

# heart\_\_disease

October 23, 2023

```
[ ]: # IMPORTING NECESSARY PACKAGES
import warnings
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.tools.tools import add_constant

from scipy.stats import chi2_contingency
from scipy.stats import ttest_ind

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report

from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler
from sklearn.tree import DecisionTreeClassifier

warnings.filterwarnings("ignore", category=DeprecationWarning)
warnings.filterwarnings("ignore", category=FutureWarning)

from sklearn.tree import export_graphviz

# Specify the URL of the dataset
url = "https://raw.githubusercontent.com/AAI-500-Team/aai_500_dataset/main/
      ↪heart_2022_no_nans.csv"

# Use pandas to read the CSV file from the URL into a DataFrame
df = pd.read_csv(url)
```

## 0.1 Introduction

First, we're going to understand the given dataset.

```
[ ]: display(df)
```

	State	Sex	GeneralHealth	PhysicalHealthDays	\
0	Alabama	Female	Very good	4.0	
1	Alabama	Male	Very good	0.0	
2	Alabama	Male	Very good	0.0	
3	Alabama	Female	Fair	5.0	
4	Alabama	Female	Good	3.0	
...	...	...	...	...	
246017	Virgin Islands	Male	Very good	0.0	
246018	Virgin Islands	Female	Fair	0.0	
246019	Virgin Islands	Male	Good	0.0	
246020	Virgin Islands	Female	Excellent	2.0	
246021	Virgin Islands	Male	Very good	0.0	

	MentalHealthDays	LastCheckupTime	\
0	0.0	Within past year (anytime less than 12 months ...	
1	0.0	Within past year (anytime less than 12 months ...	
2	0.0	Within past year (anytime less than 12 months ...	
3	0.0	Within past year (anytime less than 12 months ...	
4	15.0	Within past year (anytime less than 12 months ...	
...	...	...	
246017	0.0	Within past 2 years (1 year but less than 2 ye...	
246018	7.0	Within past year (anytime less than 12 months ...	
246019	15.0	Within past year (anytime less than 12 months ...	
246020	2.0	Within past year (anytime less than 12 months ...	
246021	0.0	Within past year (anytime less than 12 months ...	

	PhysicalActivities	SleepHours	RemovedTeeth	HadHeartAttack	\
0	Yes	9.0	None of them	No	
1	Yes	6.0	None of them	No	
2	No	8.0	6 or more, but not all	No	
3	Yes	9.0	None of them	No	
4	Yes	5.0	1 to 5	No	
...	...	...	...	...	
246017	Yes	6.0	None of them	No	
246018	Yes	7.0	None of them	No	
246019	Yes	7.0	1 to 5	No	
246020	Yes	7.0	None of them	No	
246021	No	5.0	None of them	Yes	

	...	HeightInMeters	WeightInKilograms	BMI	AlcoholDrinkers	\
0	...	1.60	71.67	27.99	No	
1	...	1.78	95.25	30.13	No	
2	...	1.85	108.86	31.66	Yes	
3	...	1.70	90.72	31.32	No	
4	...	1.55	79.38	33.07	No	
...	...	...	...	...	...	
246017	...	1.78	102.06	32.28	Yes	
246018	...	1.93	90.72	24.34	No	

246019	...	1.68	83.91	29.86	Yes
246020	...	1.70	83.01	28.66	No
246021	...	1.83	108.86	32.55	No

	HIVTesting	FluVaxLast12	PneumoVaxEver	\
0	No	Yes	Yes	
1	No	Yes	Yes	
2	No	No	Yes	
3	No	Yes	Yes	
4	No	Yes	Yes	
...	...	...	...	
246017	No	No	No	
246018	No	No	No	
246019	Yes	Yes	Yes	
246020	Yes	Yes	No	
246021	Yes	Yes	Yes	

	TetanusLast10Tdap	HighRiskLastYear	\
0	Yes, received Tdap	No	
1	Yes, received tetanus shot but not sure what type	No	
2	No, did not receive any tetanus shot in the pa...	No	
3	No, did not receive any tetanus shot in the pa...	No	
4	No, did not receive any tetanus shot in the pa...	No	
...	...	...	
246017	Yes, received tetanus shot but not sure what type	No	
246018	No, did not receive any tetanus shot in the pa...	No	
246019	Yes, received tetanus shot but not sure what type	No	
246020	Yes, received tetanus shot but not sure what type	No	
246021	No, did not receive any tetanus shot in the pa...	No	

	CovidPos
0	No
1	No
2	Yes
3	Yes
4	No
...	...
246017	No
246018	Yes
246019	Yes
246020	No
246021	Yes

[246022 rows x 40 columns]

```
[ ]: # Use the describe method to find descriptive statistics (including the
      ↪ 5-summary stats)
```

```
df.describe()
```

```
[ ]: PhysicalHealthDays MentalHealthDays SleepHours HeightInMeters \
count      246022.000000      246022.000000  246022.000000  246022.000000
mean         4.119026         4.167140      7.021331      1.705150
std          8.405844         8.102687      1.440681      0.106654
min           0.000000         0.000000      1.000000      0.910000
25%           0.000000         0.000000      6.000000      1.630000
50%           0.000000         0.000000      7.000000      1.700000
75%           3.000000         4.000000      8.000000      1.780000
max          30.000000        30.000000     24.000000      2.410000

      WeightInKilograms      BMI
count      246022.000000  246022.000000
mean         83.615179     28.668136
std         21.323156      6.513973
min         28.120000     12.020000
25%         68.040000     24.270000
50%         81.650000     27.460000
75%         95.250000     31.890000
max        292.570000     97.650000
```

### 0.1.1 Conclusion:

The dataset has **40** columns, with numerical and categorical data. Most of the columns are categorical, with **5** numerical columns.

```
[ ]: rows, columns = df.shape
print(f"Number of rows: {rows}, Number of columns: {columns}")
```

Number of rows: 246022, Number of columns: 40

## 0.2 Data Cleaning / Preparation

Let's inspect any missing, incomplete data.

```
[ ]: print(f"Number of duplicates: {df.duplicated().sum()}")
print(f"Number of missing values: {df.isnull().sum().sum()}")
```

Number of duplicates: 9  
Number of missing values: 0  
Number of missing values: 0

There is no missing values, but. there are duplicates. Let's drop them. We're also going to drop BMI, since it is a function of height and weight, and there is multicollinearity. Lastly, we're going to drop the features that are relevant to our research question.

```
[ ]: # Drop duplicated
df.drop_duplicates(inplace=True)
```

```
# Drop Unrelated variables and BMI for multicollinearity with Height and Weight
df = df.drop(columns=['State', 'LastCheckupTime', 'BMI'])
```

```
[ ]: # Create lists of numerical variables, categorical variables and target
      ↪ variable for future use
numerical_vars = ['PhysicalHealthDays', 'MentalHealthDays', 'SleepHours',
                  ↪ 'HeightInMeters', 'WeightInKilograms']
categorical_includes_taget = ['Sex', 'GeneralHealth', 'PhysicalActivities',
                              ↪ 'RemovedTeeth', 'HadAngina',
                              'HadStroke', 'HadAsthma', 'HadSkinCancer', 'HadCOPD',
                              'HadDepressiveDisorder', 'HadKidneyDisease', 'HadArthritis',
                              'HadDiabetes', 'DeafOrHardOfHearing', 'BlindOrVisionDifficulty',
                              'DifficultyConcentrating', 'DifficultyWalking',
                              'DifficultyDressingBathing', 'DifficultyErrands', 'SmokerStatus',
                              'ECigaretteUsage', 'ChestScan', 'RaceEthnicityCategory', 'AgeCategory',
                              ↪ 'AlcoholDrinkers',
                              'HIVTesting', 'FluVaxLast12', 'PneumoVaxEver', 'TetanusLast10Tdap',
                              'HighRiskLastYear', 'CovidPos', 'HadHeartAttack']

categorical_vars = ['Sex', 'GeneralHealth', 'PhysicalActivities',
                   ↪ 'RemovedTeeth', 'HadAngina',
                   'HadStroke', 'HadAsthma', 'HadSkinCancer', 'HadCOPD',
                   'HadDepressiveDisorder', 'HadKidneyDisease', 'HadArthritis',
                   'HadDiabetes', 'DeafOrHardOfHearing', 'BlindOrVisionDifficulty',
                   'DifficultyConcentrating', 'DifficultyWalking',
                   'DifficultyDressingBathing', 'DifficultyErrands', 'SmokerStatus',
                   'ECigaretteUsage', 'ChestScan', 'RaceEthnicityCategory', 'AgeCategory',
                   ↪ 'AlcoholDrinkers',
                   'HIVTesting', 'FluVaxLast12', 'PneumoVaxEver', 'TetanusLast10Tdap',
                   'HighRiskLastYear', 'CovidPos']
target = 'HadHeartAttack'

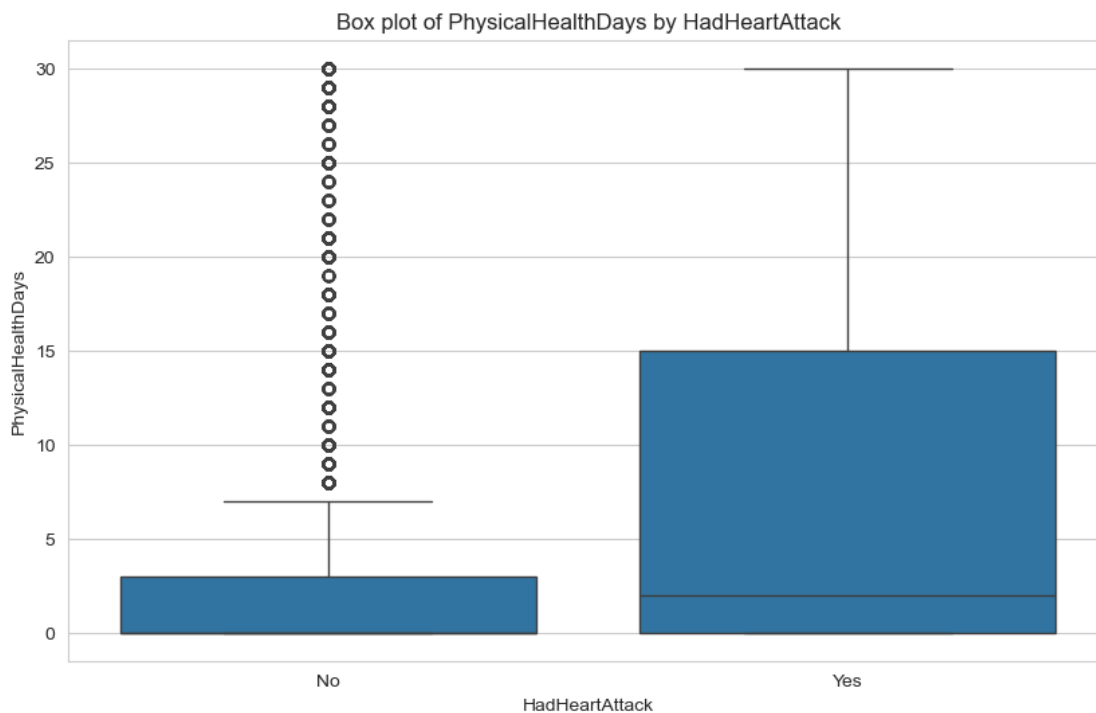
print(f"Numerical variables: {numerical_vars}")
print(f"Categorical variables: {categorical_vars}")
print(f"Target variable: {target}")
```

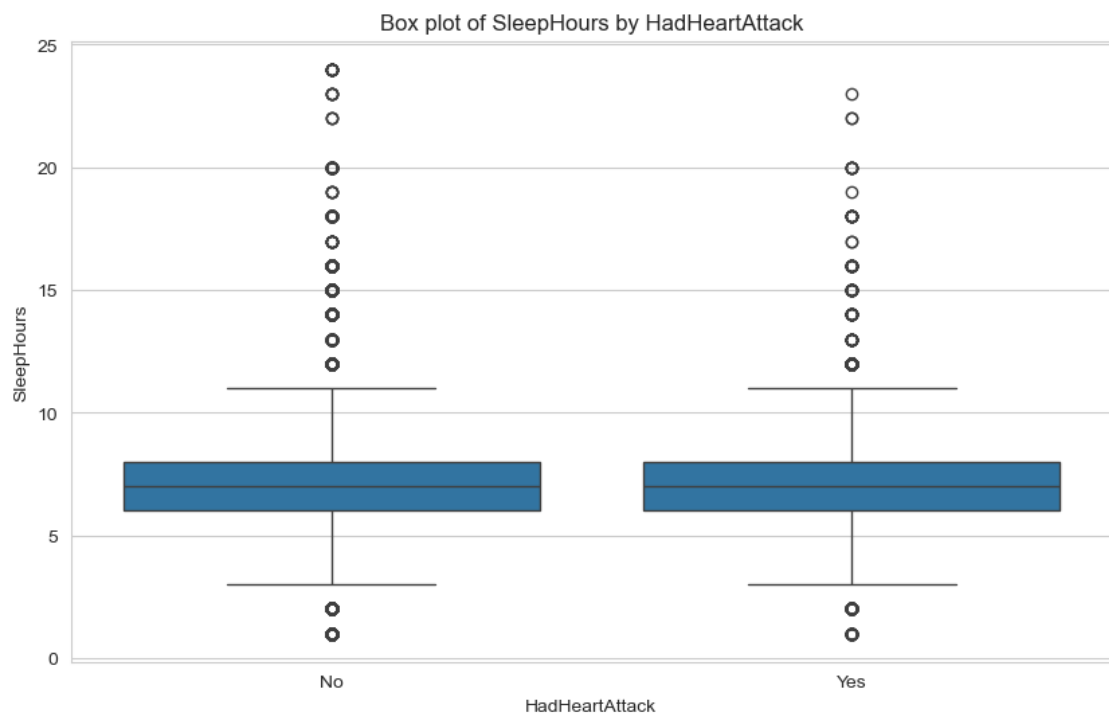
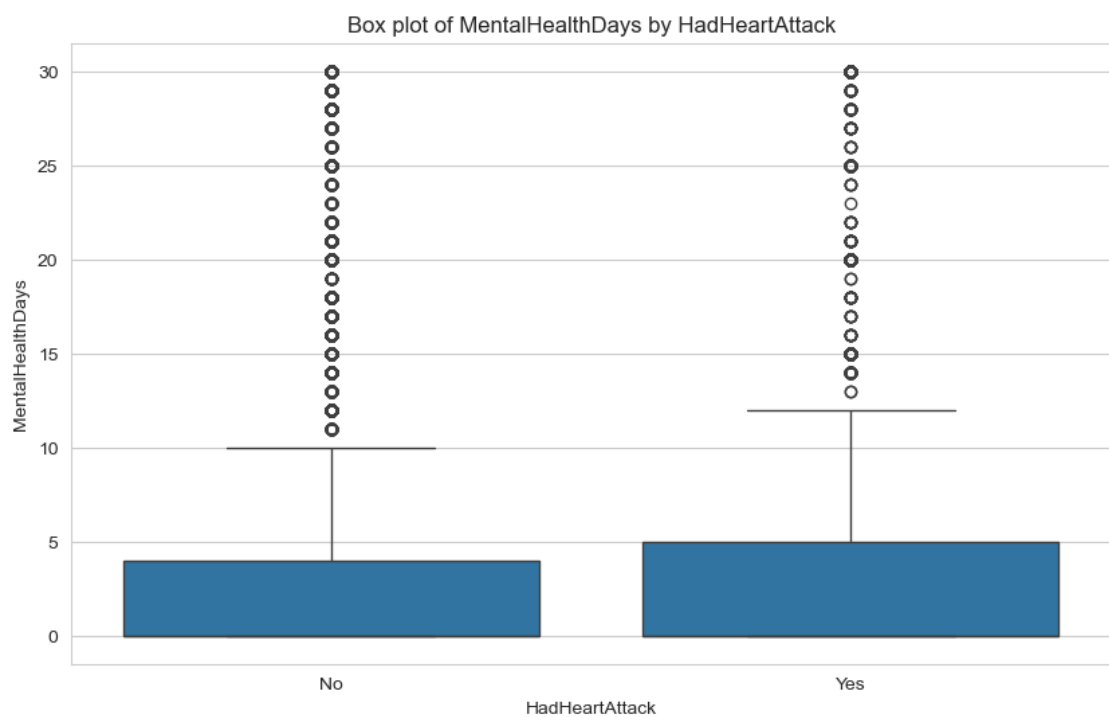
```
Numerical variables: ['PhysicalHealthDays', 'MentalHealthDays', 'SleepHours',
'HeightInMeters', 'WeightInKilograms']
Categorical variables: ['Sex', 'GeneralHealth', 'PhysicalActivities',
'RemovedTeeth', 'HadAngina', 'HadStroke', 'HadAsthma', 'HadSkinCancer',
'HadCOPD', 'HadDepressiveDisorder', 'HadKidneyDisease', 'HadArthritis',
'HadDiabetes', 'DeafOrHardOfHearing', 'BlindOrVisionDifficulty',
'DifficultyConcentrating', 'DifficultyWalking', 'DifficultyDressingBathing',
'DifficultyErrands', 'SmokerStatus', 'ECigaretteUsage', 'ChestScan',
'RaceEthnicityCategory', 'AgeCategory', 'AlcoholDrinkers', 'HIVTesting',
'FluVaxLast12', 'PneumoVaxEver', 'TetanusLast10Tdap', 'HighRiskLastYear',
'CovidPos']
```

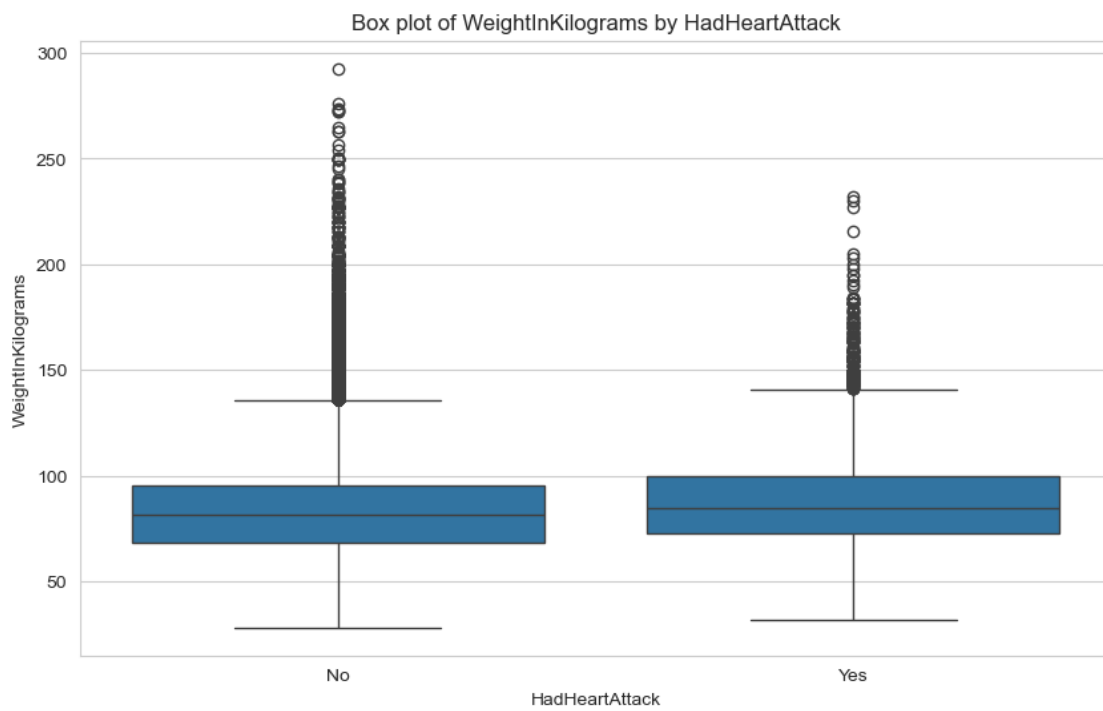
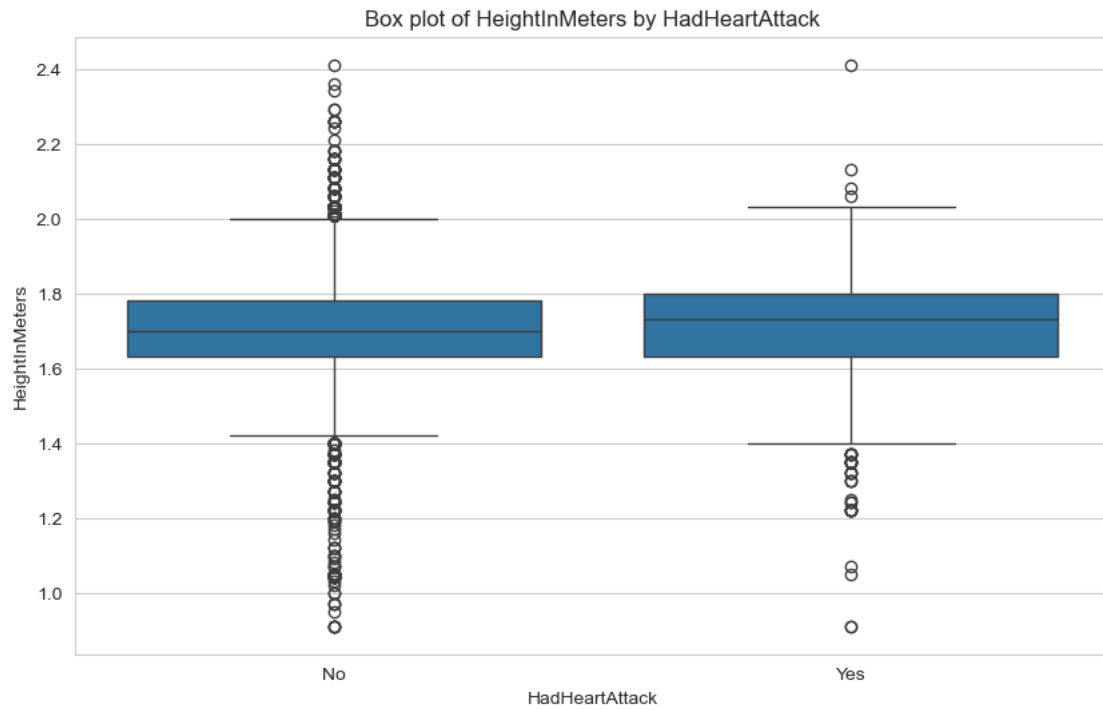
Target variable: HadHeartAttack

### 0.3 Exploratory Data Analysis

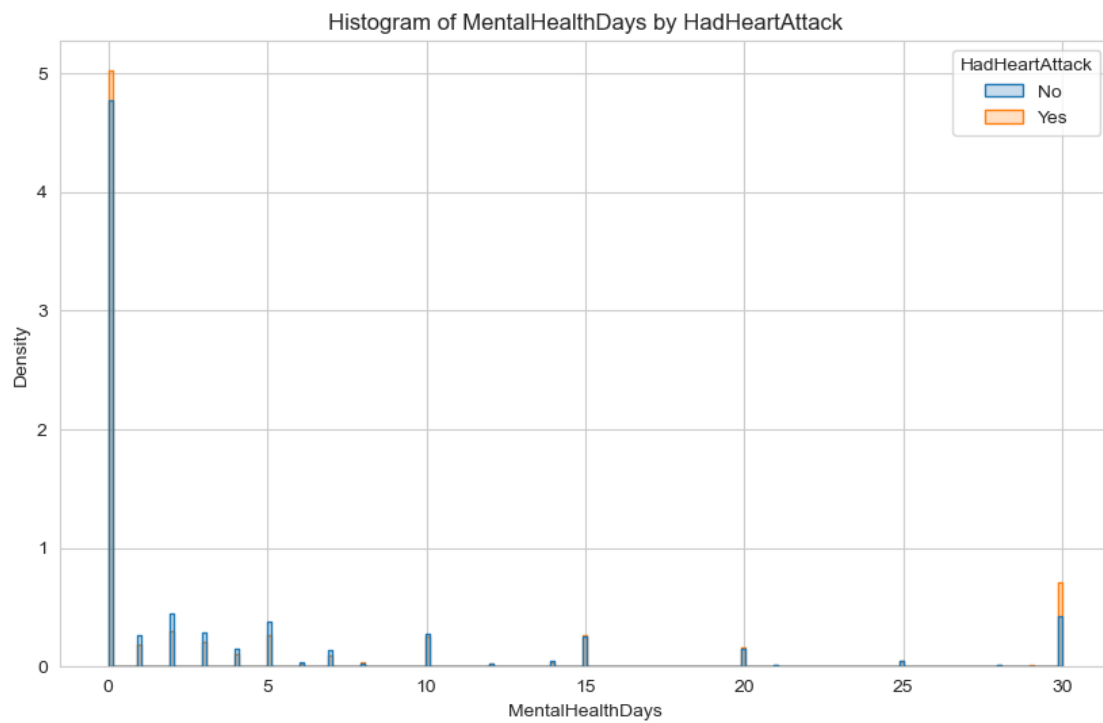
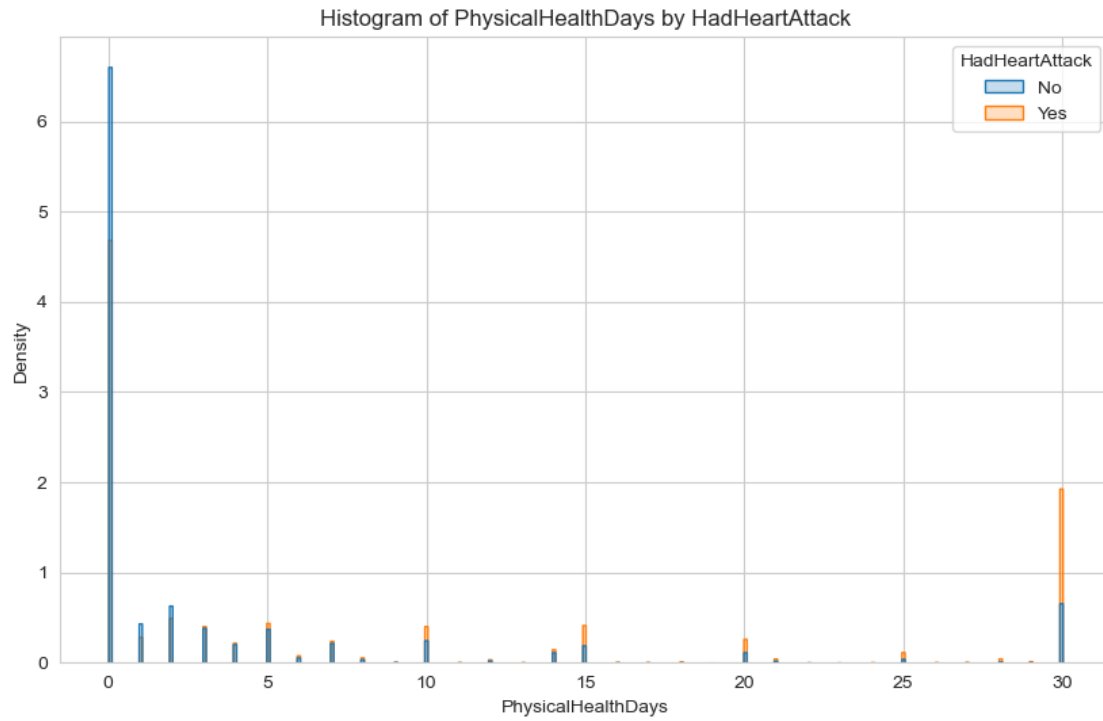
```
[ ]: # Create box plots, histograms, and violin plots for numerical data
sns.set_style("whitegrid")
# Box Plots
for var in numerical_vars:
    plt.figure(figsize=(10, 6))
    sns.boxplot(x=target, y=var, data=df)
    plt.title(f"Box plot of {var} by {target}")
    plt.show()
# Histograms
for var in numerical_vars:
    plt.figure(figsize=(10, 6))
    sns.histplot(df, x=var, hue=target, element="step", stat="density",
common_norm=False)
    plt.title(f"Histogram of {var} by {target}")
    plt.show()
# Violin Plots
for var in numerical_vars:
    plt.figure(figsize=(10, 6))
    sns.violinplot(x=target, y=var, data=df)
    plt.title(f"Violin plot of {var} by {target}")
    plt.show()
```

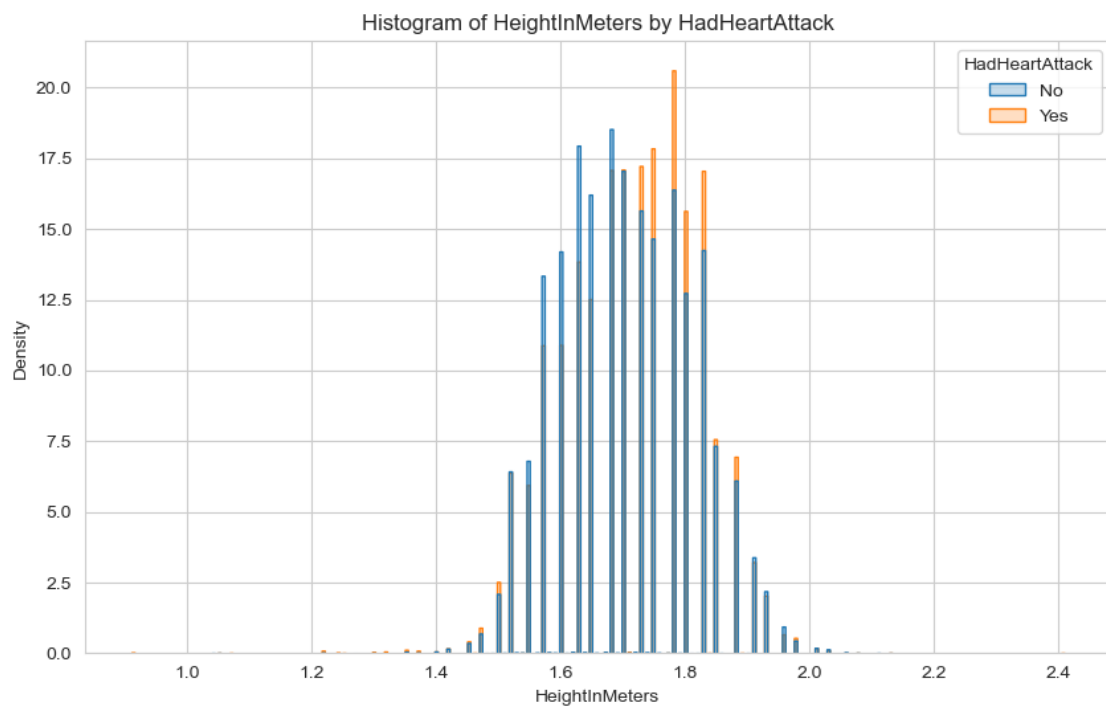
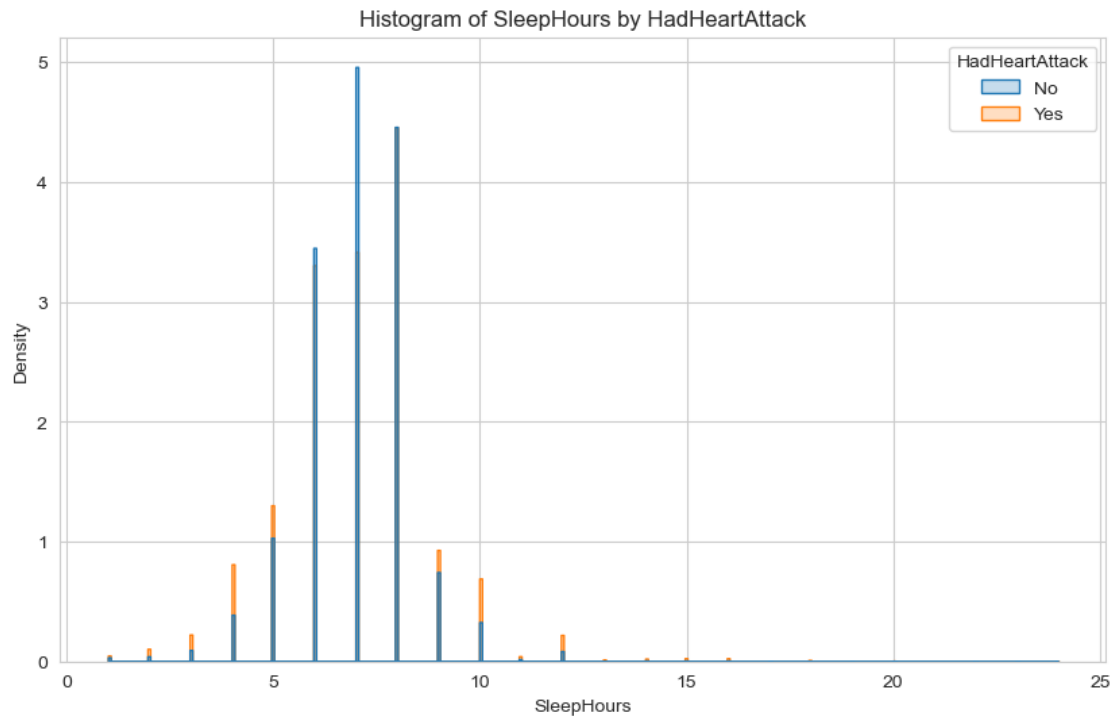


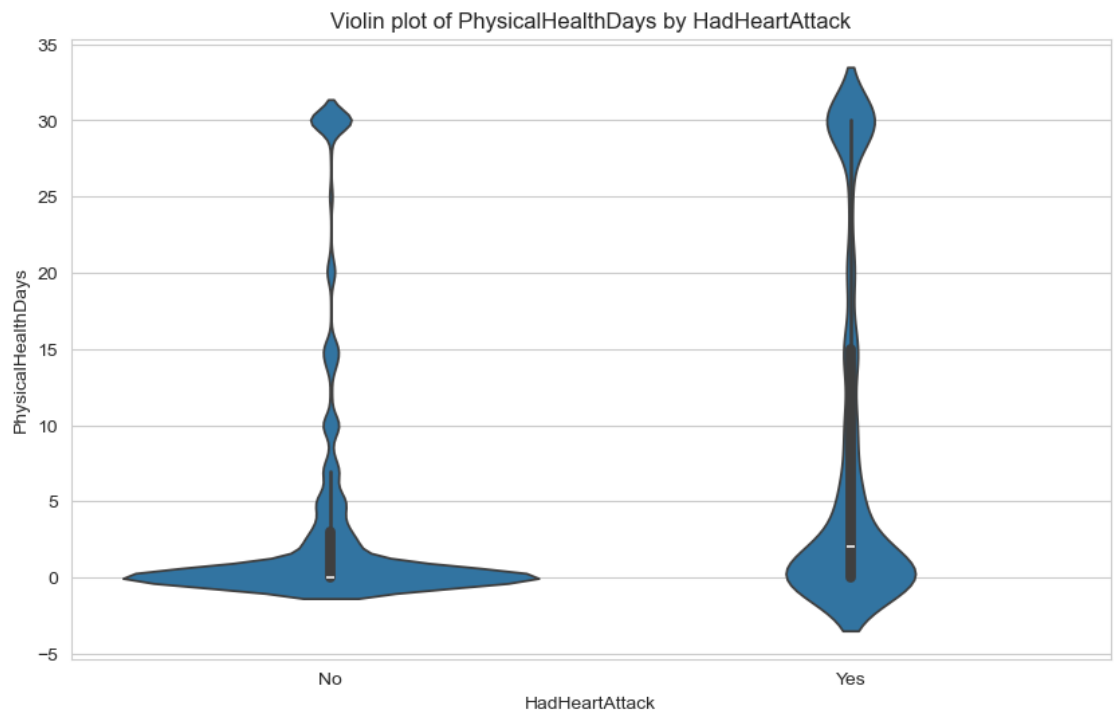
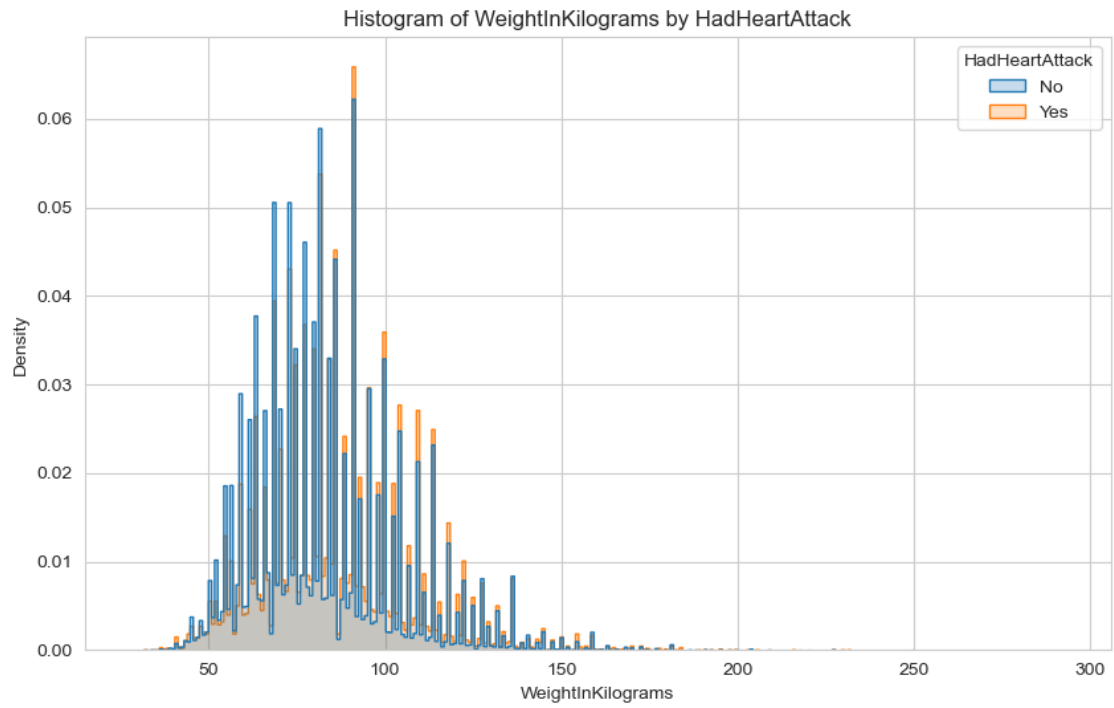


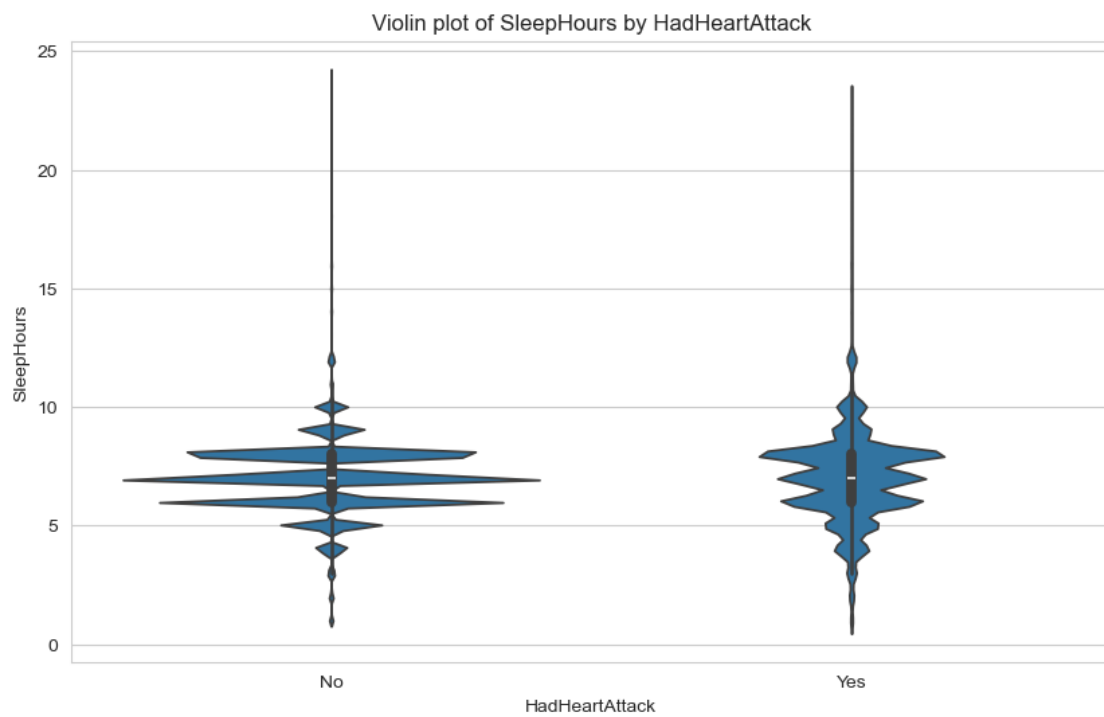
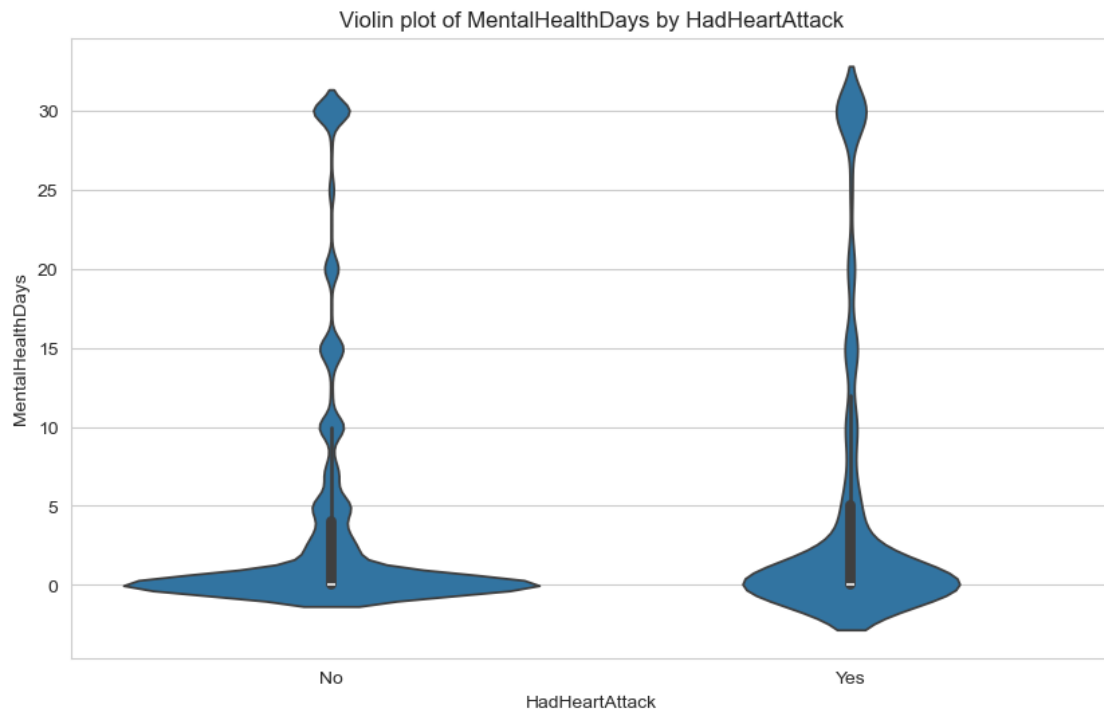


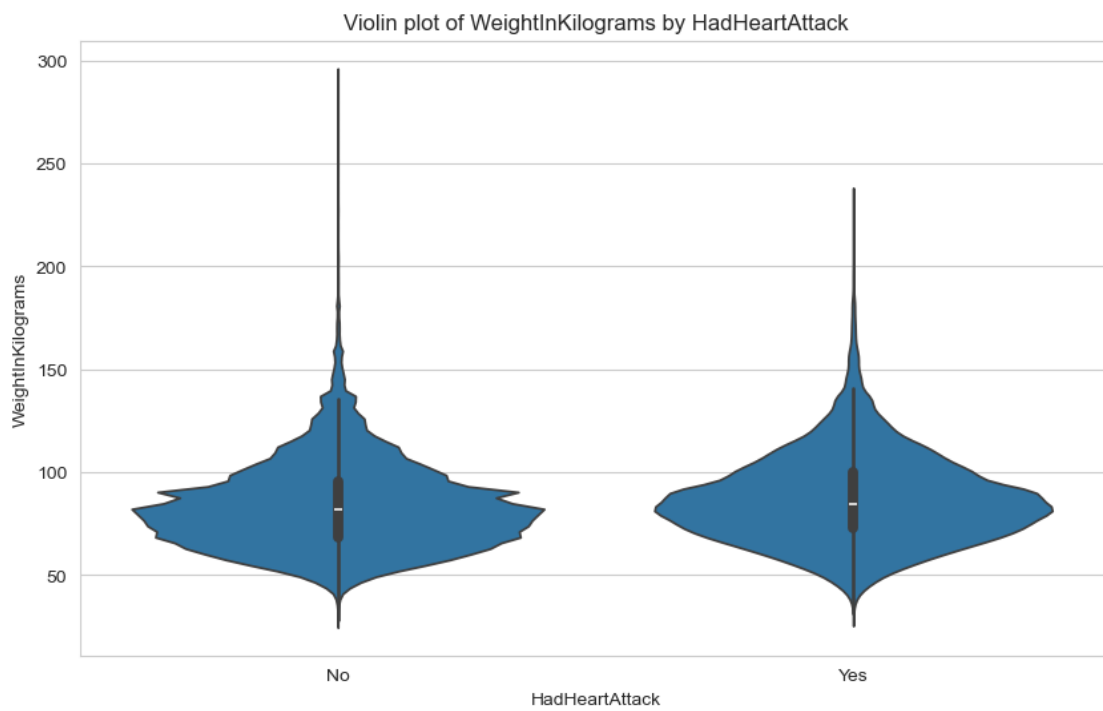
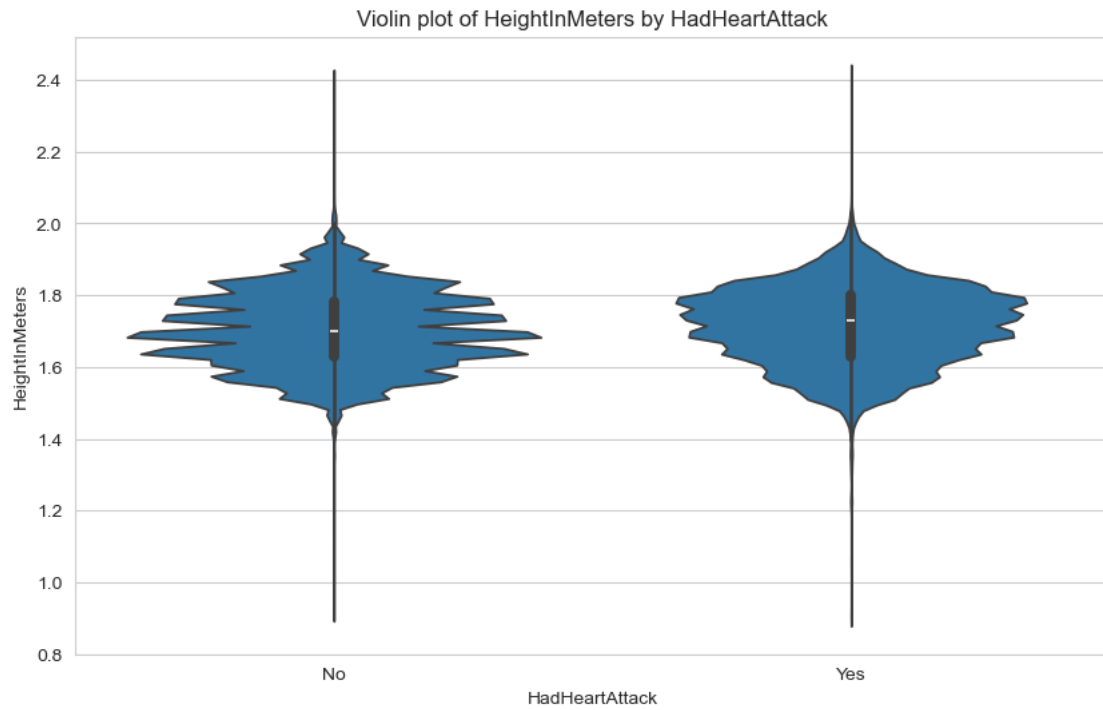












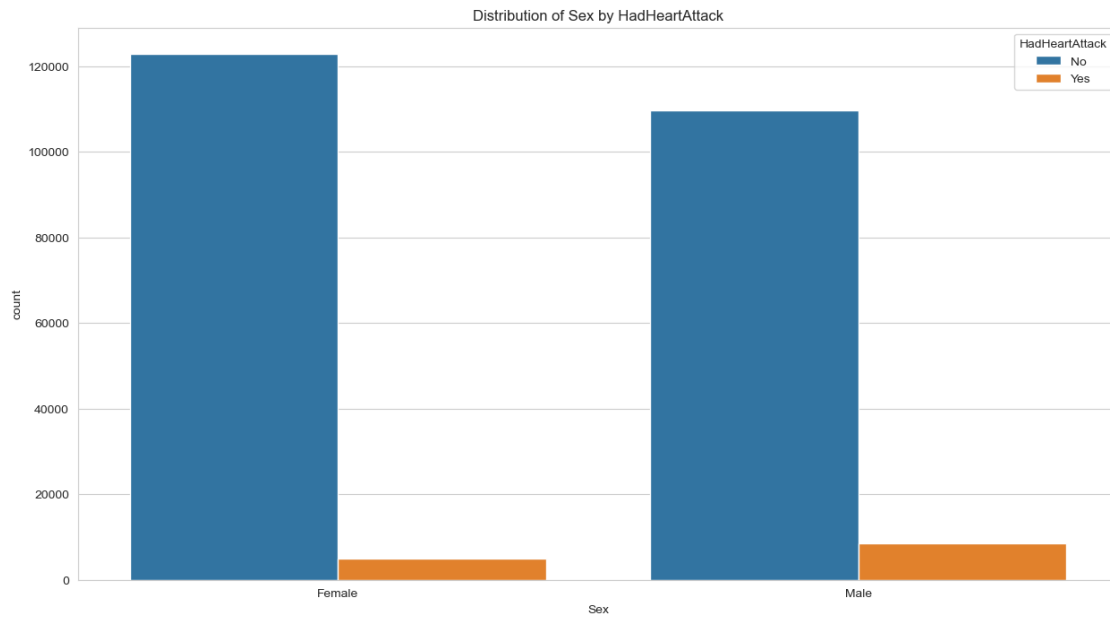
```
[ ]: # Dataframe to store result of Chi2 test
results_df_cat = pd.DataFrame(columns=['Feature', 'Chi2', 'P-Value'])

# Copy to keep the original dataframe
cat_df = df.copy()
cat_df["HadHeartAttack"] = cat_df["HadHeartAttack"].astype('category')

# For each categorical var perform Chi2 test
# Print results, create bar plot
for var in categorical_vars:
    cat_df[var] = cat_df[var].astype('category')
    contingency_table = pd.crosstab(cat_df[var], cat_df["HadHeartAttack"])
    chi2, p, _, _ = chi2_contingency(contingency_table)
    print(contingency_table)
    print(f"Chi-Squared Test for {var} and {target}")
    print(f"Chi2 value = {chi2}, p-value = {p}\n")
    # Add the results to the DataFrame
    new_row = {'Feature': var, 'Chi2': chi2, 'P-Value': p}
    results_df_cat = pd.concat([results_df_cat, pd.DataFrame(new_row,
        index=[0])], ignore_index=True)
    # Bar Plots
    plt.figure(figsize=(15, 8))
    sns.countplot(data=df, x=var, hue=target)
    plt.title(f"Distribution of {var} by {target}")
    plt.show()
```

HadHeartAttack	No	Yes
Sex		
Female	122874	4932
Male	109704	8503

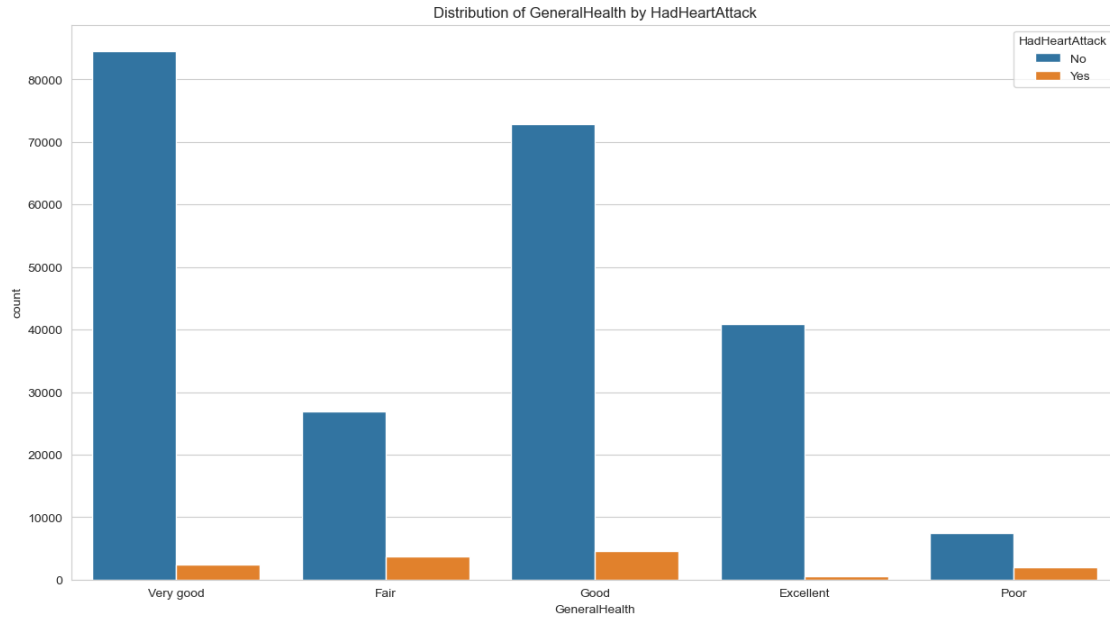
Chi-Squared Test for Sex and HadHeartAttack  
Chi2 value = 1321.7634745274654, p-value = 2.1073833823909984e-289



HadHeartAttack	No	Yes
GeneralHealth		
Excellent	40928	594
Fair	26910	3748
Good	72808	4599
Poor	7406	2024
Very good	84526	2470

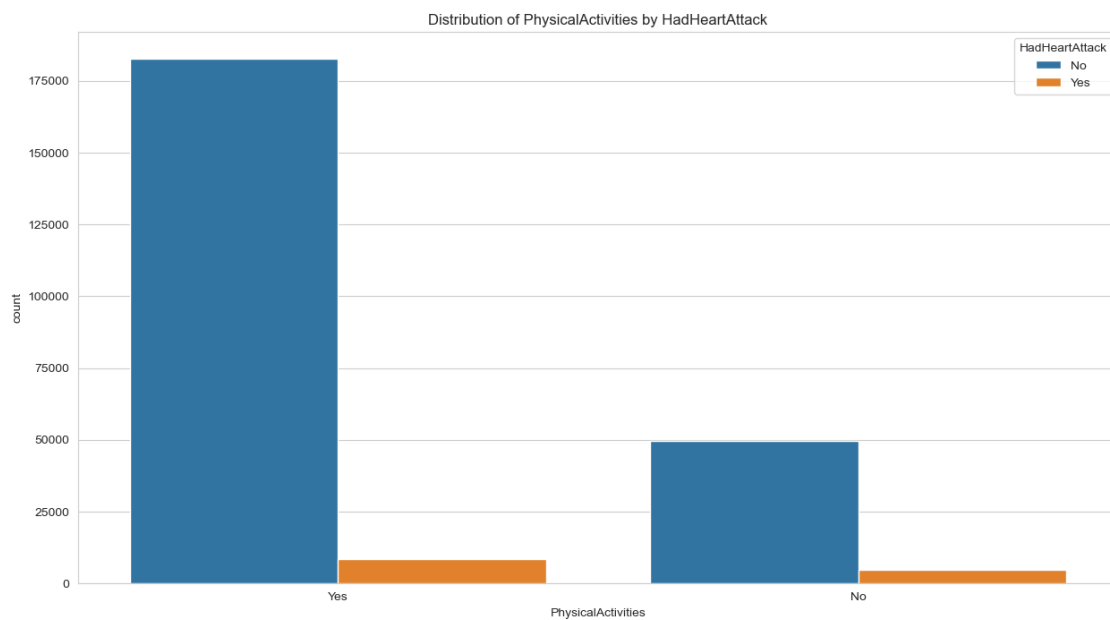
Chi-Squared Test for GeneralHealth and HadHeartAttack

Chi2 value = 9893.539444125969, p-value = 0.0



HadHeartAttack	No	Yes
PhysicalActivities		
No	49782	4921
Yes	182796	8514

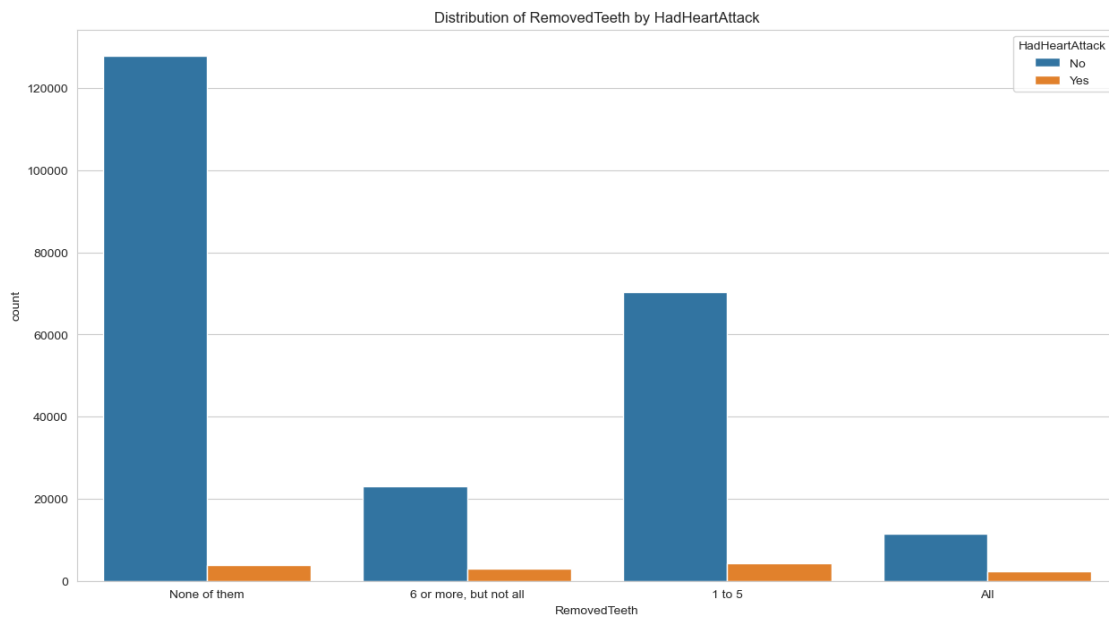
Chi-Squared Test for PhysicalActivities and HadHeartAttack  
 Chi2 value = 1701.5150212822982, p-value = 0.0





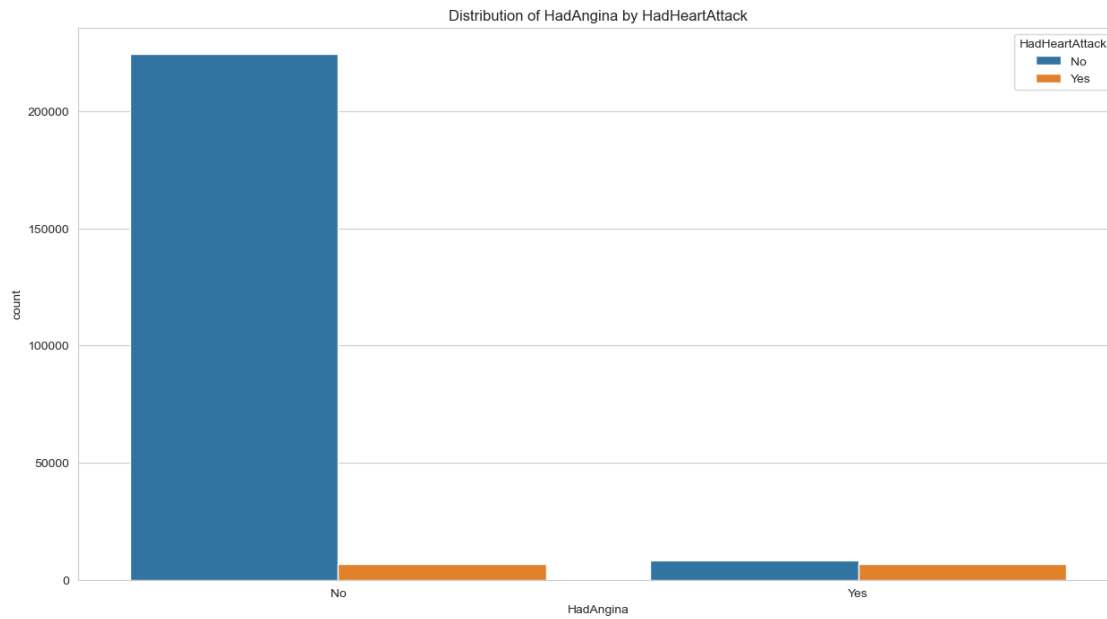
HadHeartAttack	No	Yes
RemovedTeeth		
1 to 5	70342	4359
6 or more, but not all	22944	3005
All	11476	2302
None of them	127816	3769

Chi-Squared Test for RemovedTeeth and HadHeartAttack  
Chi2 value = 6996.544849252672, p-value = 0.0



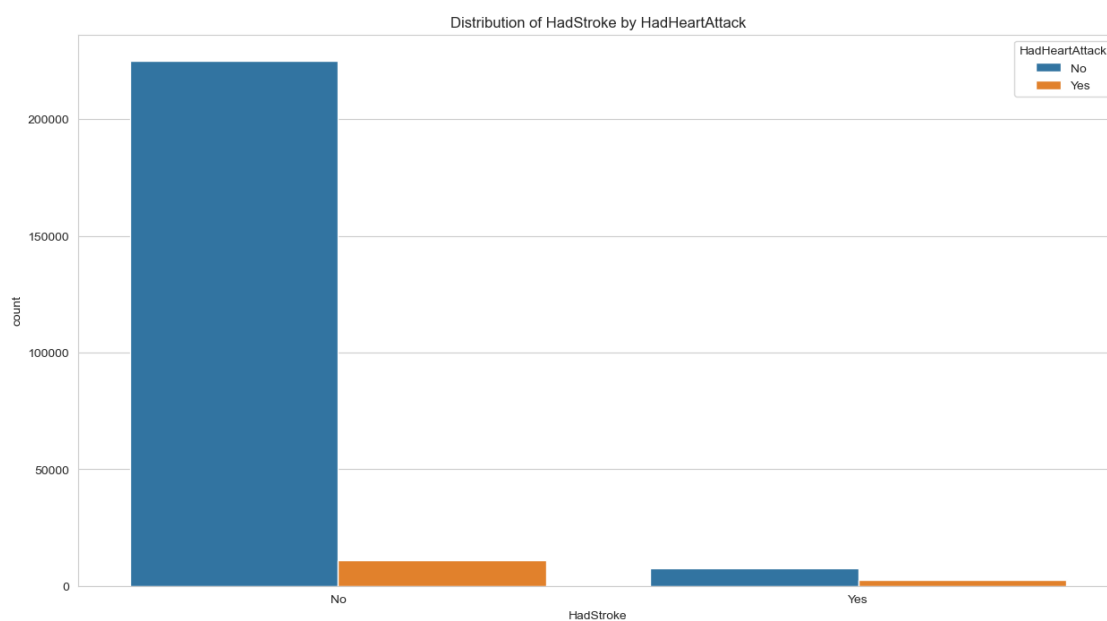
HadHeartAttack	No	Yes
HadAngina		
No	224397	6663
Yes	8181	6772

Chi-Squared Test for HadAngina and HadHeartAttack  
Chi2 value = 48906.22074894924, p-value = 0.0



HadHeartAttack	No	Yes
HadStroke		
No	224985	10917
Yes	7593	2518

Chi-Squared Test for HadStroke and HadHeartAttack  
 Chi2 value = 7716.361887180489, p-value = 0.0



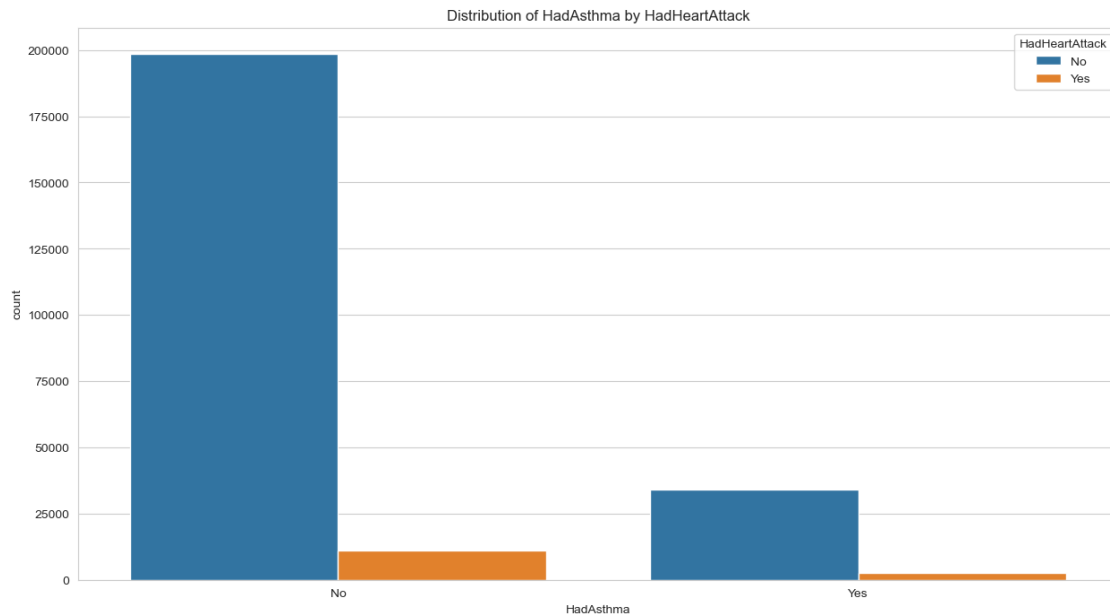
HadHeartAttack	No	Yes
HadAsthma		

No	198518	10968
----	--------	-------

Yes	34060	2467
-----	-------	------

Chi-Squared Test for HadAsthma and HadHeartAttack

Chi2 value = 138.57317541492714, p-value = 5.460574633393451e-32



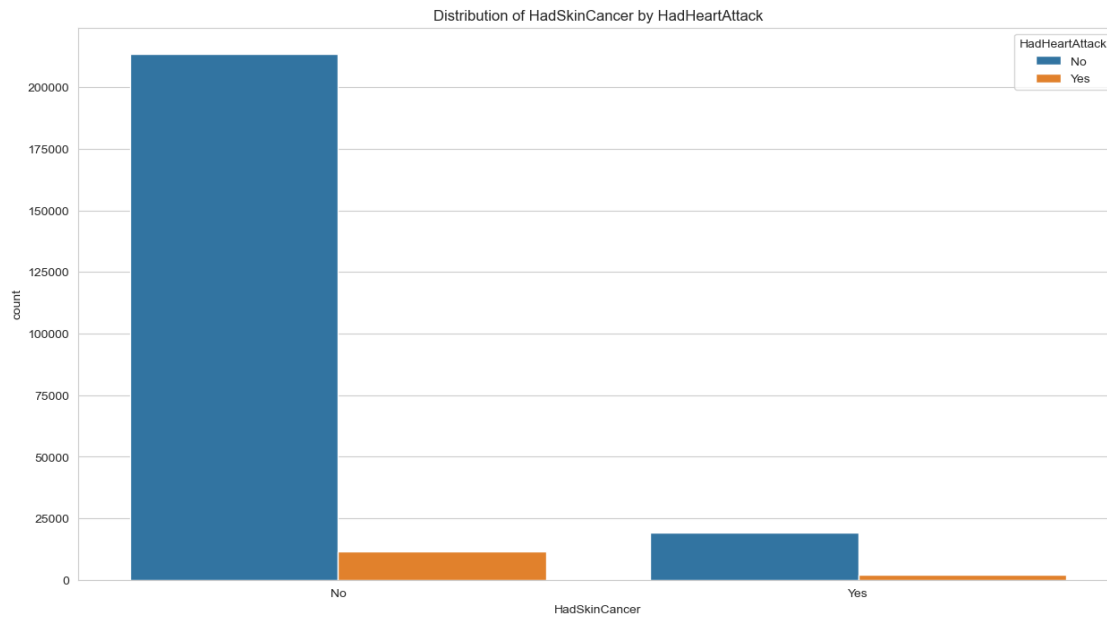
HadHeartAttack	No	Yes
HadSkinCancer		

No	213479	11515
----	--------	-------

Yes	19099	1920
-----	-------	------

Chi-Squared Test for HadSkinCancer and HadHeartAttack

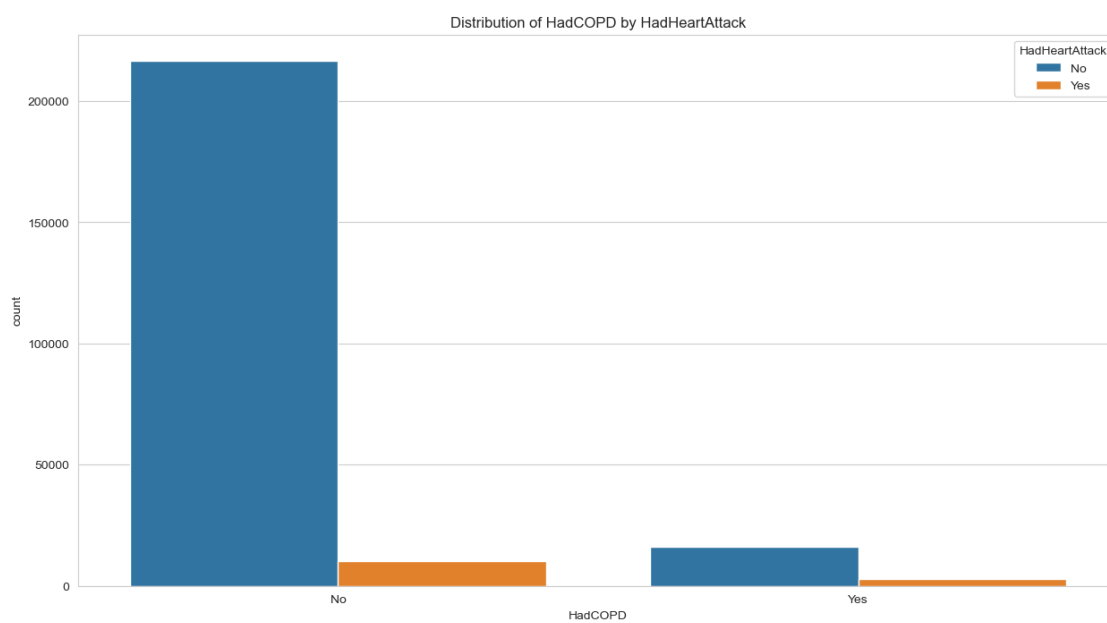
Chi2 value = 599.9377487258555, p-value = 1.7271862867830458e-132



```

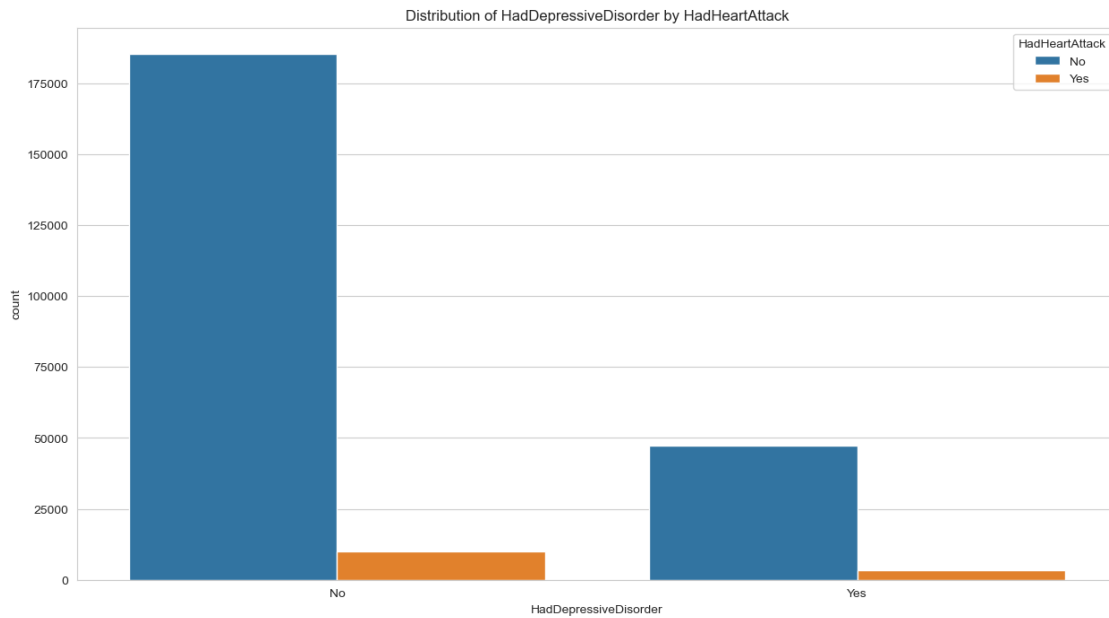
HadHeartAttack      No      Yes
HadCOPD
No                  216609  10410
Yes                  15969   3025
Chi-Squared Test for HadCOPD and HadHeartAttack
Chi2 value = 4363.963228084566, p-value = 0.0

```



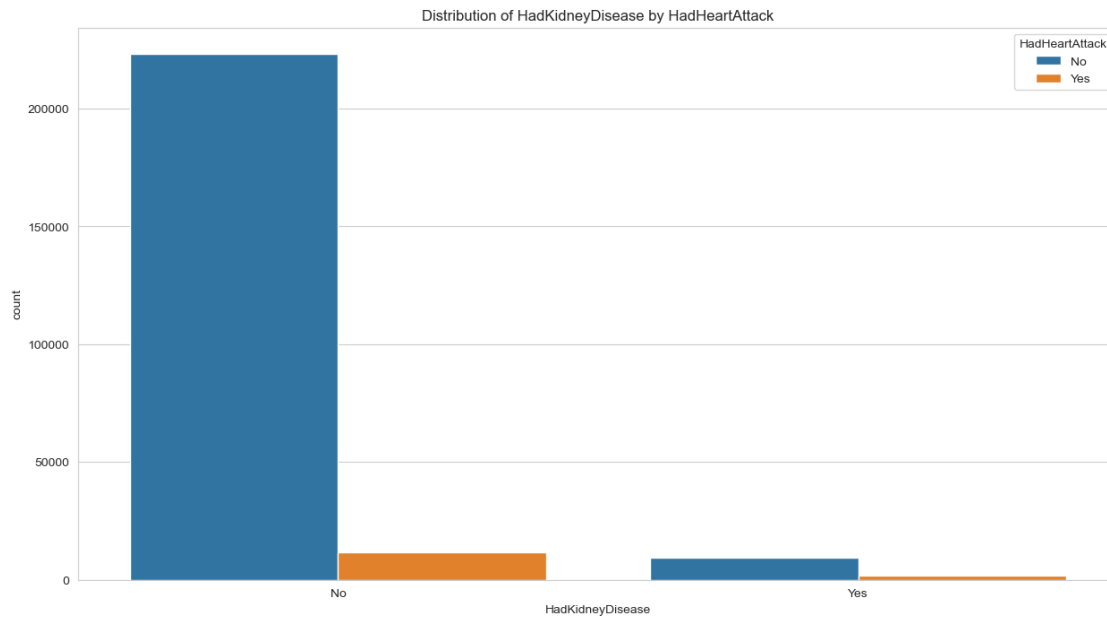
HadHeartAttack	No	Yes
HadDepressiveDisorder		
No	185258	10135
Yes	47320	3300

Chi-Squared Test for HadDepressiveDisorder and HadHeartAttack  
Chi2 value = 137.94235523398163, p-value = 7.502329516886957e-32



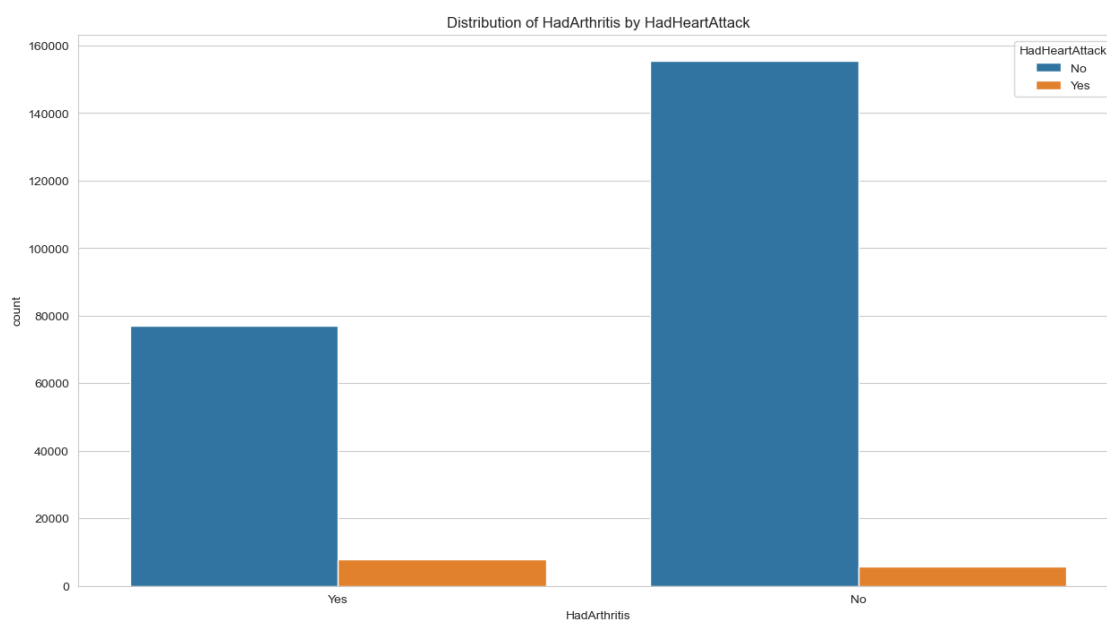
HadHeartAttack	No	Yes
HadKidneyDisease		
No	223189	11540
Yes	9389	1895

Chi-Squared Test for HadKidneyDisease and HadHeartAttack  
Chi2 value = 2939.5670891414943, p-value = 0.0



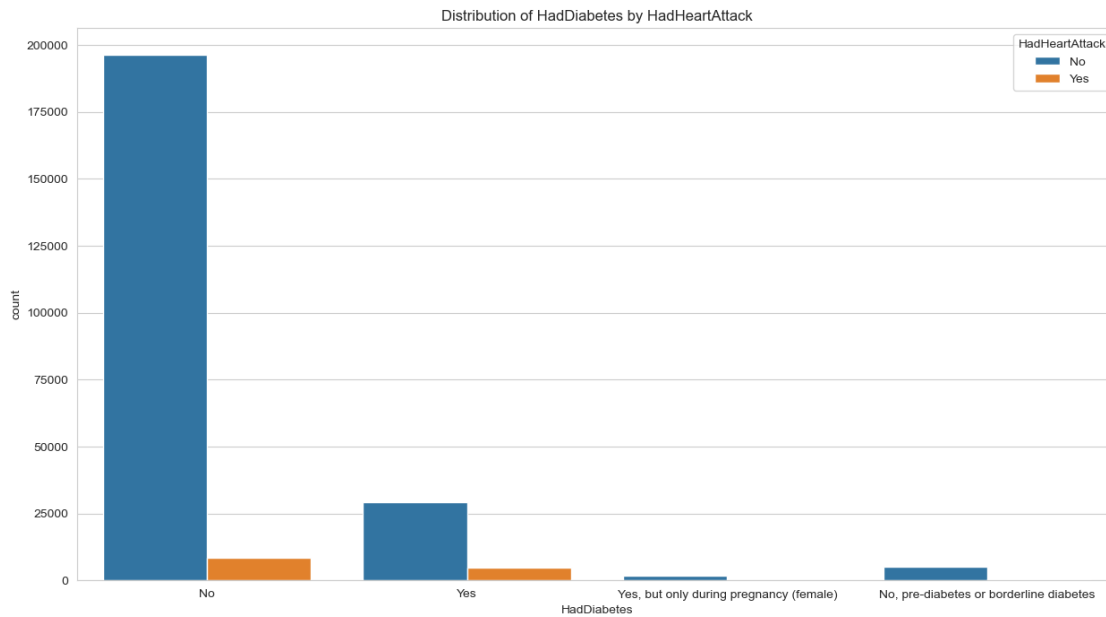
HadHeartAttack	No	Yes
HadArthritis		
No	155462	5670
Yes	77116	7765

Chi-Squared Test for HadArthritis and HadHeartAttack  
 Chi2 value = 3411.190093972503, p-value = 0.0



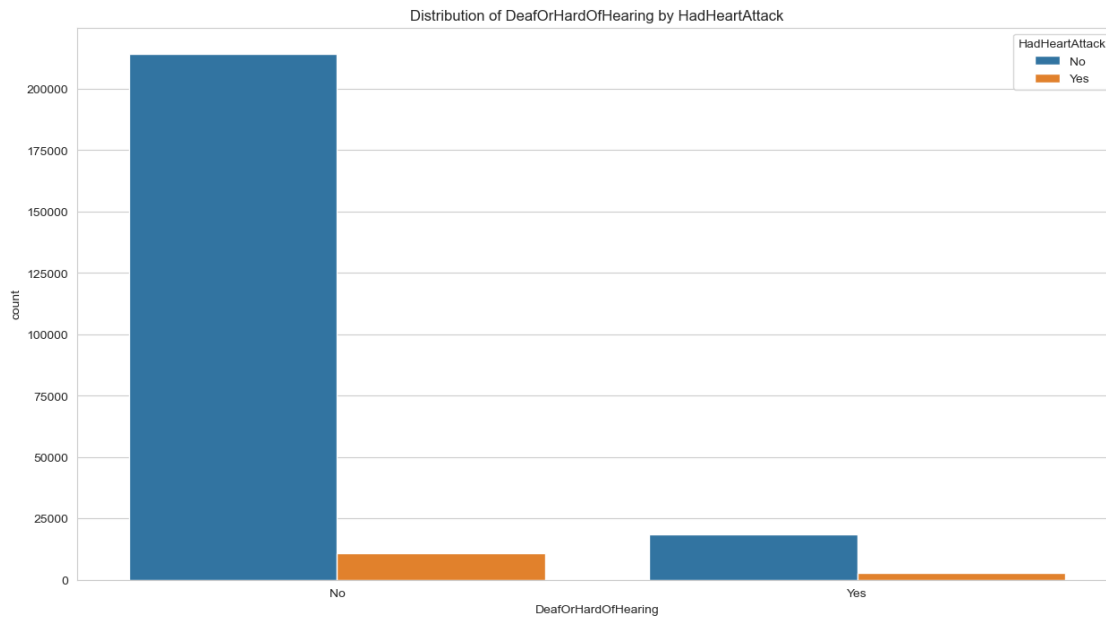
HadHeartAttack	No	Yes
HadDiabetes		
No	196494	8333
No, pre-diabetes or borderline diabetes	5000	392
Yes	29157	4654
Yes, but only during pregnancy (female)	1927	56

Chi-Squared Test for HadDiabetes and HadHeartAttack  
Chi2 value = 5345.9912570977585, p-value = 0.0



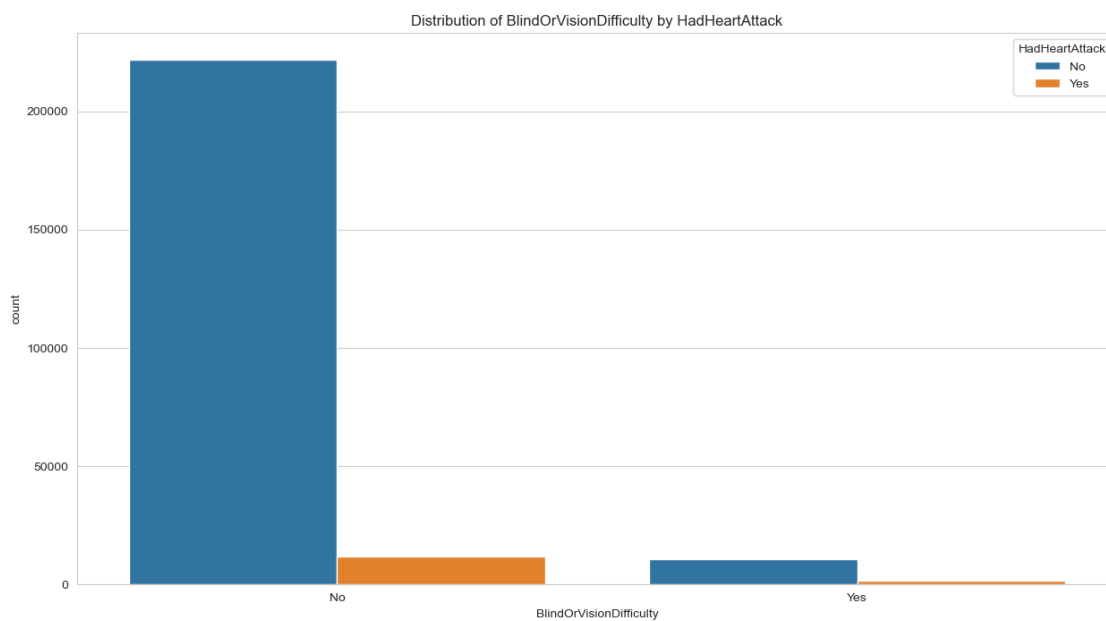
HadHeartAttack	No	Yes
DeafOrHardOfHearing		
No	214221	10760
Yes	18357	2675

Chi-Squared Test for DeafOrHardOfHearing and HadHeartAttack  
Chi2 value = 2344.8042006382593, p-value = 0.0



HadHeartAttack	No	Yes
BlindOrVisionDifficulty		
No	221906	11881
Yes	10672	1554

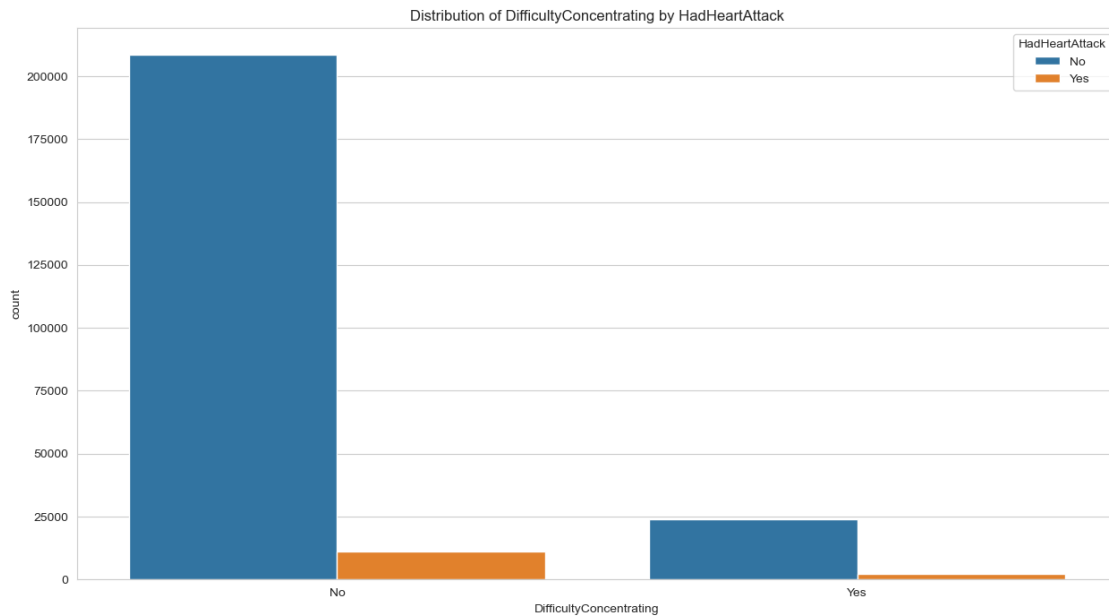
Chi-Squared Test for BlindOrVisionDifficulty and HadHeartAttack  
 Chi2 value = 1308.1593754891833, p-value = 1.9058085152167356e-286





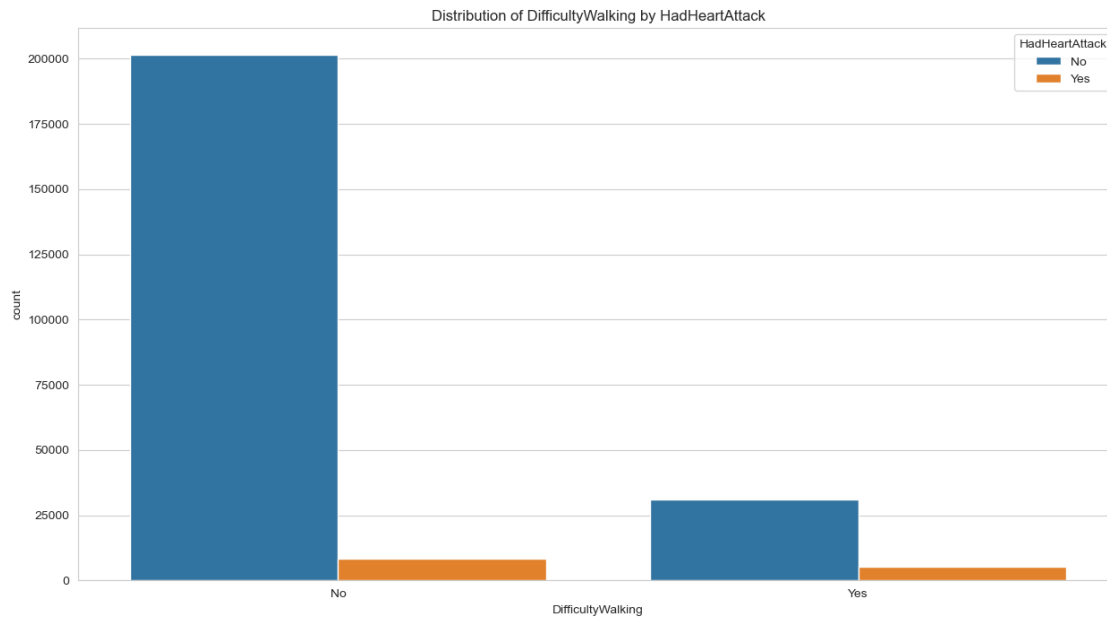
HadHeartAttack	No	Yes
DifficultyConcentrating		
No	208681	11112
Yes	23897	2323

Chi-Squared Test for DifficultyConcentrating and HadHeartAttack  
Chi2 value = 655.8249785059869, p-value = 1.2086533205176142e-144



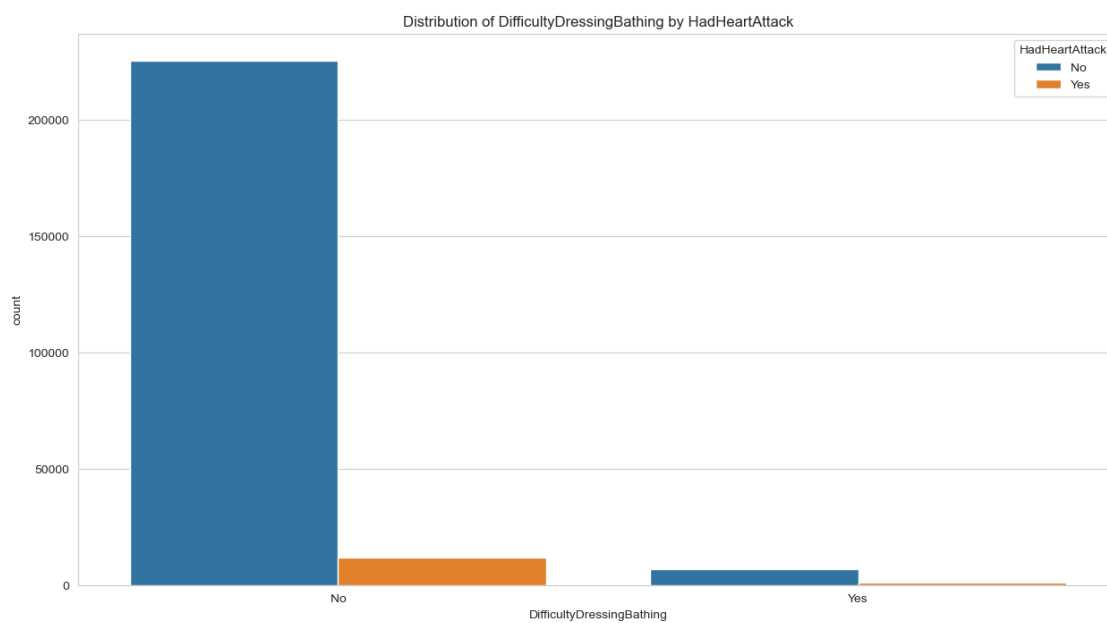
HadHeartAttack	No	Yes
DifficultyWalking		
No	201641	8304
Yes	30937	5131

Chi-Squared Test for DifficultyWalking and HadHeartAttack  
Chi2 value = 6286.838781453804, p-value = 0.0



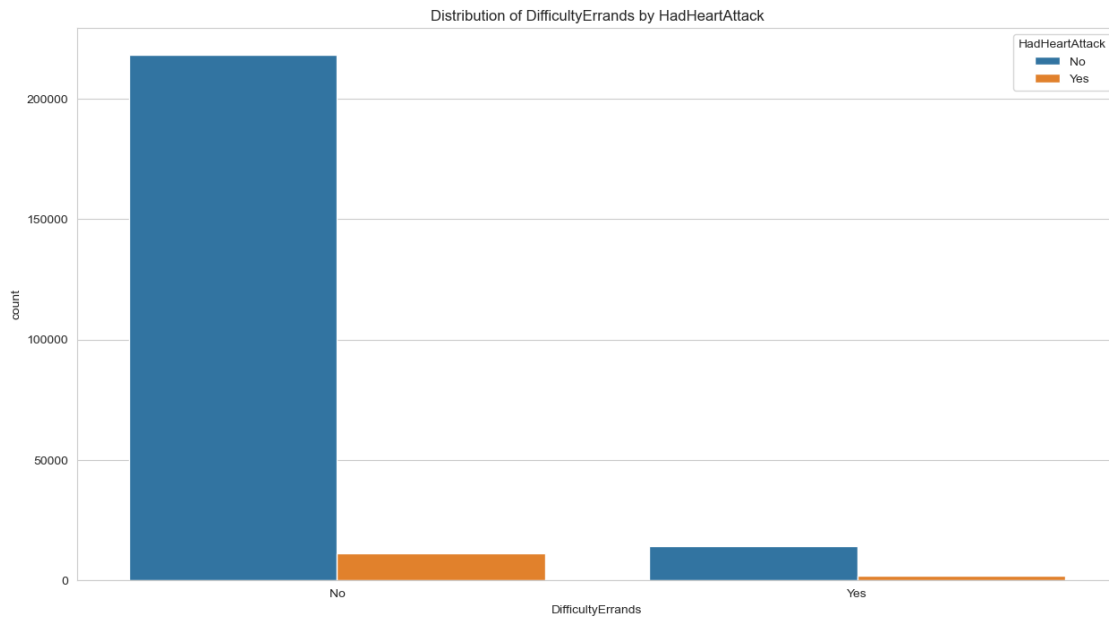
HadHeartAttack	No	Yes
DifficultyDressingBathing		
No	225534	12139
Yes	7044	1296

Chi-Squared Test for DifficultyDressingBathing and HadHeartAttack  
 Chi2 value = 1696.394540678655, p-value = 0.0



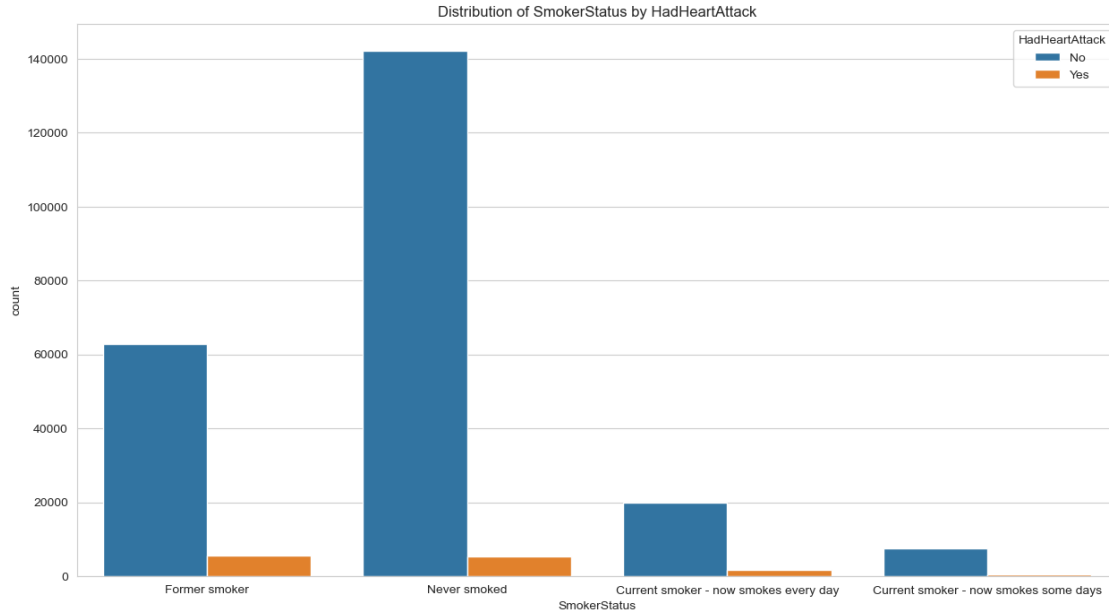
HadHeartAttack	No	Yes
DifficultyErrands		
No	218336	11293
Yes	14242	2142

Chi-Squared Test for DifficultyErrands and HadHeartAttack  
Chi2 value = 1968.7158617259954, p-value = 0.0



HadHeartAttack	No	Yes
SmokerStatus		
Current smoker - now smokes every day	19858	1801
Current smoker - now smokes some days	7546	553
Former smoker	62914	5610
Never smoked	142260	5471

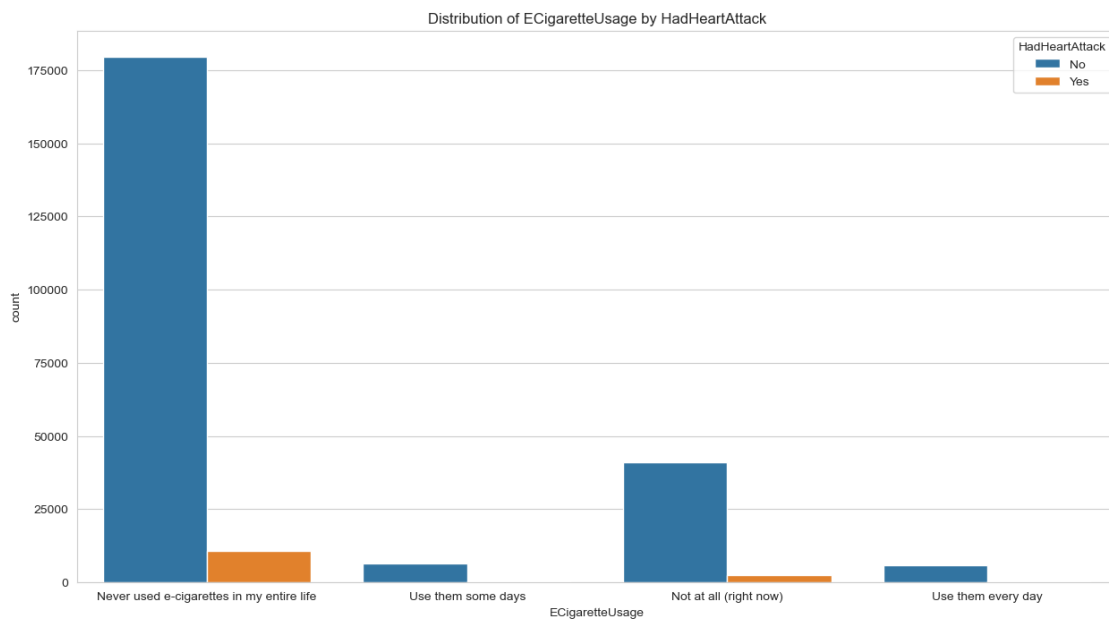
Chi-Squared Test for SmokerStatus and HadHeartAttack  
Chi2 value = 2241.293874288016, p-value = 0.0



HadHeartAttack	No	Yes
ECigaretteUsage		
Never used e-cigarettes in my entire life	179547	10572
Not at all (right now)	40846	2435
Use them every day	5778	177
Use them some days	6407	251

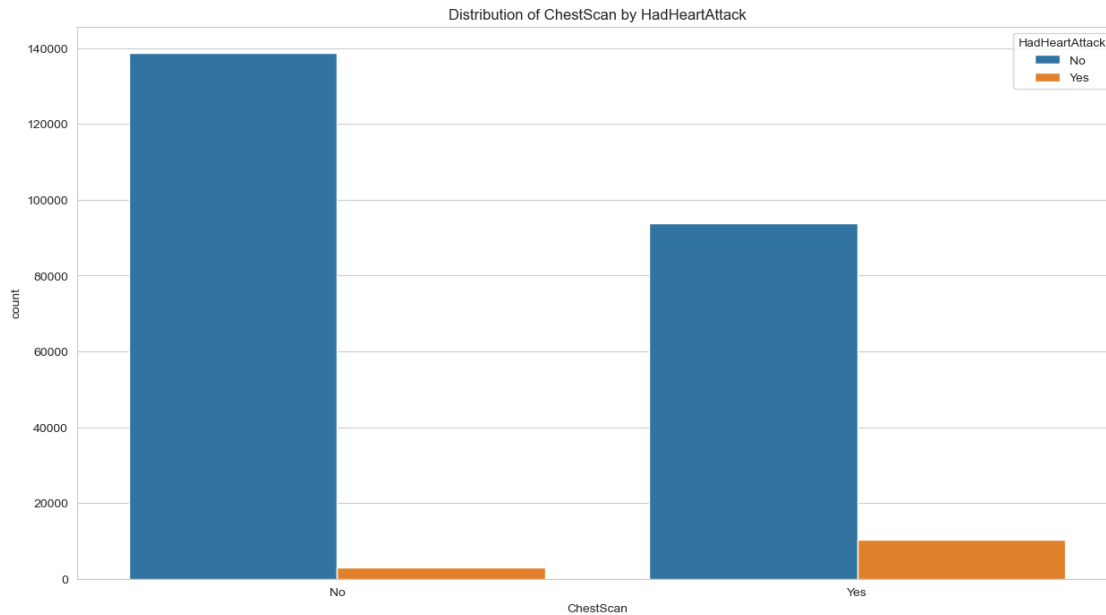
Chi-Squared Test for ECigaretteUsage and HadHeartAttack

Chi2 value = 114.26515381908608, p-value = 1.3252144336233886e-24



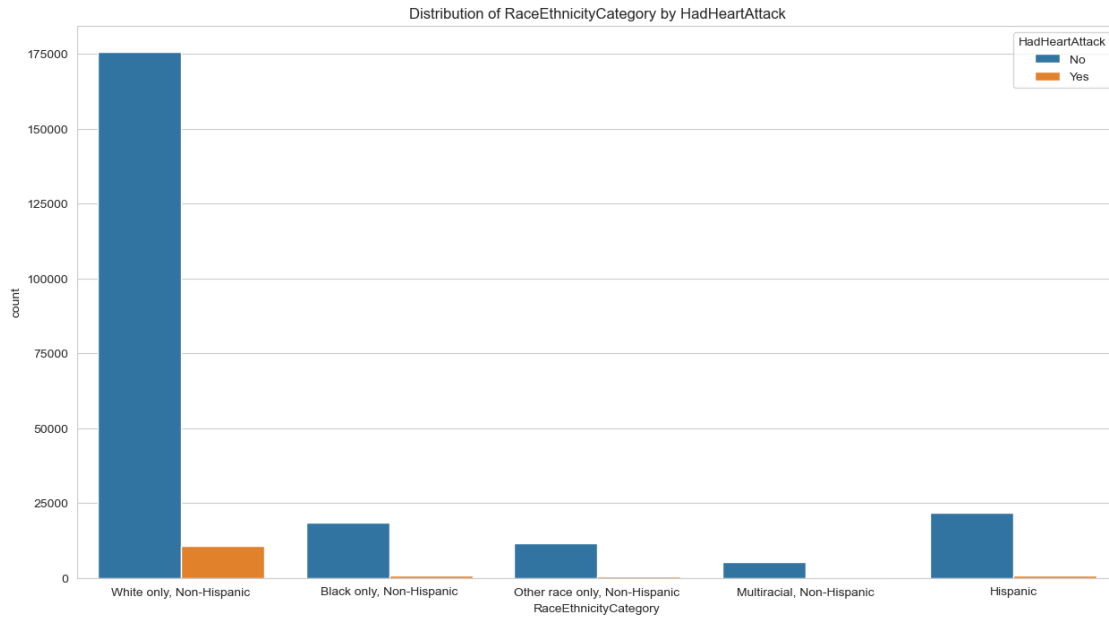
HadHeartAttack	No	Yes
ChestScan		
No	138707	3111
Yes	93871	10324

Chi-Squared Test for ChestScan and HadHeartAttack  
Chi2 value = 6922.660386789881, p-value = 0.0



HadHeartAttack	No	Yes
RaceEthnicityCategory		
Black only, Non-Hispanic	18441	889
Hispanic	21711	859
Multiracial, Non-Hispanic	5241	340
Other race only, Non-Hispanic	11614	591
White only, Non-Hispanic	175571	10756

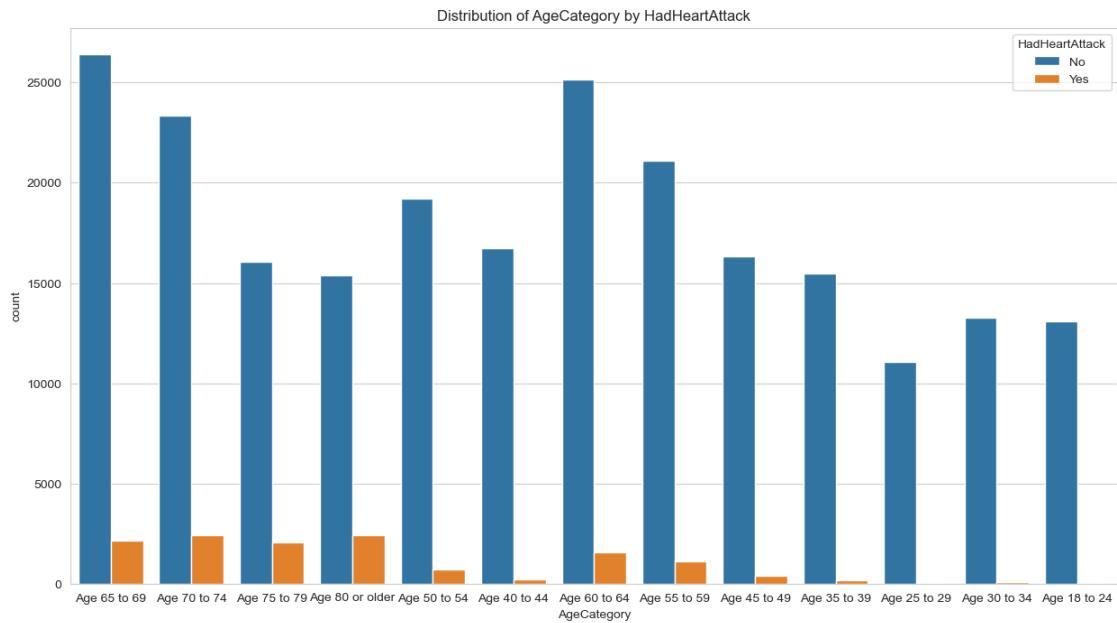
Chi-Squared Test for RaceEthnicityCategory and HadHeartAttack  
Chi2 value = 195.9712006643616, p-value = 2.760364866338809e-41



