Survivor Analysis Python Project

John Torres

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```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
import statistics as stats
import seaborn as sns
```

1 First Step: Let's Create the mock the Dataset

```
#Create the dataset
# Set seed for reproducibility
np.random.seed(42)

# Number of samples
n_samples = 500

# Generate mock data
data = {
    "PatientID": np.arange(1, n_samples + 1),
    "Group": np.random.choice([0, 1], size=n_samples),  # 0 for control, 1 for experimental
    "Age": np.random.randint(18, 90, size=n_samples),
    "Gender": np.random.choice(["Male", "Female"], size=n_samples),
    "BMI": np.round(np.random.uniform(18.5, 40, size=n_samples), 1),
    "BloodPressure": np.round(np.random.uniform(90, 180, size=n_samples), 1),
    "Cholesterol": np.round(np.random.uniform(100, 300, size=n_samples), 1),
    "Glucose": np.round(np.random.uniform(70, 200, size=n_samples), 1),
    "SmokingStatus": np.random.choice(["Never", "Former", "Current"], size=n_samples),
    "PhysicalActivity": np.random.choice(["Low", "Moderate", "High"], size=n_samples),
    "Comorbidities": np.random.randint(0, 5, size=n_samples),
    "Medications": np.random.choice([0, 1], size=n_samples), # 0 for No Medication, 1 for Tal
    "FollowUpTime": np.round(np.random.uniform(1, 60, size=n_samples), 1), #in months
    "Outcome": np.random.choice([0, 1], size=n_samples), # 0 for Censored, 1 for Event Occur
    "Education": np.random.choice(["High School", "Bachelor", "Master", "PhD"], size=n_sample
    "RaceEthnicity": np.random.choice(["White", "Black", "Hispanic", "Asian", "Other"], size=
    "Income": np.random.choice(["<30K", "30-60K", "60-100K", ">100K"], size=n_samples),
    "MaritalStatus": np.random.choice(["Single", "Married", "Divorced", "Widowed"], size=n_sa
    "EmploymentStatus": np.random.choice(["Employed", "Unemployed", "Retired"], size=n_sample
}

# Create DataFrame
mock_data = pd.DataFrame(data)
mock_data.head(10)
```

	PatientID	Group	Age	Gender	BMI	BloodPressure	Cholesterol	Glucose	SmokingStatus	Phys
0	1	0	80	Male	37.9	165.4	129.5	95.3	Never	High
1	2	1	49	Female	37.3	175.0	165.6	77.5	Current	High
2	3	0	50	Male	31.3	151.5	186.8	114.5	Never	Low
3	4	0	84	Male	31.4	134.7	117.7	105.1	Never	Low
4	5	0	35	Female	32.8	145.6	144.1	195.6	Current	High
5	6	1	42	Male	22.3	168.2	219.6	142.5	Former	Mod
6	7	0	71	Male	38.2	141.4	247.1	115.1	Current	Low
7	8	0	75	Male	27.5	92.7	299.7	145.5	Current	Mod
8	9	0	84	Male	26.7	173.8	286.6	88.1	Current	Low
9	10	1	63	Female	29.7	152.1	228.5	127.7	Former	Low

2 Second Step: Let's Explore the Dataset

2.1 Descriptive Stats

```
#Descriptive Stats of numerical vars
df_describe = mock_data.describe().round(2).drop(columns = ["PatientID","Group","Outcome","Mo
df_describe = df_describe.reset_index().drop(index=0).set_index("index")
df_describe.index.name=None
df_describe.head(10)
```

	Age	BMI	BloodPressure	Cholesterol	Glucose	FollowUpTime
mean	52.84	29.47	135.41	198.67	135.12	29.19
std	20.89	6.40	25.69	57.29	38.28	17.27
min	18.00	18.60	90.30	100.30	70.00	1.10
25%	34.00	23.60	113.05	151.85	103.42	14.38
50%	52.00	29.70	136.80	197.50	134.65	28.55
75%	72.00	35.02	156.65	246.50	169.42	44.20
max	89.00	40.00	179.90	299.70	199.70	59.70

2.2 Demographics

```
#Demographic Information
# Age   Gender  Education   RaceEthnicity   Income  MaritalStatus   EmploymentStatus SmokingS
```

```
df_hold = mock_data[['Age', 'Gender', 'Education', 'RaceEthnicity', 'Income', 'MaritalStatus

# Define the bins and labels for age groups
bins = [-float('inf'), 17, 24, 34, 44, 54, 64, float('inf')]
labels = ['Under 18', '18-24 years old', '25-34 years old', '35-44 years old', '45-54 years

# Create a copy of the DataFrame to avoid the warning
dem = df_hold.copy()

# Create a new column 'AgeGroup' with categorized age groups
dem.loc[:, 'AgeGroup'] = pd.cut(dem['Age'], bins=bins, labels=labels, right=True)

# Create a demographic table with counts for each category
demographic_counts = {
    'Variable': [],
    'Category': [],
    'Count': []
}

# Define a list of columns to include in the table
columns = ['AgeGroup', 'Gender', 'Education', 'RaceEthnicity', 'Income', 'MaritalStatus', 'E

# Create a demographic table with counts for each category
demographic_counts = {
    'Variable': [],
    'Category': [],
    'N': [],
}

# Define a list of columns to include in the table
columns = ['AgeGroup', 'Gender', 'Education', 'RaceEthnicity', 'Income', 'MaritalStatus', 'E

# Calculate counts for each variable and its categories
for column in columns:
    counts = dem[column].value_counts()
    for category, count in counts.items():
        demographic_counts['Variable'].append(column)
        demographic_counts['Category'].append(category)
        demographic_counts['N'].append(count)

# Create a DataFrame from the counts
demographic_table = pd.DataFrame(demographic_counts)
```

```
print(demographic_table)
```

```
            Variable         Category    N
0           AgeGroup      65 or older  176
1           AgeGroup  25-34 years old   77
2           AgeGroup  35-44 years old   75
3           AgeGroup  45-54 years old   61
4           AgeGroup  55-64 years old   60
5           AgeGroup  18-24 years old   51
6           AgeGroup         Under 18    0
7             Gender             Male  261
8             Gender           Female  239
9          Education         Bachelor  137
10         Education              PhD  134
11         Education      High School  120
12         Education           Master  109
13     RaceEthnicity            Other  109
14     RaceEthnicity            Black  108
15     RaceEthnicity         Hispanic   97
16     RaceEthnicity            White   93
17     RaceEthnicity            Asian   93
18            Income           30-60K  139
19            Income             <30K  127
20            Income          60-100K  121
21            Income             >100K  113
22     MaritalStatus         Divorced  128
23     MaritalStatus           Single  127
24     MaritalStatus          Widowed  123
25     MaritalStatus          Married  122
26  EmploymentStatus          Retired  177
27  EmploymentStatus       Unemployed  173
28  EmploymentStatus         Employed  150
29     SmokingStatus            Never  175
30     SmokingStatus          Current  165
31     SmokingStatus           Former  160
32  PhysicalActivity             High  179
33  PhysicalActivity         Moderate  170
34  PhysicalActivity              Low  151
35     Comorbidities                4  105
36     Comorbidities                3  104
37     Comorbidities                1   98
```

```
38     Comorbidities                2   97
39     Comorbidities                0   96
```

2.3 Missing Values

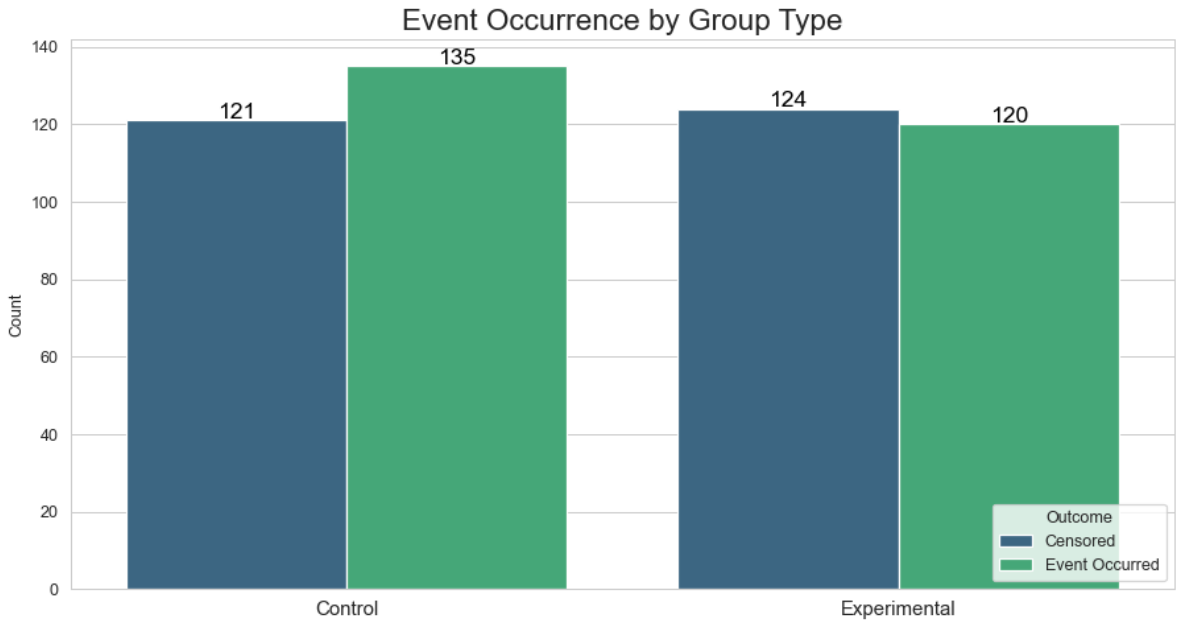
```
# Missing Value -- General Practice, but redundant here considering this is a rand-gerenrated
missing = mock_data.isnull().sum()
print(missing)
```

```
PatientID           0
Group               0
Age                 0
Gender              0
BMI                 0
BloodPressure       0
Cholesterol         0
Glucose             0
SmokingStatus       0
PhysicalActivity    0
Comorbidities       0
Medications         0
FollowUpTime        0
Outcome             0
Education           0
RaceEthnicity       0
Income              0
MaritalStatus       0
EmploymentStatus    0
dtype: int64
```

2.4 Group Distribution

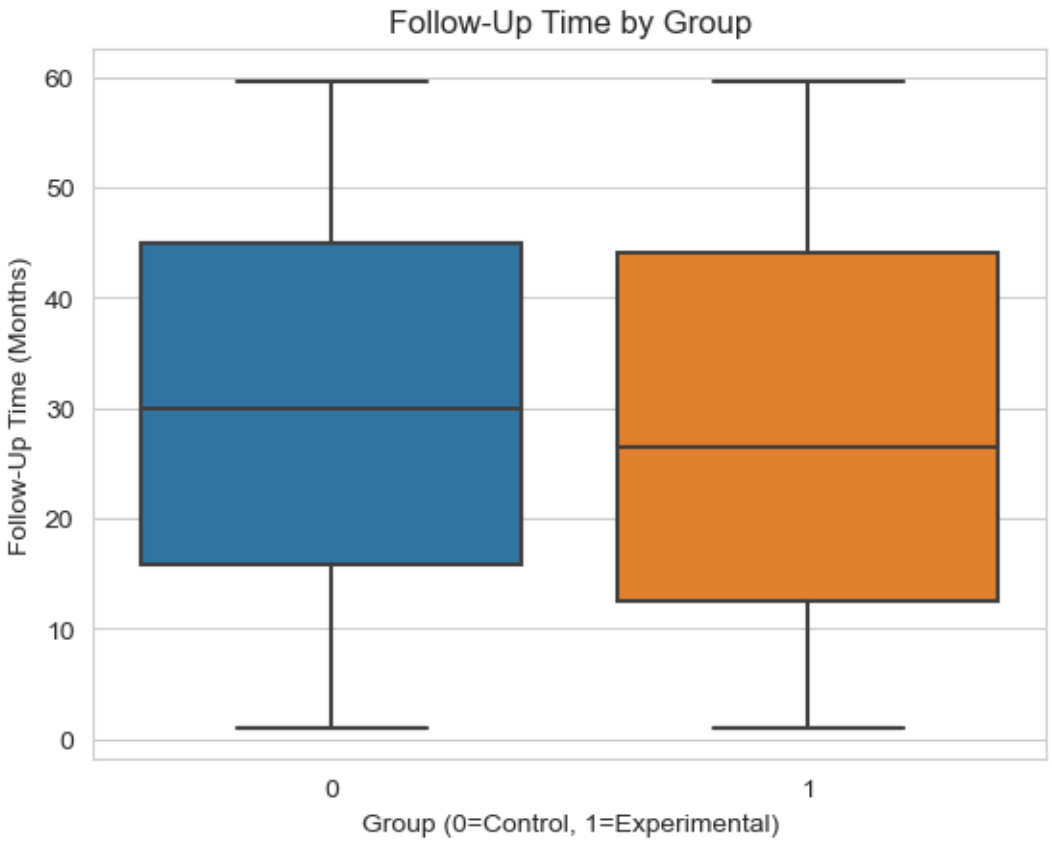
```
#Group Distribution
groups = mock_data.copy(deep=True)
groups['Group'] = groups['Group'].replace({0:'Experimental', 1:'Control'})
groups['Outcome'] = groups['Outcome'].replace({0:'Censored', 1:'Event Occurred'})

grp_outcome = groups.groupby(['Group', 'Outcome']).size().reset_index(name='Count')
```

```
# Set the aesthetic style of the plots
sns.set_style("whitegrid")

# Create the bar plot
plt.figure(figsize=(12, 6), dpi=90)
bar_plot = sns.barplot(x='Group', y='Count', hue='Outcome', data=grp_outcome, palette='viridi

# Add titles and labels
plt.title('Event Occurrence by Group Type', fontsize=18)
plt.xlabel('')
plt.ylabel('Count')
plt.legend(title='Outcome', loc="lower right")
plt.xticks(fontsize=12)

# Add count annotations to the bars
for p in bar_plot.patches:
    height = p.get_height()
    bar_plot.annotate(f'{int(height)}',
                      (p.get_x() + p.get_width() / 2., height),
                      ha='center', va='center', fontsize=14, color='black', xytext=(0, 5),
                      textcoords='offset points')

# Show the plot
plt.show()
```



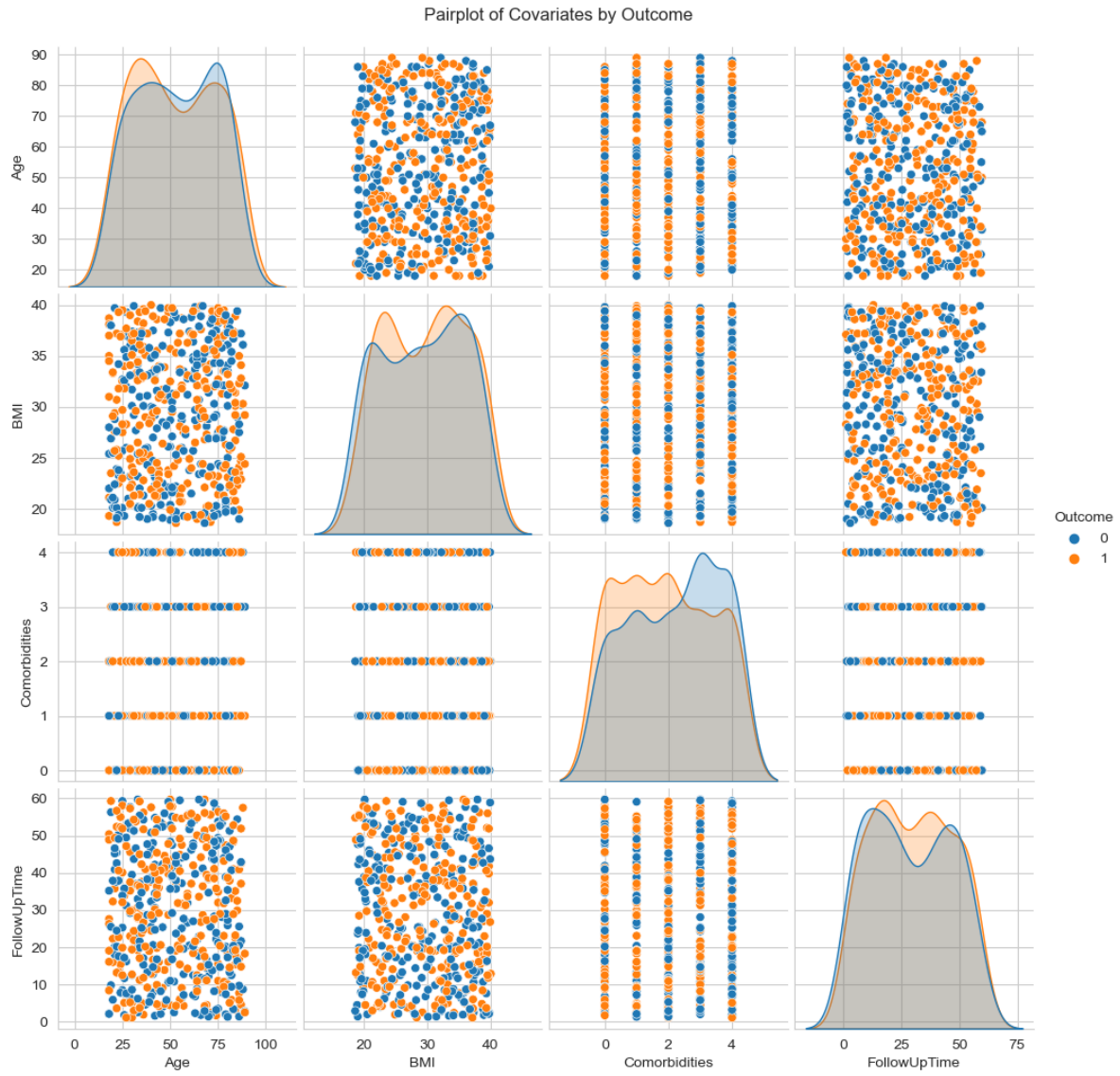
2.5 Follow-Up Time by Group

```
# Comparisoon of Follow-Up Time by Group

sns.boxplot(x='Group', y='FollowUpTime', data=mock_data)
plt.title('Follow-Up Time by Group')
plt.xlabel('Group (0=Control, 1=Experimental)')
plt.ylabel('Follow-Up Time (Months)')
plt.show()
```



2.6 Covariates

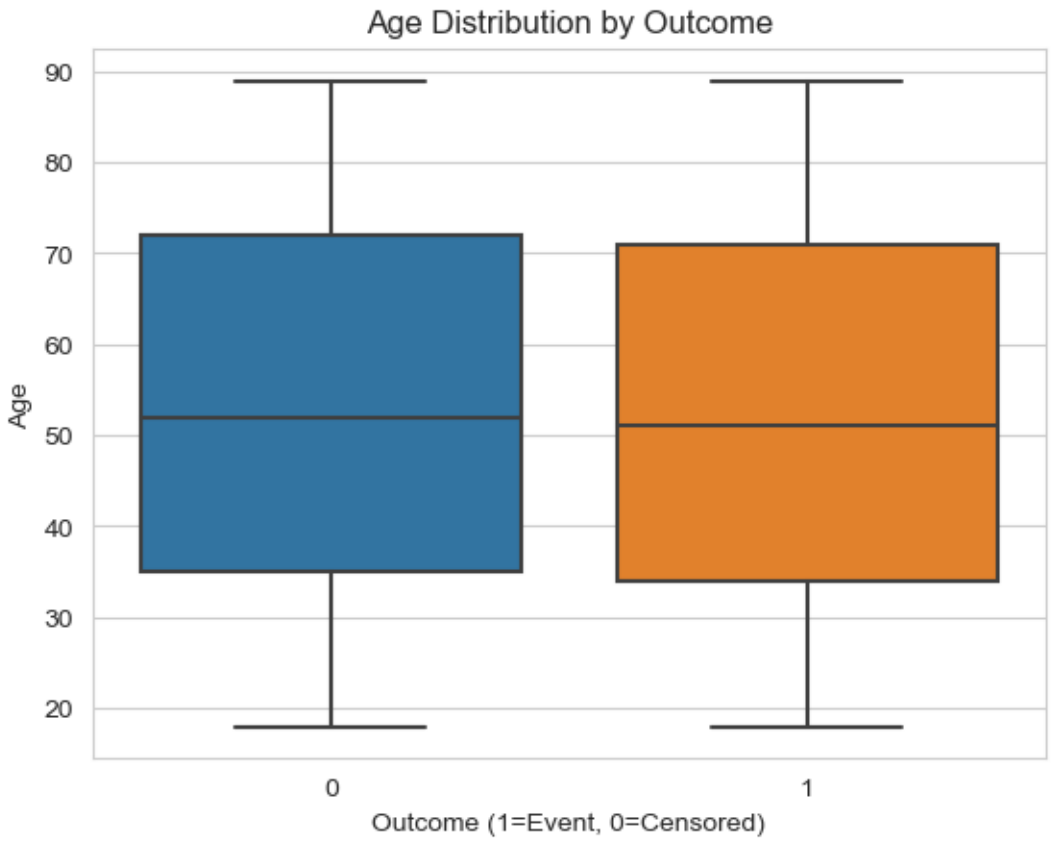
```
# Covariates

# Suppress specific FutureWarnings related to Seaborn
import warnings
warnings.filterwarnings("ignore", category=FutureWarning, module='seaborn._oldcore')
warnings.filterwarnings("ignore", category=UserWarning, module='seaborn.axisgrid')

# Ensure there are no infinite values in the
mock_data.replace([np.inf, -np.inf], np.nan, inplace=True)

# Pairplot to examine relationships
pairplot = sns.pairplot(mock_data[['Age', 'BMI', 'Comorbidities', 'FollowUpTime', 'Outcome']]
pairplot.fig.suptitle('Pairplot of Covariates by Outcome', y=1.02)
plt.show()
```

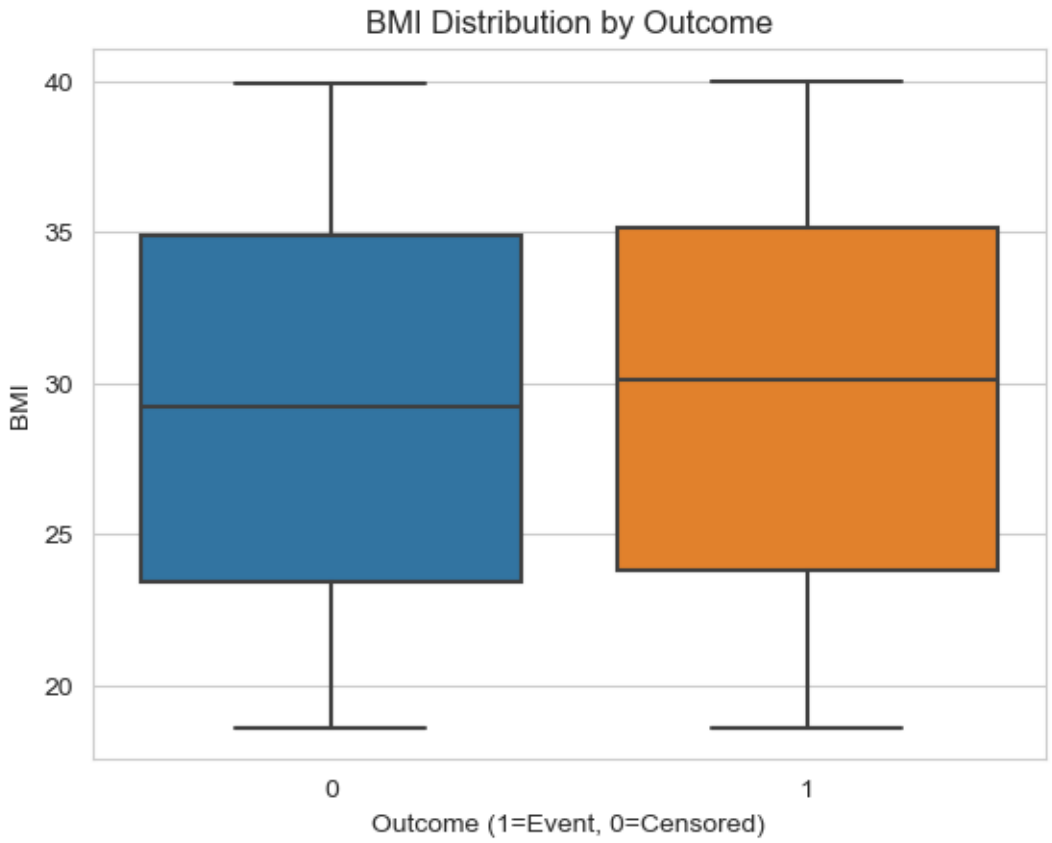


2.7 Outcomes by Age and BMI

