_medium      0.1017      0.048      2.133      0.033       0.008       0.195
back_pain            -0.0816      0.043     -1.918      0.055      -0.165       0.002
days_hospitalized     0.0015      0.001      1.922      0.055   -3.02e-05       0.003
const                -0.6679      0.048    -13.783      0.000      -0.763      -0.573
=====================================================================================
```

In [53]:
```
# BACKWARD ELIMINATION # 9: Seek highest p-value above 0.10 (eliminated comp_risk_low, p-value of 0.377)
y = regress_df.arthritis
X = regress_df[["comp_risk_medium", "back_pain", "days_hospitalized"]].assign(const=1)
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.651393
         Iterations 4
                           Logit Regression Results
==============================================================================
Dep. Variable:              arthritis   No. Observations:                10000
Model:                          Logit   Df Residuals:                     9996
Method:                           MLE   Df Model:                            3
Date:                Sat, 21 Oct 2023   Pseudo R-squ.:               0.0007894
Time:                        17:43:22   Log-Likelihood:                -6513.9
converged:                       True   LL-Null:                       -6519.1
Covariance Type:            nonrobust   LLR p-value:                   0.01624
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
comp_risk_medium      0.0732      0.042      1.747      0.081      -0.009       0.155
back_pain            -0.0807      0.043     -1.897      0.058      -0.164       0.003
days_hospitalized     0.0015      0.001      1.942      0.052   -1.44e-05       0.003
const                -0.6403      0.043    -14.843      0.000      -0.725      -0.556
=====================================================================================
```

In [54]:
```
# All p-values for independent variables are < 0.10, this is the final reduced model
y = regress_df.arthritis
X = regress_df[["comp_risk_medium", "back_pain", "days_hospitalized"]].assign(const=1)
logit_model=sm.Logit(y,X)
result=logit_model.fit()
print(result.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.651393
         Iterations 4
                           Logit Regression Results
==============================================================================
Dep. Variable:              arthritis   No. Observations:                10000
Model:                          Logit   Df Residuals:                     9996
Method:                           MLE   Df Model:                            3
Date:                Sat, 21 Oct 2023   Pseudo R-squ.:               0.0007894
Time:                        17:44:21   Log-Likelihood:                -6513.9
converged:                       True   LL-Null:                       -6519.1
Covariance Type:            nonrobust   LLR p-value:                   0.01624
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
comp_risk_medium      0.0732      0.042      1.747      0.081      -0.009       0.155
back_pain            -0.0807      0.043     -1.897      0.058      -0.164       0.003
days_hospitalized     0.0015      0.001      1.942      0.052   -1.44e-05       0.003
const                -0.6403      0.043    -14.843      0.000      -0.725      -0.556
=====================================================================================
```

In [55]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
y_pred = logreg.predict(X_test)
print('Accuracy of logistic regression classifier on test set: {:.2f}'.format(logreg.score(X_test, y_test)))
final_matrix = confusion_matrix(y_test, y_pred)
print(final_matrix)
```

```
Accuracy of logistic regression classifier on test set: 0.65
[[1957    0]
 [1043    0]]
```

In [56]:
```
result.params
```

Out[56]:
```
comp_risk_medium     0.073224
back_pain           -0.080667
days_hospitalized    0.001541
const               -0.640284
dtype: float64
```

In [60]:
```
# Calculate odds ratios for each coefficient
print(f"The odds ratio for comp_risk_medium is {round(np.exp(0.073224), 3)}. Given this, the change in odds fo
print(f"The odds ratio for back_pain is {round(np.exp(0.080667), 3)}. Given this, the change in odds for arthr
print(f"The odds ratio for days_hospitalized is {round(np.exp (0.001541), 3)}. Given this, the change in odds
```

```
The odds ratio for comp_risk_medium is 1.076. Given this, the change in odds for arthritis is 7.597
The odds ratio for back_pain is 1.084. Given this, the change in odds for arthritis is 8.401
The odds ratio for days_hospitalized is 1.002. Given this, the change in odds for arthritis is 0.154
```

In [ ]: