```
#import necessary libraries
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm

from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeClassifier, plot_tree, export_graphviz
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import SMOTE
from sklearn import tree
```

```
# Loading in the data from csv files.
features_df = pd.read_csv("training_set_features.csv")
target = pd.read_csv("training_set_labels.csv")
submission = pd.read_csv("submission_format.csv")
test_feature = pd.read_csv("test_set_feature.csv")
```

```
# summary of the data in the training_set_features
features_df.head()
```

	respondent_id	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_
0	0	1.0	0.0	0.0	0.0	0.0	
1	1	3.0	2.0	0.0	1.0	0.0	
2	2	1.0	1.0	0.0	1.0	0.0	
3	3	1.0	1.0	0.0	1.0	0.0	
4	4	2.0	1.0	0.0	1.0	0.0	

Creating a copy...

5 rows × 36 columns

```
# summary of the data in the training_set_lables
target.head()
```

	respondent_id	h1n1_vaccine	seasonal_vaccine
0	0	0	0
1	1	0	1
2	2	0	0
3	3	0	1
4	4	0	0

```
# summary of the data in the submission_format
submission.head()
```

	respondent_id	h1n1_vaccine	seasonal_vaccine
0	26707	0.5	0.7
1	26708	0.5	0.7
2	26709	0.5	0.7
3	26710	0.5	0.7
4	26711	0.5	0.7

```
# summary of the data in the test_set_features
test_feature.head()
```

	respondent_id	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_
0	26707	2.0	2.0	0.0	1.0	0.0	
1	26708	1.0	1.0	0.0	0.0	0.0	
2	26709	2.0	2.0	0.0	0.0	1.0	
3	26710	1.0	1.0	0.0	0.0	0.0	
4	26711	3.0	1.0	1.0	1.0	0.0	

5 rows × 36 columns

Data Preparation

> Indented block

```
#summary of the data
features_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26707 entries, 0 to 26706
Data columns (total 36 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   respondent_id                26707 non-null  int64
 1   h1n1_concern                 26615 non-null  float64
 2   h1n1_knowledge               26591 non-null  float64
 3   behavioral_antiviral_meds    26636 non-null  float64
 4   behavioral_avoidance         26499 non-null  float64
 5   behavioral_face_mask         26688 non-null  float64
 6   behavioral_wash_hands        26665 non-null  float64
 7   behavioral_large_gatherings  26620 non-null  float64
 8   behavioral_outside_home      26625 non-null  float64
 9   behavioral_touch_face        26579 non-null  float64
 10  doctor_recc_h1n1             24547 non-null  float64
 11  doctor_recc_seasonal         24547 non-null  float64
 12  chronic_med_condition        25736 non-null  float64
 13  child_under_6_months         25887 non-null  float64
 14  health_worker                25903 non-null  float64
 15  health_insurance             14433 non-null  float64
 16  opinion_h1n1_vacc_effective  26316 non-null  float64
 17  opinion_h1n1_risk            26319 non-null  float64
 18  opinion_h1n1_sick_from_vacc  26312 non-null  float64
 19  opinion_seas_vacc_effective  26245 non-null  float64
 20  opinion_seas_risk            26193 non-null  float64
 21  opinion_seas_sick_from_vacc  26170 non-null  float64
 22  age_group                    26707 non-null  object
 23  education                    25300 non-null  object
 24  race                         26707 non-null  object
 25  sex                          26707 non-null  object
 26  income_poverty               22284 non-null  object
 27  marital_status               25299 non-null  object
 28  rent_or_own                  24665 non-null  object
 29  employment_status            25244 non-null  object
 30  hhs_geo_region               26707 non-null  object
 31  census_msa                   26707 non-null  object
 32  household_adults             26458 non-null  float64
 33  household_children           26458 non-null  float64
 34  employment_industry          13377 non-null  object
 35  employment_occupation        13237 non-null  object
dtypes: float64(23), int64(1), object(12)
memory usage: 7.3+ MB
```



```
#summary of the target data
target.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26707 entries, 0 to 26706
```

```
Data columns (total 3 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   respondent_id     26707 non-null  int64
 1   h1n1_vaccine      26707 non-null  int64
 2   seasonal_vaccine  26707 non-null  int64
dtypes: int64(3)
memory usage: 626.1 KB
```

```
# Load the training set features
features_df = pd.read_csv("training_set_features.csv")

# Load the training set labels
target = pd.read_csv("training_set_labels.csv")
```

```
# Merge the features and labels on 'respondent_id'
merged_df = pd.merge(features_df, target, on='respondent_id')
merged_df.head()
```

	respondent_id	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_
0	0	1.0	0.0	0.0	0.0	0.0	
1	1	3.0	2.0	0.0	1.0	0.0	
2	2	1.0	1.0	0.0	1.0	0.0	
3	3	1.0	1.0	0.0	1.0	0.0	
4	4	2.0	1.0	0.0	1.0	0.0	