```
# Distribution of Age by Outcome
sns.boxplot(x='Outcome', y='Age', data=mock_data)
plt.title('Age Distribution by Outcome')
plt.xlabel('Outcome (1=Event, 0=Censored)')
plt.ylabel('Age')
plt.show()
```

```
# Distribution of BMI by Outcome
sns.boxplot(x='Outcome', y='BMI', data=mock_data)
plt.title('BMI Distribution by Outcome')
plt.xlabel('Outcome (1=Event, 0=Censored)')
plt.ylabel('BMI')
plt.show()
```



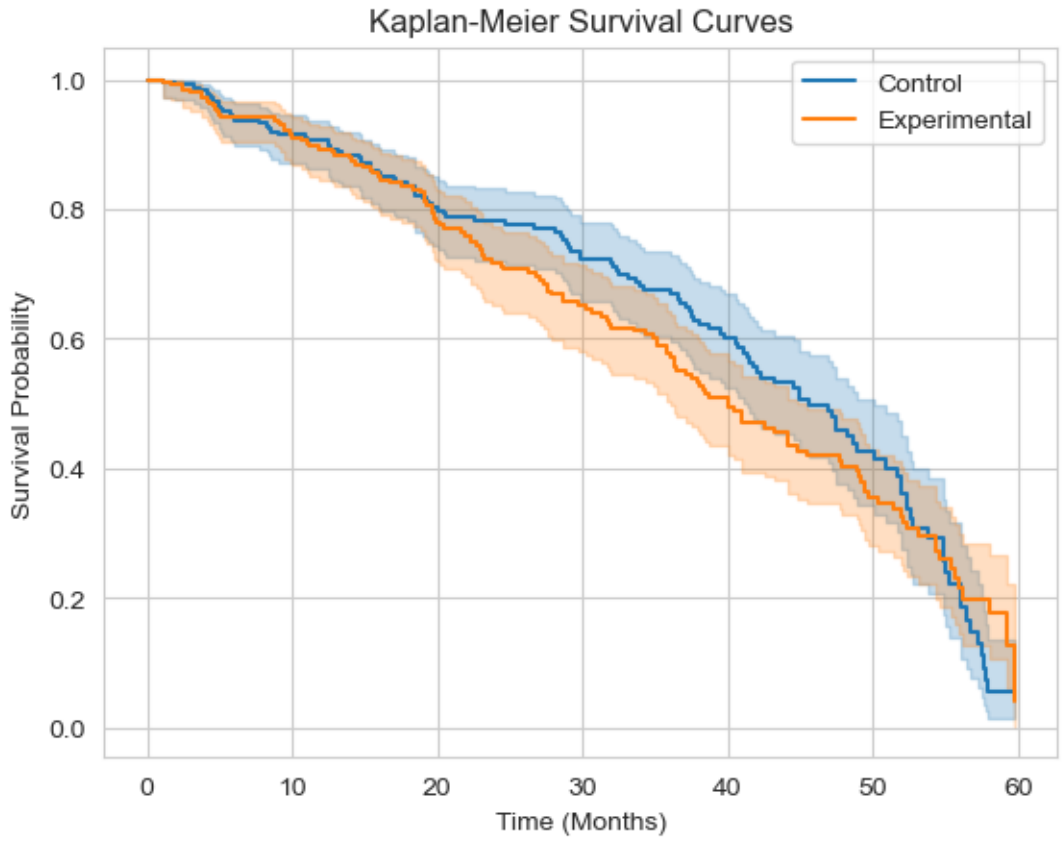


3 Third Step: Survivor Analysis of Experimental and Control Group

3.1 Kaplan-Meier Curves

```
# Kaplan-Meier Curves
from lifelines import KaplanMeierFitter

kmf = KaplanMeierFitter()

# Filter data for each group and check if they are empty
control_group = mock_data[mock_data['Group'] == 0]
experimental_group = mock_data[mock_data['Group'] == 1]

# Fit the data for the control group
kmf.fit(control_group['FollowUpTime'], event_observed=control_group['Outcome'], label='Contr
```

```
ax = kmf.plot_survival_function()

# Fit the data for the experimental group
kmf.fit(experimental_group['FollowUpTime'], event_observed=experimental_group['Outcome'], la
kmf.plot_survival_function(ax=ax)

plt.title('Kaplan-Meier Survival Curves')
plt.xlabel('Time (Months)')
plt.ylabel('Survival Probability')
plt.show()
```



3.2 Log-Rank Test

```
# Statistical Testing: Log-Rank Test
from lifelines.statistics import logrank_test
```

```
# Extract survival times and event indicators
control_times = control_group['FollowUpTime']
control_events = control_group['Outcome']
experimental_times = experimental_group['FollowUpTime']
experimental_events = experimental_group['Outcome']

# Perform the log-rank test
results = logrank_test(control_times, experimental_times, event_observed_A=control_events, ev

# Print the results
print(results)
```

```
<lifelines.StatisticalResult: logrank_test>
               t_0 = -1
 null_distribution = chi squared
degrees_of_freedom = 1
         test_name = logrank_test

---
 test_statistic    p  -log2(p)
           0.42 0.52      0.95
```

3.3 Cox Proportional Hazards Model: Check for Multicollinearity

```
# Cox Proportional Hazards Model
from lifelines import CoxPHFitter
from sklearn.preprocessing import StandardScaler
from statsmodels.stats.outliers_influence import variance_inflation_factor
import statsmodels.api as sm
from lifelines import CoxPHFitter

# Opt into future downcasting behavior
pd.set_option('future.no_silent_downcasting', True)

# Combine groups into a single DataFrame with the 'Group' as an additional covariate
combined_data = mock_data
combined_data['Gender'] = combined_data['Gender'].replace({'Male':1, 'Female':2})
combined_data['SmokingStatus'] = combined_data['SmokingStatus'].replace({'Never':0, 'Current
combined_data['PhysicalActivity'] = combined_data['PhysicalActivity'].replace({'Low':1, 'Mode
```

```
combined_data['Education'] = combined_data['Education'].replace({'High School':1, 'Bachelor'
combined_data['RaceEthnicity'] = combined_data['RaceEthnicity'].replace({'White':1, 'Black':1
combined_data['Income'] = combined_data['Income'].replace({'<30K':1, '30-60K':2,'60-100K':3,
combined_data['MaritalStatus'] = combined_data['MaritalStatus'].replace({'Single':1, 'Marriec
combined_data['EmploymentStatus'] = combined_data['EmploymentStatus'].replace({'Employed':1,
combined_data['Group'] = combined_data['Group'].astype('category')

# Standardize features
X = combined_data.drop(columns=['FollowUpTime', 'Outcome'])
X = sm.add_constant(X)  # adds a constant term to the predictors
scaler = StandardScaler()
scaled_features = scaler.fit_transform(X)
scaled_data = pd.DataFrame(scaled_features, columns=X.columns)
scaled_data['FollowUpTime'] = combined_data['FollowUpTime'].values
scaled_data['Outcome'] = combined_data['Outcome'].values

# Check for multicollinearity
vif = pd.DataFrame()
vif['Feature'] = scaled_data.columns
vif['VIF'] = [variance_inflation_factor(scaled_data.values, i) for i in range(scaled_data.sha
print(vif)
```

```
             Feature       VIF
0              const       NaN
1          PatientID  1.031726
2              Group  1.035117
3                Age  1.032283
4             Gender  1.054207
5                BMI  1.042135
6      BloodPressure  1.020399
7        Cholesterol  1.029551
8            Glucose  1.037837
9      SmokingStatus  1.036154
10  PhysicalActivity  1.053474
11     Comorbidities  1.052314
12       Medications  1.021336
13         Education  1.022416
14     RaceEthnicity  1.048298
15            Income  1.036021
16     MaritalStatus  1.045388
17  EmploymentStatus  1.048011
18      FollowUpTime  1.712549
```

```
19           Outcome  1.732979
```

3.4 Cox Proportional Hazards Model: Check Infinte Values

```
# Check for NaNs and infinite values -- We know there are none, but good practice.
print(scaled_data.isna().sum())
print((scaled_data == float('inf')).sum())
```

```
const               0
PatientID           0
Group               0
Age                 0
Gender              0
BMI                 0
BloodPressure       0
Cholesterol         0
Glucose             0
SmokingStatus       0
PhysicalActivity    0
Comorbidities       0
Medications         0
Education           0
RaceEthnicity       0
Income              0
MaritalStatus       0
EmploymentStatus    0
FollowUpTime        0
Outcome             0
dtype: int64
const               0
PatientID           0
Group               0
Age                 0
Gender              0
BMI                 0
BloodPressure       0
Cholesterol         0
Glucose             0
SmokingStatus       0
PhysicalActivity    0
```