HadHeartAttack	No	Yes
AgeCategory		
Age 18 to 24	13072	50
Age 25 to 29	11062	47
Age 30 to 34	13256	90
Age 35 to 39	15458	156
Age 40 to 44	16745	228
Age 45 to 49	16333	420
Age 50 to 54	19209	703
Age 55 to 59	21112	1112
Age 60 to 64	25144	1575
Age 65 to 69	26400	2155
Age 70 to 74	23329	2408
Age 75 to 79	16068	2065
Age 80 or older	15390	2426

Chi-Squared Test for AgeCategory and HadHeartAttack

Chi2 value = 7925.704390290559, p-value = 0.0



HadHeartAttack            No    Yes

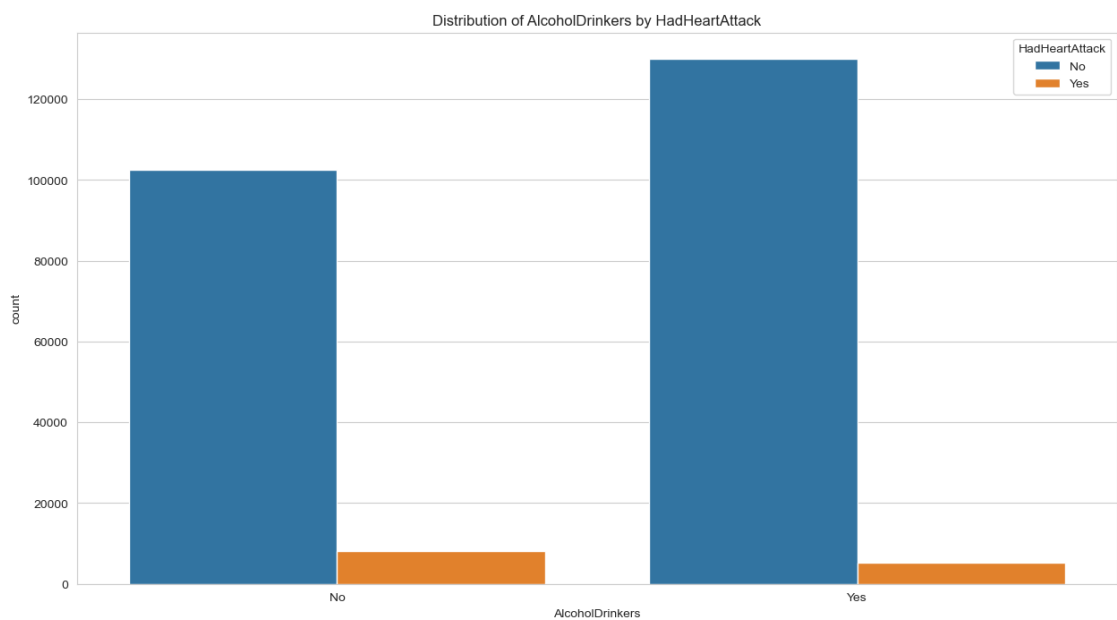
AlcoholDrinkers

No                        102605    8109

Yes                        129973    5326

Chi-Squared Test for AlcoholDrinkers and HadHeartAttack

Chi2 value = 1352.9336428746574, p-value = 3.5495529688639013e-296



HadHeartAttack	No	Yes
----------------	----	-----

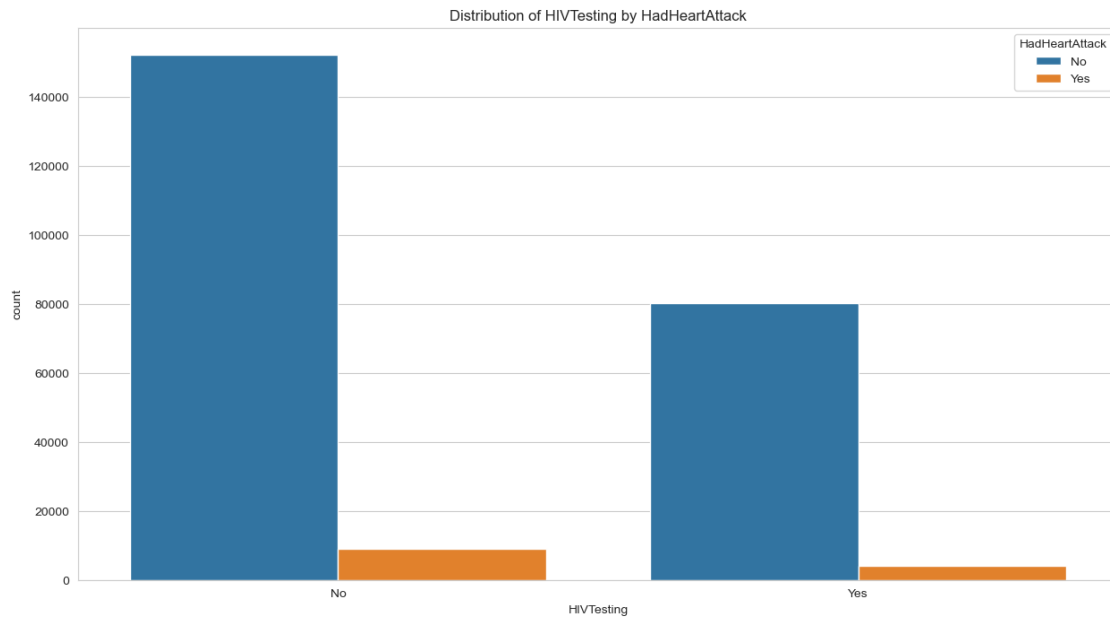
HIVTesting		
------------	--	--

No	152306	9207
----	--------	------

Yes	80272	4228
-----	-------	------

Chi-Squared Test for HIVTesting and HadHeartAttack

Chi2 value = 52.054385349053376, p-value = 5.398452954756739e-13



HadHeartAttack	No	Yes
----------------	----	-----

FluVaxLast12		
--------------	--	--

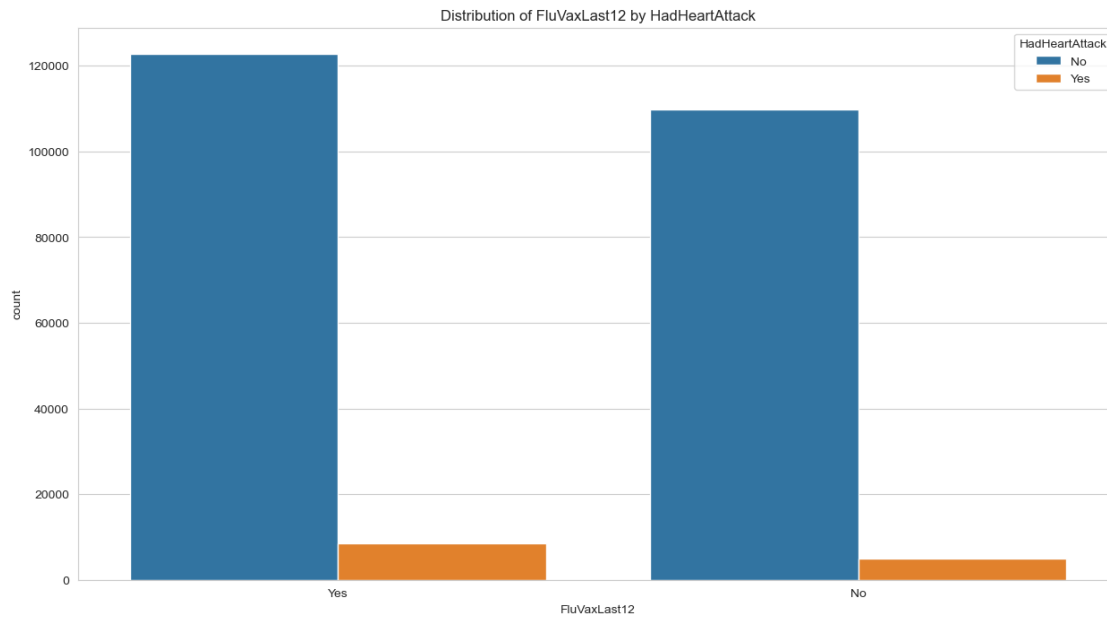
No	109816	5009
----	--------	------

Yes	122762	8426
-----	--------	------

Chi-Squared Test for FluVaxLast12 and HadHeartAttack

Chi2 value = 503.1594851068325, p-value = 1.952245327911882e-111





HadHeartAttack	No	Yes
----------------	----	-----

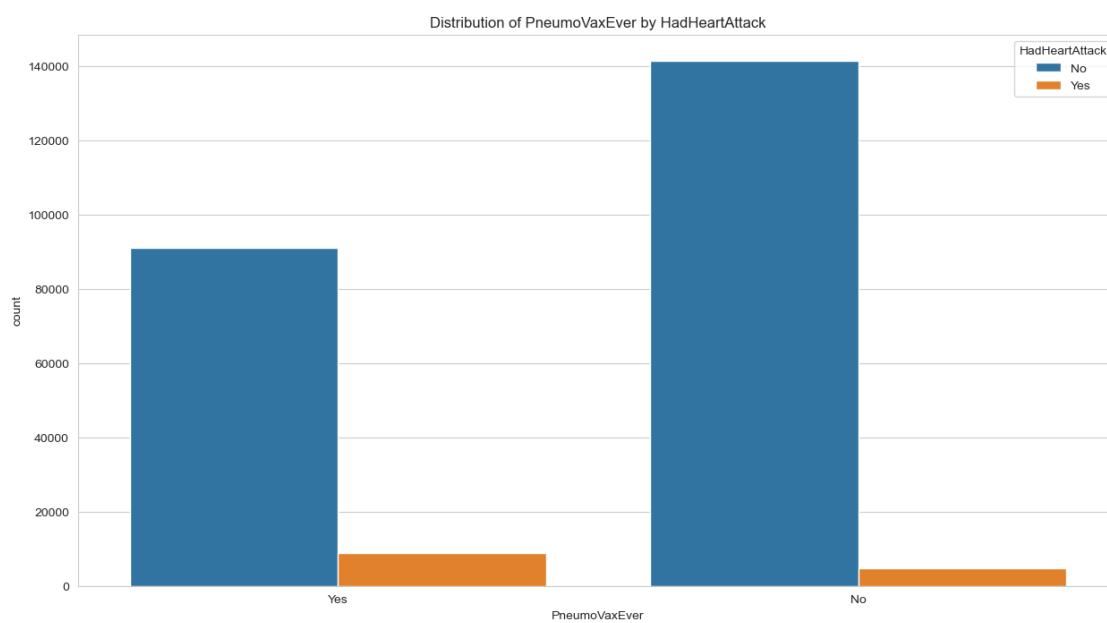
PneumoVaxEver	No	Yes
---------------	----	-----

No	141441	4687
----	--------	------

Yes	91137	8748
-----	-------	------

Chi-Squared Test for PneumoVaxEver and HadHeartAttack

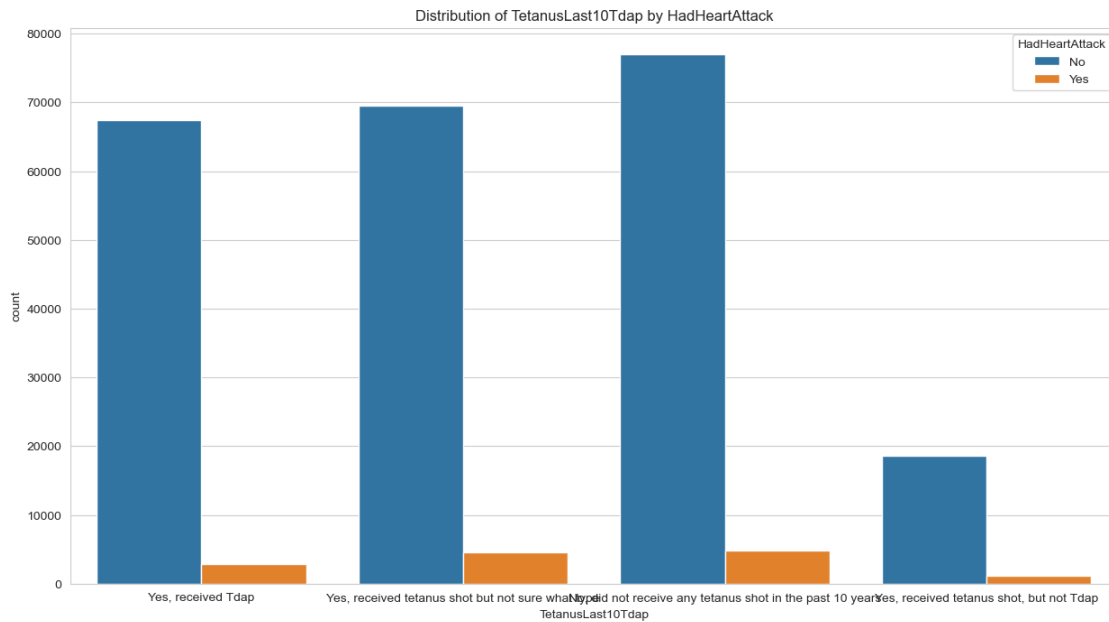
Chi2 value = 3539.4434942388366, p-value = 0.0



HadHeartAttack	No	Yes
TetanusLast10Tdap		
No, did not receive any tetanus shot in the pas...	76966	4777
Yes, received Tdap	67463	2819
Yes, received tetanus shot but not sure what type	69513	4605
Yes, received tetanus shot, but not Tdap	18636	1234

Chi-Squared Test for TetanusLast10Tdap and HadHeartAttack

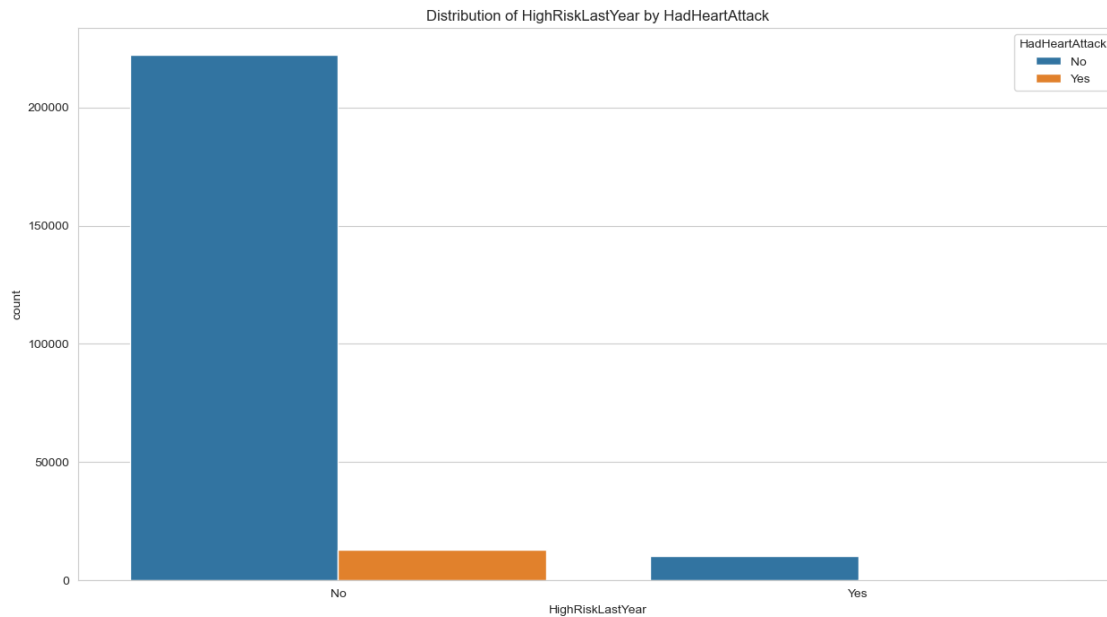
Chi2 value = 412.2456977489708, p-value = 4.9266526646514085e-89



HadHeartAttack	No	Yes
HighRiskLastYear		
No	222340	13097
Yes	10238	338

Chi-Squared Test for HighRiskLastYear and HadHeartAttack

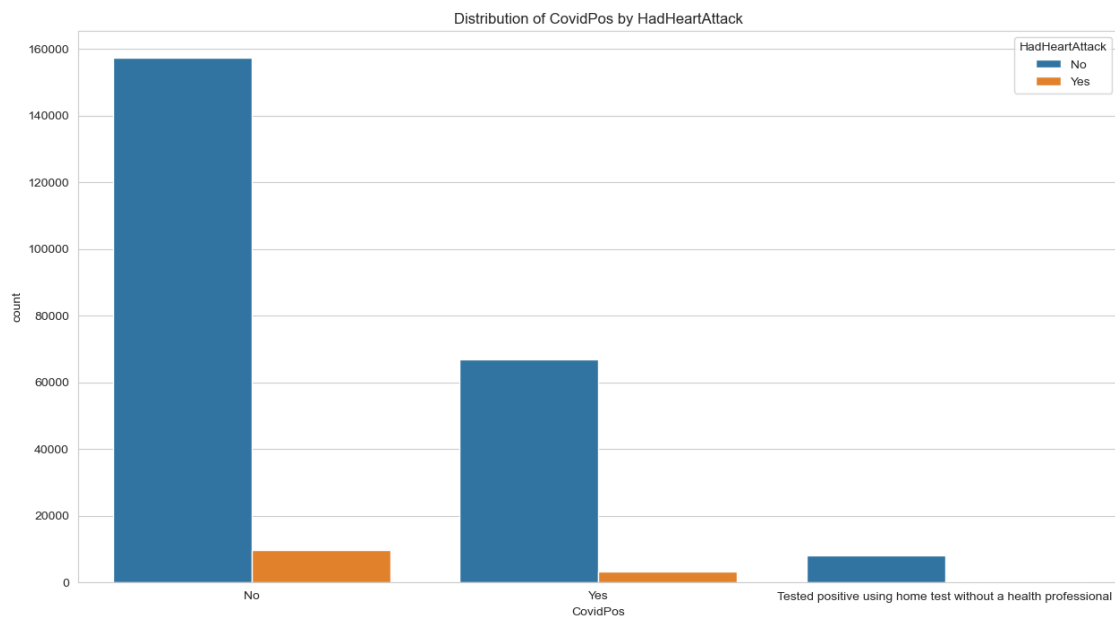
Chi2 value = 109.3716134286175, p-value = 1.3454258258489073e-25