Creating a copy...

```
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26707 entries, 0 to 26706
Data columns (total 38 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   respondent_id                26707 non-null  int64
 1   h1n1_concern                 26615 non-null  float64
 2   h1n1_knowledge               26591 non-null  float64
 3   behavioral_antiviral_meds    26636 non-null  float64
 4   behavioral_avoidance         26499 non-null  float64
 5   behavioral_face_mask         26688 non-null  float64
 6   behavioral_wash_hands        26665 non-null  float64
 7   behavioral_large_gatherings  26620 non-null  float64
 8   behavioral_outside_home      26625 non-null  float64
 9   behavioral_touch_face        26579 non-null  float64
 10  doctor_recc_h1n1             24547 non-null  float64
 11  doctor_recc_seasonal         24547 non-null  float64
 12  chronic_med_condition        25736 non-null  float64
 13  child_under_6_months         25887 non-null  float64
 14  health_worker                25903 non-null  float64
 15  health_insurance             14433 non-null  float64
 16  opinion_h1n1_vacc_effective  26316 non-null  float64
 17  opinion_h1n1_risk            26319 non-null  float64
 18  opinion_h1n1_sick_from_vacc  26312 non-null  float64
 19  opinion_seas_vacc_effective  26245 non-null  float64
 20  opinion_seas_risk            26193 non-null  float64
 21  opinion_seas_sick_from_vacc  26170 non-null  float64
 22  age_group                    26707 non-null  object
 23  education                    25300 non-null  object
 24  race                         26707 non-null  object
 25  sex                          26707 non-null  object
 26  income_poverty               22284 non-null  object
 27  marital_status               25299 non-null  object
 28  rent_or_own                  24665 non-null  object
 29  employment_status            25244 non-null  object
 30  hhs_geo_region               26707 non-null  object
 31  census_msa                   26707 non-null  object
```

```
 32  household_adults             26458 non-null  float64
 33  household_children           26458 non-null  float64
 34  employment_industry          13377 non-null  object
 35  employment_occupation        13237 non-null  object
 36  h1n1_vaccine                 26707 non-null  int64
 37  seasonal_vaccine             26707 non-null  int64
dtypes: float64(23), int64(3), object(12)
memory usage: 7.9+ MB
```

```
# Check for missing values
print(merged_df.isnull().sum())
```

```
respondent_id                    0
h1n1_concern                    92
h1n1_knowledge                 116
behavioral_antiviral_meds       71
behavioral_avoidance           208
behavioral_face_mask            19
behavioral_wash_hands           42
behavioral_large_gatherings     87
behavioral_outside_home         82
behavioral_touch_face          128
doctor_recc_h1n1              2160
doctor_recc_seasonal          2160
chronic_med_condition          971
child_under_6_months           820
health_worker                  804
health_insurance             12274
opinion_h1n1_vacc_effective    391
opinion_h1n1_risk              388
opinion_h1n1_sick_from_vacc    395
opinion_seas_vacc_effective    462
opinion_seas_risk              514
opinion_seas_sick_from_vacc    537
age_group                        0
education                     1407
race                             0
                                 0
                              4423
                              1408
rent_or_own                   2042
employment_status             1463
hhs_geo_region                   0
census_msa                       0
household_adults               249
household_children             249
employment_industry          13330
employment_occupation        13470
h1n1_vaccine                     0
seasonal_vaccine                 0
dtype: int64
```



```
merged_df.head()
```

	respondent_id	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_
0	0	1.0	0.0	0.0	0.0	0.0	
1	1	3.0	2.0	0.0	1.0	0.0	
2	2	1.0	1.0	0.0	1.0	0.0	
3	3	1.0	1.0	0.0	1.0	0.0	
4	4	2.0	1.0	0.0	1.0	0.0	

5 rows × 38 columns

```
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26707 entries, 0 to 26706
```

```
Data columns (total 38 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   respondent_id                26707 non-null  int64  
 1   h1n1_concern                 26615 non-null  float64
 2   h1n1_knowledge               26591 non-null  float64
 3   behavioral_antiviral_meds    26636 non-null  float64
 4   behavioral_avoidance         26499 non-null  float64
 5   behavioral_face_mask         26688 non-null  float64
 6   behavioral_wash_hands        26665 non-null  float64
 7   behavioral_large_gatherings  26620 non-null  float64
 8   behavioral_outside_home      26625 non-null  float64
 9   behavioral_touch_face        26579 non-null  float64
 10  doctor_recc_h1n1             24547 non-null  float64
 11  doctor_recc_seasonal         24547 non-null  float64
 12  chronic_med_condition        25736 non-null  float64
 13  child_under_6_months         25887 non-null  float64
 14  health_worker                25903 non-null  float64
 15  health_insurance             14433 non-null  float64
 16  opinion_h1n1_vacc_effective  26316 non-null  float64
 17  opinion_h1n1_risk            26319 non-null  float64
 18  opinion_h1n1_sick_from_vacc  26312 non-null  float64
 19  opinion_seas_vacc_effective  26245 non-null  float64
 20  opinion_seas_risk            26193 non-null  float64
 21  opinion_seas_sick_from_vacc  26170 non-null  float64
 22  age_group                    26707 non-null  object 
 23  education                    25300 non-null  object 
 24  race                         26707 non-null  object 
 25  sex                          26707 non-null  object 
 26  income_poverty               22284 non-null  object 
 27  marital_status               25299 non-null  object 
 28  rent_or_own                  24665 non-null  object 
 29  employment_status            25244 non-null  object 
 30  hhs_geo_region               26707 non-null  object 
 31  census_msa                   26707 non-null  object 
 32  household_adults             26458 non-null  float64
 33  household_children           26458 non-null  float64
 34  employment_industry          13377 non-null  object 
                                  13237 non-null  object 
                                  26707 non-null  int64  
                                  26707 non-null  int64  
dtypes: float64(23), int64(3), object(12)
memory usage: 7.9+ MB
```