```
Comorbidities       0
Medications         0
Education           0
RaceEthnicity       0
Income              0
MaritalStatus       0
EmploymentStatus    0
FollowUpTime        0
Outcome             0
dtype: int64
```

3.5 Initialize and fit the Cox Proportional Hazards model

```
# Initialize and fit the Cox Proportional Hazards model

#Remove variables that express multicollinearity and also those with low variance
scaled_data = scaled_data.drop(columns=['RaceEthnicity', 'Income'])
scaled_data = scaled_data.drop(columns=['const'], errors='ignore')

# Initialize CoxPHFitter with L1 regularization (Lasso)
cph = CoxPHFitter(penalizer=0.1)  # Adjust the penalizer as needed

# Fit the model
cph.fit(scaled_data, duration_col='FollowUpTime', event_col='Outcome', show_progress=True)

# Print the summary
print(cph.summary)
```

```
Iteration 1: norm_delta = 2.21e-01, step_size = 0.9500, log_lik = -1327.35045, newton_decreme
Iteration 2: norm_delta = 8.35e-03, step_size = 0.9500, log_lik = -1320.64049, newton_decreme
Iteration 3: norm_delta = 4.24e-04, step_size = 0.9500, log_lik = -1320.63034, newton_decreme
Iteration 4: norm_delta = 2.40e-08, step_size = 1.0000, log_lik = -1320.63032, newton_decreme
Convergence success after 4 iterations.
                     coef  exp(coef)  se(coef)  coef lower 95%  \
covariate
PatientID         0.017891   1.018052  0.057673       -0.095147
Group             0.027470   1.027851  0.059287       -0.088731
Age               0.021111   1.021336  0.059988       -0.096463
Gender            0.024839   1.025150  0.059020       -0.090839
BMI               0.065713   1.067920  0.059624       -0.051149
```

```
BloodPressure     0.043430   1.044387  0.056973       -0.068235
Cholesterol      -0.001280   0.998721  0.060051       -0.118978
Glucose           0.003125   1.003130  0.059146       -0.112798
SmokingStatus    -0.065860   0.936262  0.055772       -0.175171
PhysicalActivity  0.125096   1.133257  0.058294        0.010841
Comorbidities    -0.111948   0.894091  0.058645       -0.226891
Medications      -0.015634   0.984487  0.057895       -0.129106
Education         0.050015   1.051287  0.058423       -0.064492
MaritalStatus     0.050143   1.051422  0.060367       -0.068173
EmploymentStatus -0.017431   0.982720  0.059560       -0.134167

                  coef upper 95%  exp(coef) lower 95%  exp(coef) upper 95%  \
covariate
PatientID                0.130929             0.909239             1.139886
Group                    0.143671             0.915092             1.154504
Age                      0.138685             0.908044             1.148762
Gender                   0.140516             0.913165             1.150868
BMI                      0.182574             0.950137             1.200303
BloodPressure            0.155095             0.934041             1.167769
Cholesterol              0.116419             0.887827             1.123467
Glucose                  0.119049             0.893331             1.126425
SmokingStatus            0.043451             0.839314             1.044409
PhysicalActivity         0.239351             1.010900             1.270424
Comorbidities            0.002995             0.797008             1.002999
Medications              0.097838             0.878881             1.102784
Education                0.164523             0.937544             1.178831
MaritalStatus            0.168460             0.934099             1.183481
EmploymentStatus         0.099305             0.874444             1.104403

                  cmp to         z         p  -log2(p)
covariate
PatientID            0.0  0.310208  0.756403  0.402773
Group                0.0  0.463340  0.643121  0.636839
Age                  0.0  0.351926  0.724894  0.464159
Gender               0.0  0.420849  0.673865  0.569468
BMI                  0.0  1.102112  0.270413  1.886763
BloodPressure        0.0  0.762291  0.445887  1.165251
Cholesterol          0.0 -0.021309  0.982999  0.024738
Glucose              0.0  0.052840  0.957859  0.062114
SmokingStatus        0.0 -1.180876  0.237652  2.073079
PhysicalActivity     0.0  2.145935  0.031878  4.971288
Comorbidities        0.0 -1.908900  0.056275  4.151362
Medications          0.0 -0.270045  0.787126  0.345334
```

```
Education            0.0  0.856088  0.391949  1.351261
MaritalStatus        0.0  0.830647  0.406173  1.299833
EmploymentStatus     0.0 -0.292664  0.769779  0.377484
```

4 Fourth Step: Model Validation and Sensitiviy Analysis

4.1 Model Validation

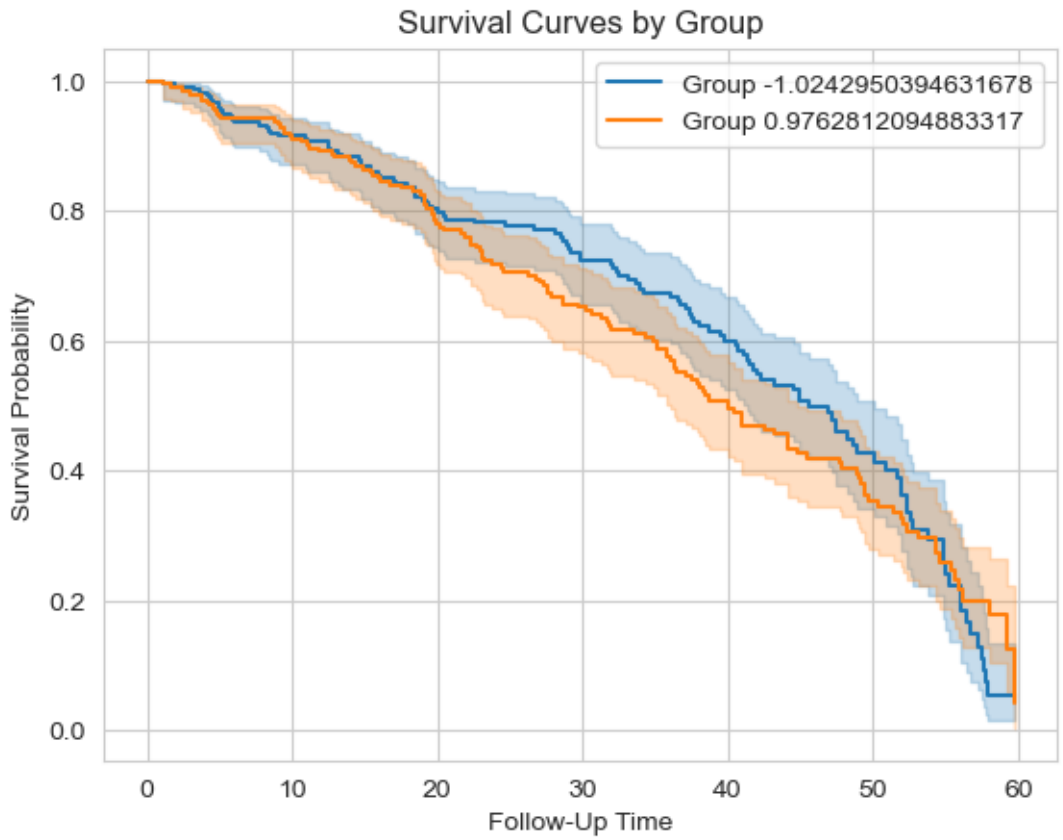
```python
# Model Validation
from lifelines.utils import concordance_index
from statsmodels.stats.proportion import proportion_confint

#Schoenfeld Residuals

# Fit the Cox model
cph = CoxPHFitter(penalizer=0.1)
cph.fit(scaled_data, duration_col='FollowUpTime', event_col='Outcome')

# Extract Schoenfeld residuals
residuals = cph.compute_residuals(scaled_data, kind='schoenfeld')
print(residuals.head())
```