HadHeartAttack	No	Yes
CovidPos		
No	157521	9776
Tested positive using home test without a health...	8158	234
Yes	66899	3425

Chi-Squared Test for CovidPos and HadHeartAttack

Chi2 value = 211.03994555450967, p-value = 1.490246437343113e-46



```
[ ]: # Perform t-tests for numerical data
results_df_nums = pd.DataFrame(columns=['Feature', 'Statistic', 'P-Value'])

for var in numerical_vars:
    # Statistical Test (e.g., t-test) for significance
    for category in df[target].unique():
        group1 = df[df[target] == category][var]
        group2 = df[df[target] != category][var]

        stat, p = ttest_ind(group1, group2)

    # Add the results to the DataFrame
    new_row = {'Feature': var, 'Statistic': stat, 'P-Value': p}
    results_df_nums = pd.concat([results_df_nums, pd.DataFrame(new_row,
        ↪index=[0])], ignore_index=True)

[ ]: # Sort the DataFrame by p-values in ascending order and then by chi2 values in
    ↪descending order
results_df_cat = results_df_cat.sort_values(by=['P-Value', 'Chi2'],
    ↪ascending=[True, False])

# Display the sorted DataFrame
display(results_df_cat)
```

	Feature	Chi2	P-Value
4	HadAngina	48906.220749	0.000000e+00
1	GeneralHealth	9893.539444	0.000000e+00
23	AgeCategory	7925.704390	0.000000e+00
5	HadStroke	7716.361887	0.000000e+00
3	RemovedTeeth	6996.544849	0.000000e+00
21	ChestScan	6922.660387	0.000000e+00
16	DifficultyWalking	6286.838781	0.000000e+00
12	HadDiabetes	5345.991257	0.000000e+00
8	HadCOPD	4363.963228	0.000000e+00
27	PneumoVaxEver	3539.443494	0.000000e+00
11	HadArthritis	3411.190094	0.000000e+00
10	HadKidneyDisease	2939.567089	0.000000e+00
13	DeafOrHardOfHearing	2344.804201	0.000000e+00
19	SmokerStatus	2241.293874	0.000000e+00
18	DifficultyErrands	1968.715862	0.000000e+00
2	PhysicalActivities	1701.515021	0.000000e+00
17	DifficultyDressingBathing	1696.394541	0.000000e+00
24	AlcoholDrinkers	1352.933643	3.549553e-296
0	Sex	1321.763475	2.107383e-289
14	BlindOrVisionDifficulty	1308.159375	1.905809e-286

15	DifficultyConcentrating	655.824979	1.208653e-144
7	HadSkinCancer	599.937749	1.727186e-132
26	FluVaxLast12	503.159485	1.952245e-111
28	TetanusLast10Tdap	412.245698	4.926653e-89
30	CovidPos	211.039946	1.490246e-46
22	RaceEthnicityCategory	195.971201	2.760365e-41
6	HadAsthma	138.573175	5.460575e-32
9	HadDepressiveDisorder	137.942355	7.502330e-32
29	HighRiskLastYear	109.371613	1.345426e-25
20	ECigaretteUsage	114.265154	1.325214e-24
25	HIVTesting	52.054385	5.398453e-13

```
[ ]: # Sort the DataFrame by p-values in ascending order
results_df_nums = results_df_nums.sort_values(by='P-Value', ascending=True)

# Display the sorted DataFrame
display(results_df_nums)
```

	Feature	Statistic	P-Value
0	PhysicalHealthDays	66.773602	0.000000e+00
4	WeightInKilograms	19.076335	4.546370e-81
1	MentalHealthDays	12.844421	9.506448e-38
3	HeightInMeters	11.440249	2.678179e-30
2	SleepHours	1.802562	7.145820e-02

### 0.3.1 Null Hypothesis Testing

We're intersted to test the following *null* hypothesis:

$H_0$ : General health and Smoker status don't have effect on the possibility of a heart attack

$H_A$ : General health and Smoker have effect on the possibility of a heart attack

```
[ ]: hypothesis_df = results_df_cat[results_df_cat['Feature'].isin(['GeneralHealth',
↪ 'SmokerStatus'])]

# Define the significance level (alpha)
alpha = 0.05 # You can choose a different alpha value if needed

# Verify the null hypothesis for each feature
for index, row in hypothesis_df.iterrows():
    feature = row['Feature']
    chi2 = row['Chi2']
    p_value = row['P-Value']

    print(f"Feature: {feature}")
    print(f"Chi-Squared Value: {chi2}")
    print(f"P-Value: {p_value}")
```

```

if p_value < alpha:
    print("Reject the null hypothesis (0)")
    print(f"{feature} has an effect on the possibility of a heart attack.")
else:
    print("Fail to reject the null hypothesis (0)")
    print(f"{feature} does not have an effect on the possibility of a heart_
↪attack.")

print("\n")

```

Feature: GeneralHealth  
Chi-Squared Value: 9893.539444125969  
P-Value: 0.0  
Reject the null hypothesis (0)  
GeneralHealth has an effect on the possibility of a heart attack.

Feature: SmokerStatus  
Chi-Squared Value: 2241.293874288016  
P-Value: 0.0  
Reject the null hypothesis (0)  
SmokerStatus has an effect on the possibility of a heart attack.

### 0.3.2 Conclusion

- We have completed chi square test and we are able to reject the *null* hypothesis.

## 0.4 Model Selection

```

[ ]: # TESTING FOR MULTICOLLINEARITY
# Add a constant term to the predictor variables
X = add_constant(df[['PhysicalHealthDays', 'MentalHealthDays', 'SleepHours',
↪'HeightInMeters', 'WeightInKilograms']])

vif_data = pd.DataFrame()
vif_data["Variable"] = X.columns
vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.
↪shape[1])]

print(vif_data)

```

	Variable	VIF
0	const	304.683975
1	PhysicalHealthDays	1.115540
2	MentalHealthDays	1.123823
3	SleepHours	1.019942

```

4      HeightInMeters      1.306575
5      WeightInKilograms    1.311968

```

```

[ ]: # HERE WE ADD DUMMIES TO THE CATEGORICAL VARIABLES
heart_df = pd.get_dummies(df, columns=categorical_includes_target,
    drop_first=True, dtype='int32')
heart_df.head(5)

```

```

[ ]:      PhysicalHealthDays  MentalHealthDays  SleepHours  HeightInMeters  \
0                4.0            0.0            9.0            1.60
1                0.0            0.0            6.0            1.78
2                0.0            0.0            8.0            1.85
3                5.0            0.0            9.0            1.70
4                3.0            15.0            5.0            1.55

      WeightInKilograms  Sex_Male  GeneralHealth_Fair  GeneralHealth_Good  \
0                71.67          0                0                0
1                95.25          1                0                0
2               108.86          1                0                0
3                90.72          0                1                0
4                79.38          0                0                1

      GeneralHealth_Poor  GeneralHealth_Very good  ...  HIVTesting_Yes  \
0                0                1  ...                0
1                0                1  ...                0
2                0                1  ...                0
3                0                0  ...                0
4                0                0  ...                0

      FluVaxLast12_Yes  PneumoVaxEver_Yes  TetanusLast10Tdap_Yes, received Tdap  \
0                1                1                1
1                1                1                0
2                0                1                0
3                1                1                0
4                1                1                0

      TetanusLast10Tdap_Yes, received tetanus shot but not sure what type  \
0                0
1                1
2                0
3                0
4                0

      TetanusLast10Tdap_Yes, received tetanus shot, but not Tdap  \
0                0
1                0
2                0

```

3	0
4	0

	HighRiskLastYear_Yes \
0	0
1	0
2	0
3	0
4	0

	CovidPos_Tested positive using home test without a health professional \
0	0
1	0
2	0
3	0
4	0

	CovidPos_Yes	HadHeartAttack_Yes
0	0	0
1	0	0
2	1	0
3	1	0
4	0	0

[5 rows x 65 columns]

```
[ ]: # REMOVE OUR DEPENDENT VARIABLE
target = 'HadHeartAttack_Yes'
X = heart_df.drop(target, axis=1)
y = heart_df[target]
```

Since, the dataset description suggested unbalanced data, we are going to perform model training:

- On the original data
- On the data with oversampling with *SMOTE* (Synthetic Minority Oversampling Technique)
- On the data with undersampling

```
[ ]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳ random_state=42)

# GENERATING THE OVERSAMPLE:
smote = SMOTE(random_state=42)
X_ovsampled, y_ovsampled = smote.fit_resample(X_train, y_train)

# GENERATING THE UNDERSAMPLE:
undersampler = RandomUnderSampler(random_state=42)
X_undersampled, y_undersampled = undersampler.fit_resample(X_train, y_train)
```



```
[ ]: # LOGISTIC REGRESSION
def train_and_evaluate_logit(X_train, X_test, y_train, y_test, random_state=42):
    X_train_ = X_train.copy()
    X_test_ = X_test.copy()

    X_train_ = sm.add_constant(X_train_)
    X_test_ = sm.add_constant(X_test_)
    result = sm.Logit(y_train, X_train_).fit()

    y_pred = result.predict(X_test_)
    y_pred = np.where(y_pred > 0.5, 1, 0)

    report_df = pd.DataFrame(classification_report(y_test, y_pred,
↪output_dict=True)).transpose()
    return (result, report_df)
```

```
[ ]: # DECISION TREE MODEL
def train_and_evaluate_decision_tree(X_train, X_test, y_train, y_test,
↪random_state=42):
    # Create and fit a DecisionTreeClassifier
    classifier = DecisionTreeClassifier(random_state=random_state)
    classifier.fit(X_train, y_train)

    y_pred = classifier.predict(X_test)

    report_df = pd.DataFrame(classification_report(y_test, y_pred,
↪output_dict=True)).transpose()
    return (classifier, report_df)
```

```
[ ]: # RESULTS FOR LOGISTIC REGRESSION WITH ORIGINAL DATA
result_log, report_df_log = train_and_evaluate_logit(X_train, X_test, y_train,
↪y_test)
display(report_df_log)
```

Optimization terminated successfully.

Current function value: 0.145333

Iterations 10

	precision	recall	f1-score	support
0	0.958957	0.988616	0.973561	46558.00000
1	0.560166	0.255198	0.350649	2645.00000
accuracy	0.949190	0.949190	0.949190	0.94919
macro avg	0.759561	0.621907	0.662105	49203.00000
weighted avg	0.937519	0.949190	0.940075	49203.00000

```
[ ]: # RESULTS FOR LOGISTIC REGRESSION WITH OVERSAMPLE WITH SMOTE
result_log_ov, report_df_log_ov = train_and_evaluate_logit(X_ovsampled, X_test,
↪y_ovsampled, y_test)
```

```
display(report_df_log_ov)
```

Optimization terminated successfully.

Current function value: 0.210823

Iterations 9

	precision	recall	f1-score	support
0	0.962747	0.926436	0.944243	46558.00000
1	0.221768	0.368998	0.277037	2645.00000
accuracy	0.896470	0.896470	0.896470	0.89647
macro avg	0.592257	0.647717	0.610640	49203.00000
weighted avg	0.922914	0.896470	0.908376	49203.00000

```
[ ]: # RESULTS FOR LOGISTIC REGRESSION WITH UNDERSAMPLE
result_log_un, report_df_log_un = train_and_evaluate_logit(X_undersampled,
↳X_test, y_undersampled, y_test)
display(report_df_log_un)
```

Optimization terminated successfully.

Current function value: 0.421748

Iterations 7

	precision	recall	f1-score	support
0	0.984156	0.836505	0.904343	46558.000000
1	0.209553	0.762949	0.328798	2645.000000
accuracy	0.832551	0.832551	0.832551	0.832551
macro avg	0.596855	0.799727	0.616571	49203.000000
weighted avg	0.942516	0.832551	0.873404	49203.000000

```
[ ]: # RESULTS FOR DECISION TREE (ORIGINAL DATA)
result_tree, report_df_tree = train_and_evaluate_decision_tree(X_train, X_test,
↳y_train, y_test)
display(report_df_tree)
```

	precision	recall	f1-score	support
0	0.959465	0.949697	0.954556	46558.000000
1	0.249118	0.293762	0.269604	2645.000000
accuracy	0.914436	0.914436	0.914436	0.914436
macro avg	0.604292	0.621729	0.612080	49203.000000
weighted avg	0.921279	0.914436	0.917735	49203.000000

```
[ ]: # RESULTS FOR DECISION TREE WITH OVERSAMPLE
result_tree_ov, report_df_tree_ov =
↳train_and_evaluate_decision_tree(X_ovsampled, X_test, y_ovsampled, y_test)
display(report_df_tree_ov)
```

	precision	recall	f1-score	support
0	0.960106	0.922162	0.940751	46558.000000
1	0.191973	0.325520	0.241515	2645.000000
accuracy	0.890088	0.890088	0.890088	0.890088

macro avg	0.576039	0.623841	0.591133	49203.000000
weighted avg	0.918813	0.890088	0.903162	49203.000000

```
[ ]: # RESULTS FOR DECISION TREE WITH UNDERSAMPLE
result_tree_un, report_df_tree_un =
    ↪train_and_evaluate_decision_tree(X_undersampled, X_test, y_undersampled,
    ↪y_test)
display(report_df_tree_un)
```

	precision	recall	f1-score	support
0	0.978397	0.721788	0.830727	46558.000000
1	0.128096	0.719471	0.217473	2645.000000
accuracy	0.721663	0.721663	0.721663	0.721663
macro avg	0.553247	0.720629	0.524100	49203.000000
weighted avg	0.932687	0.721663	0.797761	49203.000000

#### 0.4.1 Conclusion

- Neither oversampling, nor undersampling produced desired results improving precision, i.e. the accuracy of the positive predictions made by the model
- Compared by the accuracy of the model on the entire dataset, and by mimizing the poor precision performance, **Logistic Regression** trained on the original data performed the best.
- Selected model has recall for **0** class of  $\approx 98\%$ , meaning low probability of false negatives, which is very important for the health data.

### 0.5 Model Analysis

```
[ ]: result_log_sum = result_log.summary()
```

```
[ ]: result_log_sum_df = pd.DataFrame(result_log_sum.tables[1].data[1:],
    ↪columns=result_log_sum.tables[1].data[0])
result_log_sum_sorted = result_log_sum_df.sort_values(by="P>|z|",
    ↪ascending=True)
display(result_log_sum_sorted)
```

		coef	std err	\
0	const	-5.6427	0.321	
63	CovidPos_Tested positive using home test witho...	-0.3420	0.084	
33	SmokerStatus_Former smoker	-0.1972	0.040	
34	SmokerStatus_Never smoked	-0.4333	0.042	
57	FluVaxLast12_Yes	-0.1404	0.026	
..	...	...	...	
37	ECigaretteUsage_Use them some days	0.0449	0.085	
60	TetanusLast10Tdap_Yes, received tetanus shot b...	-0.0143	0.029	
17	HadAsthma_Yes	0.0138	0.033	
36	ECigaretteUsage_Use them every day	-0.0210	0.103	
32	SmokerStatus_Current smoker - now smokes some ...	-0.0045	0.067	

	z	P> z	[0.025	0.975]
0	-17.585	0.000	-6.272	-5.014
63	-4.068	0.000	-0.507	-0.177
33	-4.924	0.000	-0.276	-0.119
34	-10.428	0.000	-0.515	-0.352
57	-5.370	0.000	-0.192	-0.089
..	...	...	...	...
37	0.528	0.598	-0.122	0.212
60	-0.502	0.616	-0.070	0.042
17	0.422	0.673	-0.050	0.078
36	-0.204	0.838	-0.222	0.180
32	-0.068	0.946	-0.135	0.126

[65 rows x 7 columns]

```
[ ]: result_log_sum_df_feature_of_interest =
↳ result_log_sum_sorted[result_log_sum_sorted[''].isin(['SmokerStatus_Former_
↳ smoker', 'SmokerStatus_Never smoked', 'GeneralHealth_Fair',
↳ 'GeneralHealth_Poor', 'GeneralHealth_Good', 'GeneralHealth_Very good',
↳ 'SmokerStatus_Current smoker - now smokes some days'])]
```

```
[ ]: display(result_log_sum_df_feature_of_interest)
```

		coef	std err	\
33	SmokerStatus_Former smoker	-0.1972	0.040	
34	SmokerStatus_Never smoked	-0.4333	0.042	
7	GeneralHealth_Fair	0.8915	0.058	
8	GeneralHealth_Good	0.6649	0.053	
9	GeneralHealth_Poor	1.0154	0.071	
10	GeneralHealth_Very good	0.3281	0.054	
32	SmokerStatus_Current smoker - now smokes some ...	-0.0045	0.067	

	z	P> z	[0.025	0.975]
33	-4.924	0.000	-0.276	-0.119
34	-10.428	0.000	-0.515	-0.352
7	15.372	0.000	0.778	1.005
8	12.550	0.000	0.561	0.769
9	14.360	0.000	0.877	1.154
10	6.054	0.000	0.222	0.434
32	-0.068	0.946	-0.135	0.126

### 0.5.1 Conclusion

- Smoker status related features have the following results:
  - SmokerStatus\_Former smoker has coefficient  $-0.1972$ , SmokerStatus\_Never smoked has coefficient  $-0.4333$ , suggesting negative direction of the effects on the probability of a heart attack. In other words, quitting smoking is associated with reduced probability of having a heart attack

- `SmokerStatus_Current smoker - now smokes some days` has a small negative coefficient of  $-0.0045$ , however the  $p$ -value for this feature indicates, that the effect is not statistically significant.
- All features for `GeneralHealth` have  $p$ -values indicating that the effects are statistically significant
- `GeneralHealth_Poor` has the highest magnitude of the coefficient, suggesting an increase in the corresponding independent variable is associated with an increased probability a heart attack