```
covariate  PatientID     Group       Age    Gender       BMI  BloodPressure  \
289         0.260823  0.939134 -1.131451 -0.970501  1.116561      -0.230472
442         1.320840 -1.061442 -1.275173  1.031437 -0.260495       1.670712
189        -0.432768  0.943606  0.979582  1.039508  1.068002      -0.409806
74         -1.239359 -1.047581 -0.835946  1.039990 -0.783947       1.465723
56         -1.368195  0.953607  0.836305  1.046399  0.673628      -0.603815

covariate  Cholesterol   Glucose  SmokingStatus  PhysicalActivity  \
289           1.385313  1.674101      -1.113951          1.223827
442           0.672464  1.145871       0.108565         -0.862061
189          -1.461020  1.589793       1.326780          1.223479
74            0.208752 -1.234285       0.102925          1.231311
56           -0.871949  1.548478      -1.113243          1.224259

covariate  Comorbidities  Medications  Education  MaritalStatus  \
289             0.070170     0.967612  -0.993463      -0.462838
442             1.480968    -1.033685   1.276660       1.326042
189            -1.338596     0.968266  -0.997465       1.328285
```

```
74              -1.341011     0.973654  -0.998420      -1.356827
56               0.770485    -1.021119   1.268430      -0.467605

covariate  EmploymentStatus
289                1.187289
442               -0.052025
189               -0.050001
74                 1.192341
56                -0.049878
```

4.2 Log-Log Survival Plot

```
#Log-Log Survival Plot

# Calculate survival functions for a categorical variable
for group in scaled_data['Group'].unique():
    subset = scaled_data[scaled_data['Group'] == group]
    kmf = KaplanMeierFitter()
    kmf.fit(durations=subset['FollowUpTime'], event_observed=subset['Outcome'])
    kmf.plot(label=f'Group {group}')

plt.xlabel('Follow-Up Time')
plt.ylabel('Survival Probability')
plt.title('Survival Curves by Group')
plt.legend()
plt.show()
```



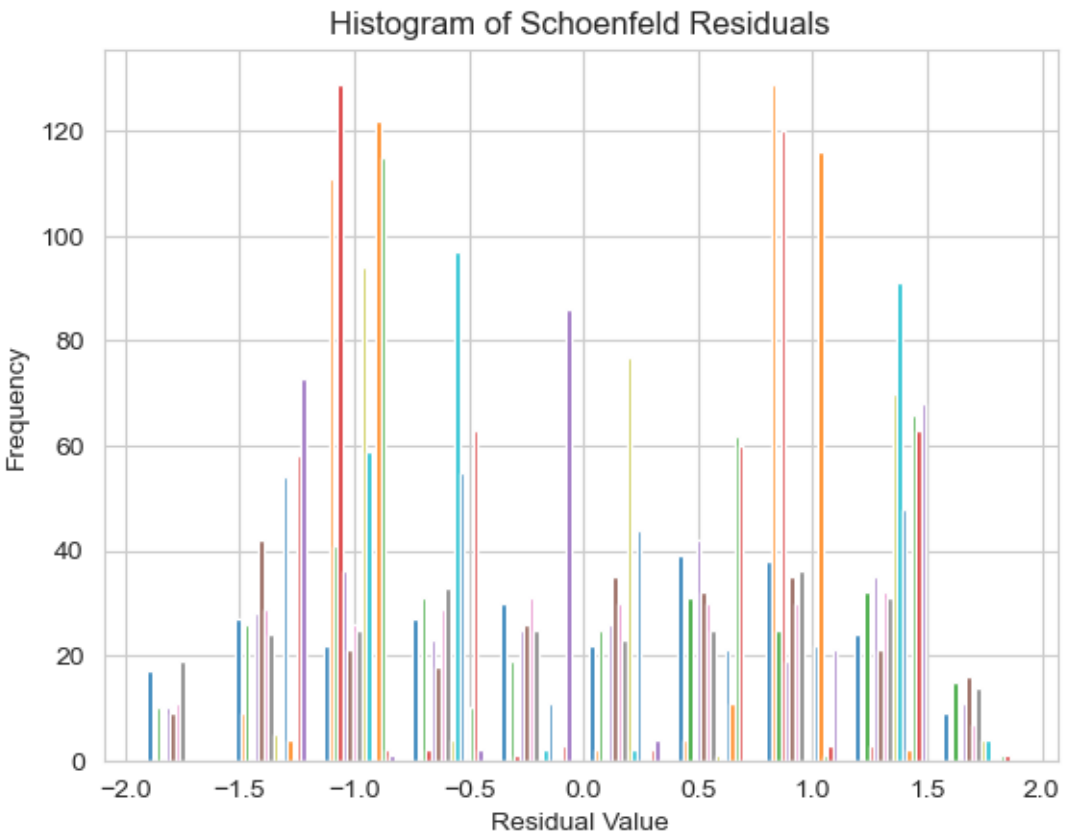
4.3 C-Index

```
#C-Index

# Calculate C-index
c_index = concordance_index(scaled_data['FollowUpTime'], -cph.predict_partial_hazard(scaled_
print(f'C-index: {c_index}')
```

```
C-index: 0.5844883799367201
```

4.4 Residuals Analysis

```
# Residuals Analysis

residuals = cph.compute_residuals(scaled_data, kind='schoenfeld')
plt.hist(residuals)
plt.title('Histogram of Schoenfeld Residuals')
plt.xlabel('Residual Value')
plt.ylabel('Frequency')
plt.show()
```



4.5 Sensitiviy Analysis

```
# Sensitiviy Analysis

# Different Penalizer Values
penalizers = [0.01, 0.1, 1.0]
```

```
for penalizer in penalizers:
    cph = CoxPHFitter(penalizer=penalizer)
    cph.fit(scaled_data, duration_col='FollowUpTime', event_col='Outcome')
    print(f'Penalizer: {penalizer}')
    print(cph.summary)
```

```
Penalizer: 0.01
                       coef  exp(coef)  se(coef)  coef lower 95%  \
covariate
PatientID          0.020774   1.020991  0.062808       -0.102327
Group              0.031319   1.031815  0.065136       -0.096345
Age                0.022836   1.023099  0.065818       -0.106165
Gender             0.030595   1.031067  0.064656       -0.096128
BMI                0.077610   1.080701  0.065577       -0.050919
BloodPressure      0.050420   1.051713  0.061929       -0.070959
Cholesterol       -0.006935   0.993089  0.066006       -0.136306
Glucose            0.003600   1.003606  0.064876       -0.123554
SmokingStatus     -0.074992   0.927751  0.060286       -0.193151
PhysicalActivity   0.150421   1.162323  0.063165        0.026619
Comorbidities     -0.133983   0.874605  0.064268       -0.259946
Medications       -0.019462   0.980726  0.062937       -0.142817
Education          0.058498   1.060243  0.063864       -0.066672
MaritalStatus      0.068355   1.070745  0.066584       -0.062146
EmploymentStatus  -0.020588   0.979623  0.065334       -0.148640

                   coef upper 95%  exp(coef) lower 95%  exp(coef) upper 95%  \
covariate
PatientID                0.143876             0.902734             1.154741
Group                    0.158984             0.908150             1.172319
Age                      0.151837             0.899276             1.163970
Gender                   0.157318             0.908347             1.170367
BMI                      0.206139             0.950356             1.228924
BloodPressure            0.171799             0.931500             1.187439
Cholesterol              0.122435             0.872576             1.130245
Glucose                  0.130754             0.883774             1.139687
SmokingStatus            0.043167             0.824358             1.044112
PhysicalActivity         0.274222             1.026977             1.315507
Comorbidities           -0.008019             0.771093             0.992013
Medications              0.103892             0.866913             1.109480
Education                0.183669             0.935502             1.201619
MaritalStatus            0.198856             0.939745             1.220007
EmploymentStatus         0.107464             0.861879             1.113451
```

	cmp to	z	p	-log2(p)
covariate				
PatientID	0.0	0.330757	0.740828	0.432789
Group	0.0	0.480828	0.630639	0.665114
Age	0.0	0.346954	0.728626	0.456750
Gender	0.0	0.473193	0.636076	0.652730
BMI	0.0	1.183493	0.236614	2.079393
BloodPressure	0.0	0.814161	0.415553	1.266897
Cholesterol	0.0	-0.105072	0.916319	0.126078
Glucose	0.0	0.055487	0.955750	0.065294
SmokingStatus	0.0	-1.243934	0.213524	2.227531
PhysicalActivity	0.0	2.381389	0.017247	5.857471
Comorbidities	0.0	-2.084746	0.037092	4.752732
Medications	0.0	-0.309236	0.757142	0.401364
Education	0.0	0.915987	0.359674	1.475239
MaritalStatus	0.0	1.026604	0.304607	1.714979
EmploymentStatus	0.0	-0.315116	0.752673	0.409904

Penalizer: 0.1

	coef	exp(coef)	se(coef)	coef lower 95%	\
covariate					
PatientID	0.017891	1.018052	0.057673	-0.095147	
Group	0.027470	1.027851	0.059287	-0.088731	
Age	0.021111	1.021336	0.059988	-0.096463	
Gender	0.024839	1.025150	0.059020	-0.090839	
BMI	0.065713	1.067920	0.059624	-0.051149	
BloodPressure	0.043430	1.044387	0.056973	-0.068235	
Cholesterol	-0.001280	0.998721	0.060051	-0.118978	
Glucose	0.003125	1.003130	0.059146	-0.112798	
SmokingStatus	-0.065860	0.936262	0.055772	-0.175171	
PhysicalActivity	0.125096	1.133257	0.058294	0.010841	
Comorbidities	-0.111948	0.894091	0.058645	-0.226891	
Medications	-0.015634	0.984487	0.057895	-0.129106	
Education	0.050015	1.051287	0.058423	-0.064492	
MaritalStatus	0.050143	1.051422	0.060367	-0.068173	
EmploymentStatus	-0.017431	0.982720	0.059560	-0.134167	

	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95%	\
covariate				
PatientID	0.130929	0.909239	1.139886	
Group	0.143671	0.915092	1.154504	
Age	0.138685	0.908044	1.148762	
Gender	0.140516	0.913165	1.150868	

```
BMI                    0.182574            0.950137            1.200303
BloodPressure          0.155095            0.934041            1.167769
Cholesterol            0.116419            0.887827            1.123467
Glucose                0.119049            0.893331            1.126425
SmokingStatus          0.043451            0.839314            1.044409
PhysicalActivity       0.239351            1.010900            1.270424
Comorbidities          0.002995            0.797008            1.002999
Medications            0.097838            0.878881            1.102784
Education              0.164523            0.937544            1.178831
MaritalStatus          0.168460            0.934099            1.183481
EmploymentStatus       0.099305            0.874444            1.104403

                 cmp to         z         p  -log2(p)
covariate
PatientID           0.0  0.310208  0.756403  0.402773
Group               0.0  0.463340  0.643121  0.636839
Age                 0.0  0.351926  0.724894  0.464159
Gender              0.0  0.420849  0.673865  0.569468
BMI                 0.0  1.102112  0.270413  1.886763
BloodPressure       0.0  0.762291  0.445887  1.165251
Cholesterol         0.0 -0.021309  0.982999  0.024738
Glucose             0.0  0.052840  0.957859  0.062114
SmokingStatus       0.0 -1.180876  0.237652  2.073079
PhysicalActivity    0.0  2.145935  0.031878  4.971288
Comorbidities       0.0 -1.908900  0.056275  4.151362
Medications         0.0 -0.270045  0.787126  0.345334
Education           0.0  0.856088  0.391949  1.351261
MaritalStatus       0.0  0.830647  0.406173  1.299833
EmploymentStatus    0.0 -0.292664  0.769779  0.377484
Penalizer: 1.0
                     coef  exp(coef)  se(coef)  coef lower 95%  \
covariate
PatientID         0.007487   1.007515  0.036339       -0.063737
Group             0.012529   1.012608  0.036596       -0.059197
Age               0.010502   1.010558  0.036880       -0.061782
Gender            0.008742   1.008780  0.036573       -0.062939
BMI               0.027403   1.027782  0.036610       -0.044351
BloodPressure     0.018975   1.019156  0.036116       -0.051811
Cholesterol       0.005099   1.005112  0.036848       -0.067122
Glucose           0.000594   1.000595  0.036625       -0.071189
SmokingStatus    -0.029269   0.971155  0.035893       -0.099618
PhysicalActivity  0.046276   1.047363  0.036774       -0.025800
Comorbidities    -0.043833   0.957113  0.036457       -0.115288
```

Medications	-0.004964	0.995048	0.036469	-0.076442
Education	0.020247	1.020454	0.036493	-0.051278
MaritalStatus	0.010270	1.010323	0.036786	-0.061830
EmploymentStatus	-0.007586	0.992443	0.036740	-0.079595

covariate	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95% \
PatientID	0.078711	0.938252	1.081892
Group	0.084256	0.942521	1.087907
Age	0.082787	0.940088	1.086310
Gender	0.080423	0.939000	1.083745
BMI	0.099157	0.956618	1.104240
BloodPressure	0.089762	0.949508	1.093914
Cholesterol	0.077320	0.935081	1.080387
Glucose	0.072378	0.931286	1.075062
SmokingStatus	0.041079	0.905183	1.041934
PhysicalActivity	0.118352	0.974530	1.125640
Comorbidities	0.027621	0.891109	1.028006
Medications	0.066514	0.926407	1.068776
Education	0.091773	0.950014	1.096116
MaritalStatus	0.082369	0.940043	1.085856
EmploymentStatus	0.064424	0.923490	1.066545

covariate	cmp to	z	p	-log2(p)
PatientID	0.0	0.206031	0.836767	0.257103
Group	0.0	0.342368	0.732074	0.449938
Age	0.0	0.284769	0.775821	0.366204
Gender	0.0	0.239021	0.811090	0.302067
BMI	0.0	0.748518	0.454148	1.138767
BloodPressure	0.0	0.525391	0.599312	0.738622
Cholesterol	0.0	0.138370	0.889948	0.168207
Glucose	0.0	0.016230	0.987051	0.018804
SmokingStatus	0.0	-0.815473	0.414802	1.269506
PhysicalActivity	0.0	1.258379	0.208255	2.263578
Comorbidities	0.0	-1.202328	0.229236	2.125092
Medications	0.0	-0.136116	0.891730	0.165321
Education	0.0	0.554818	0.579019	0.788317
MaritalStatus	0.0	0.279172	0.780113	0.358246
EmploymentStatus	0.0	-0.206463	0.836430	0.257684

4.6 Model Re-specification with Interaction Terms

```
# Model Re-specification with Interaction Terms

scaled_data['Age_BMI'] = scaled_data['Age'] * scaled_data['BMI']
cph_interaction = CoxPHFitter(penalizer=0.1)
cph_interaction.fit(scaled_data, duration_col='FollowUpTime', event_col='Outcome')
print(cph_interaction.summary)
```

```
                     coef  exp(coef)  se(coef)  coef lower 95%  \
covariate
PatientID         0.006291   1.006311  0.058243       -0.107863
Group             0.018790   1.018967  0.059425       -0.097681
Age               0.015338   1.015456  0.059972       -0.102205
Gender            0.013682   1.013776  0.059179       -0.102306
BMI               0.057375   1.059052  0.059847       -0.059923
BloodPressure     0.045101   1.046134  0.056953       -0.066524
Cholesterol       0.003012   1.003017  0.060143       -0.114865
Glucose          -0.001482   0.998520  0.059106       -0.117327
SmokingStatus    -0.060968   0.940853  0.055824       -0.170382
PhysicalActivity  0.123825   1.131818  0.058375        0.009411
Comorbidities    -0.111560   0.894438  0.058698       -0.226605
Medications      -0.024089   0.976198  0.058017       -0.137801
Education         0.039966   1.040775  0.058829       -0.075336
MaritalStatus     0.047822   1.048984  0.060303       -0.070370
EmploymentStatus -0.020991   0.979228  0.059523       -0.137654
Age_BMI          -0.135653   0.873145  0.061027       -0.255264

                  coef upper 95%  exp(coef) lower 95%  exp(coef) upper 95%  \
covariate
PatientID                0.120444             0.897751             1.127998
Group                    0.135260             0.906938             1.144835
Age                      0.132881             0.902845             1.142114
Gender                   0.129670             0.902753             1.138453
BMI                      0.174673             0.941837             1.190856
BloodPressure            0.156727             0.935640             1.169676
Cholesterol              0.120890             0.891487             1.128500
Glucose                  0.114363             0.889295             1.121159
SmokingStatus            0.048445             0.843343             1.049638
PhysicalActivity         0.238239             1.009456             1.269012
Comorbidities            0.003486             0.797235             1.003492
```

```
Medications              0.089622              0.871272              1.093761
Education                0.155268              0.927432              1.167971
MaritalStatus            0.166014              0.932049              1.180589
EmploymentStatus         0.095672              0.871400              1.100399
Age_BMI                 -0.016043              0.774712              0.984085

                  cmp to         z         p  -log2(p)
covariate
PatientID            0.0  0.108009  0.913989  0.129752
Group                0.0  0.316193  0.751856  0.411472
Age                  0.0  0.255755  0.798140  0.325286
Gender               0.0  0.231202  0.817158  0.291313
BMI                  0.0  0.958688  0.337716  1.566118
BloodPressure        0.0  0.791903  0.428417  1.222912
Cholesterol          0.0  0.050088  0.960052  0.058815
Glucose              0.0 -0.025067  0.980002  0.029144
SmokingStatus        0.0 -1.092146  0.274769  1.863708
PhysicalActivity     0.0  2.121186  0.033906  4.882310
Comorbidities        0.0 -1.900577  0.057357  4.123876
Medications          0.0 -0.415212  0.677987  0.560671
Education            0.0  0.679363  0.496908  1.008949
MaritalStatus        0.0  0.793021  0.427765  1.225109
EmploymentStatus     0.0 -0.352651  0.724350  0.465241
Age_BMI              0.0 -2.222847  0.026226  5.252852
```

4.7 Outlier Detection

```python
# Add this section after your Cox model fitting and before model validation

# 1. Outlier Detection
# Example: Using Z-scores for numerical variables
from scipy import stats

# Detect outliers
z_scores = np.abs(stats.zscore(combined_data[['Age', 'BMI', 'FollowUpTime']]))
outliers = (z_scores > 3).any(axis=1)

# 2. Fit Cox model with outliers
cph_with_outliers = CoxPHFitter(penalizer=0.1)
cph_with_outliers.fit(combined_data, duration_col='FollowUpTime', event_col='Outcome')
```

```
# 3. Fit Cox model without outliers
cph_without_outliers = CoxPHFitter(penalizer=0.1)
cph_without_outliers.fit(combined_data[~outliers], duration_col='FollowUpTime', event_col='Ou

# 4. Compare results
print("Model summary with outliers:")
print(cph_with_outliers.summary)

print("\nModel summary without outliers:")
print(cph_without_outliers.summary)
```

```
Model summary with outliers:
                      coef  exp(coef)  se(coef)  coef lower 95%  \
covariate
PatientID         0.000108   1.000108  0.000398       -0.000673
Group             0.019433   1.019623  0.119096       -0.213990
Age               0.001142   1.001143  0.002873       -0.004488
Gender            0.057489   1.059173  0.119616       -0.176955
BMI               0.011804   1.011874  0.009323       -0.006469
BloodPressure     0.002191   1.002193  0.002240       -0.002200
Cholesterol       0.000086   1.000086  0.001050       -0.001971
Glucose           0.000105   1.000105  0.001548       -0.002929
SmokingStatus    -0.078738   0.924283  0.068566       -0.213125
PhysicalActivity  0.291563   1.338518  0.122328        0.051805
Comorbidities    -0.082035   0.921240  0.041498       -0.163370
Medications      -0.028585   0.971820  0.116322       -0.256572
Education         0.032876   1.033422  0.044288       -0.053926
RaceEthnicity     0.098645   1.103675  0.041784        0.016751
Income            0.077888   1.081002  0.052825       -0.025647
MaritalStatus     0.042182   1.043084  0.054279       -0.064202
EmploymentStatus -0.011461   0.988605  0.074028       -0.156553

                  coef upper 95%  exp(coef) lower 95%  exp(coef) upper 95%  \
covariate
PatientID               0.000889             0.999328             1.000890
Group                   0.252856             0.807356             1.287698
Age                     0.006773             0.995522             1.006796
Gender                  0.291932             0.837817             1.339012
BMI                     0.030078             0.993552             1.030534
BloodPressure           0.006582             0.997803             1.006603
Cholesterol             0.002143             0.998031             1.002146
Glucose                 0.003138             0.997076             1.003143
```

```
SmokingStatus           0.055650             0.808055             1.057228
PhysicalActivity        0.531321             1.053170             1.701178
Comorbidities          -0.000701             0.849277             0.999299
Medications             0.199403             0.773699             1.220673
Education               0.119678             0.947502             1.127134
RaceEthnicity           0.180540             1.016892             1.197864
Income                  0.181424             0.974679             1.198924
MaritalStatus           0.148566             0.937816             1.160169
EmploymentStatus        0.133632             0.855086             1.142972

                  cmp to         z         p  -log2(p)
covariate
PatientID            0.0  0.272112  0.785536  0.348251
Group                0.0  0.163172  0.870383  0.200277
Age                  0.0  0.397664  0.690878  0.533497
Gender               0.0  0.480608  0.630795  0.664757
BMI                  0.0  1.266146  0.205461  2.283064
BloodPressure        0.0  0.978010  0.328069  1.607928
Cholesterol          0.0  0.082169  0.934512  0.097714
Glucose              0.0  0.067629  0.946081  0.079965
SmokingStatus        0.0 -1.148339  0.250829  1.995225
PhysicalActivity     0.0  2.383457  0.017151  5.865571
Comorbidities        0.0 -1.976852  0.048058  4.379067
Medications          0.0 -0.245736  0.805886  0.311352
Education            0.0  0.742327  0.457889  1.126930
RaceEthnicity        0.0  2.360870  0.018232  5.777372
Income               0.0  1.474451  0.140360  2.832795
MaritalStatus        0.0  0.777140  0.437076  1.194043
EmploymentStatus     0.0 -0.154813  0.876969  0.189403

Model summary without outliers:
                     coef  exp(coef)  se(coef)  coef lower 95%  \
covariate
PatientID         0.000108   1.000108  0.000398       -0.000673
Group             0.019433   1.019623  0.119096       -0.213990
Age               0.001142   1.001143  0.002873       -0.004488
Gender            0.057489   1.059173  0.119616       -0.176955
BMI               0.011804   1.011874  0.009323       -0.006469
BloodPressure     0.002191   1.002193  0.002240       -0.002200
Cholesterol       0.000086   1.000086  0.001050       -0.001971
Glucose           0.000105   1.000105  0.001548       -0.002929
SmokingStatus    -0.078738   0.924283  0.068566       -0.213125
PhysicalActivity  0.291563   1.338518  0.122328        0.051805
```

Comorbidities	-0.082035	0.921240	0.041498	-0.163370
Medications	-0.028585	0.971820	0.116322	-0.256572
Education	0.032876	1.033422	0.044288	-0.053926
RaceEthnicity	0.098645	1.103675	0.041784	0.016751
Income	0.077888	1.081002	0.052825	-0.025647
MaritalStatus	0.042182	1.043084	0.054279	-0.064202
EmploymentStatus	-0.011461	0.988605	0.074028	-0.156553

covariate	coef upper 95%	exp(coef) lower 95%	exp(coef) upper 95% \
PatientID	0.000889	0.999328	1.000890
Group	0.252856	0.807356	1.287698
Age	0.006773	0.995522	1.006796
Gender	0.291932	0.837817	1.339012
BMI	0.030078	0.993552	1.030534
BloodPressure	0.006582	0.997803	1.006603
Cholesterol	0.002143	0.998031	1.002146
Glucose	0.003138	0.997076	1.003143
SmokingStatus	0.055650	0.808055	1.057228
PhysicalActivity	0.531321	1.053170	1.701178
Comorbidities	-0.000701	0.849277	0.999299
Medications	0.199403	0.773699	1.220673
Education	0.119678	0.947502	1.127134
RaceEthnicity	0.180540	1.016892	1.197864
Income	0.181424	0.974679	1.198924
MaritalStatus	0.148566	0.937816	1.160169
EmploymentStatus	0.133632	0.855086	1.142972

covariate	cmp to	z	p	-log2(p)
PatientID	0.0	0.272112	0.785536	0.348251
Group	0.0	0.163172	0.870383	0.200277
Age	0.0	0.397664	0.690878	0.533497
Gender	0.0	0.480608	0.630795	0.664757
BMI	0.0	1.266146	0.205461	2.283064
BloodPressure	0.0	0.978010	0.328069	1.607928
Cholesterol	0.0	0.082169	0.934512	0.097714
Glucose	0.0	0.067629	0.946081	0.079965
SmokingStatus	0.0	-1.148339	0.250829	1.995225
PhysicalActivity	0.0	2.383457	0.017151	5.865571
Comorbidities	0.0	-1.976852	0.048058	4.379067
Medications	0.0	-0.245736	0.805886	0.311352
Education	0.0	0.742327	0.457889	1.126930

```
RaceEthnicity        0.0  2.360870  0.018232  5.777372
Income               0.0  1.474451  0.140360  2.832795
MaritalStatus        0.0  0.777140  0.437076  1.194043
EmploymentStatus     0.0 -0.154813  0.876969  0.189403
```