Creating a copy...

```
# Perform one-hot encoding on categorical variables
categorical_columns = ['age_group', 'education', 'race', 'sex', 'marital_status', 'rent_or_own', 'employment_status', 'hhs_geo_region',
encoded_df = pd.get_dummies(merged_df, columns=categorical_columns)
```

```
# Perform feature scaling on numerical variables
numerical_columns = ['h1n1_concern', 'h1n1_knowledge', 'behavioral_antiviral_meds', 'behavioral_avoidance', 'behavioral_face_mask', 'be
scaler = StandardScaler()
encoded_df[numerical_columns] = scaler.fit_transform(encoded_df[numerical_columns])
```

```
# Check for duplicates
duplicates = encoded_df.duplicated()
print("Number of duplicate rows:", duplicates.sum())
```

```
Number of duplicate rows: 0
```

```
# Select numerical columns for outlier detection and visualization
numerical_columns = encoded_df.select_dtypes(include=[np.number]).columns
```

```
# Select numerical columns for outlier detection and visualization
numerical_columns = encoded_df.select_dtypes(include=[np.number]).columns

num_cols = len(numerical_columns)
num_rows = int(np.ceil(num_cols / 4))  # Calculate the number of subplot rows

# Check for outliers
plt.figure(figsize=(12, num_rows * 3))
for i, column in enumerate(numerical_columns, 1):
    plt.subplot(num_rows, 4, i)
    sns.boxplot(data=encoded_df, x=column)
    plt.xlabel(column)
```

```
plt.tight_layout()
plt.show()

# Visualize histograms
plt.figure(figsize=(12, num_rows * 3))
for i, column in enumerate(numerical_columns, 1):
    plt.subplot(num_rows, 4, i)
    encoded_df[column].hist(bins=20)
    plt.xlabel(column)
plt.tight_layout()
plt.show()
```


behavioral_avoidance, behavioral_large_gatherings, behavioral_outside_home, and behavioral_touch_face variables have outliers towards the higher end. This indicates that there are respondents who exhibit extreme behaviors in these categories.

doctor_recc_h1n1 and doctor_recc_seasonal variables have outliers towards the higher end, suggesting that there are respondents who received strong recommendations from doctors for getting the H1N1 and seasonal vaccines.

opinion_h1n1_vacc_effective, opinion_h1n1_risk, opinion_h1n1_sick_from_vacc, opinion_seas_vacc_effective, opinion_seas_risk, and opinion_seas_sick_from_vacc variables have outliers towards both ends. This indicates that there is a wide range of opinions among the respondents regarding the effectiveness, risk, and perceived sickness from the vaccines.

household_adults and household_children variables have outliers towards the higher end, suggesting that some respondents have a larger number of adults and children in their households.

```
# Calculate the IQR for each numerical column
Q1 = merged_df.quantile(0.25)
Q3 = merged_df.quantile(0.75)
IQR = Q3 - Q1

# Define a threshold for outlier detection
threshold = 2.0

# Identify the indices of outliers in each column
outliers = ((merged_df < (Q1 - threshold * IQR)) | (merged_df > (Q3 + threshold * IQR))).any(axis=1)
```

```
<ipython-input-20-194007f63daa>:2: FutureWarning: The default value of numeric_only in DataFrame.quantile is deprecated. In a fut
  Q1 = merged_df.quantile(0.25)
<ipython-input-20-194007f63daa>:3: FutureWarning: The default value of numeric_only in DataFrame.quantile is deprecated. In a fut
  Q3 = merged_df.quantile(0.75)
<ipython-input-20-194007f63daa>:10: FutureWarning: Automatic reindexing on DataFrame vs Series comparisons is deprecated and will
  outliers = ((merged_df < (Q1 - threshold * IQR)) | (merged_df > (Q3 + threshold * IQR))).any(axis=1)
```

```
merged_df.head()
```

	respondent_id	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_
0	0	1.0	0.0	0.0	0.0	0.0	
1	1	3.0	2.0	0.0	1.0	0.0	
2	2	1.0	1.0	0.0	1.0	0.0	
		0	1.0	0.0	1.0	0.0	
4	4	2.0	1.0	0.0	1.0	0.0	

Creating a copy...

5 rows × 38 columns

```
merged_df.info()
```

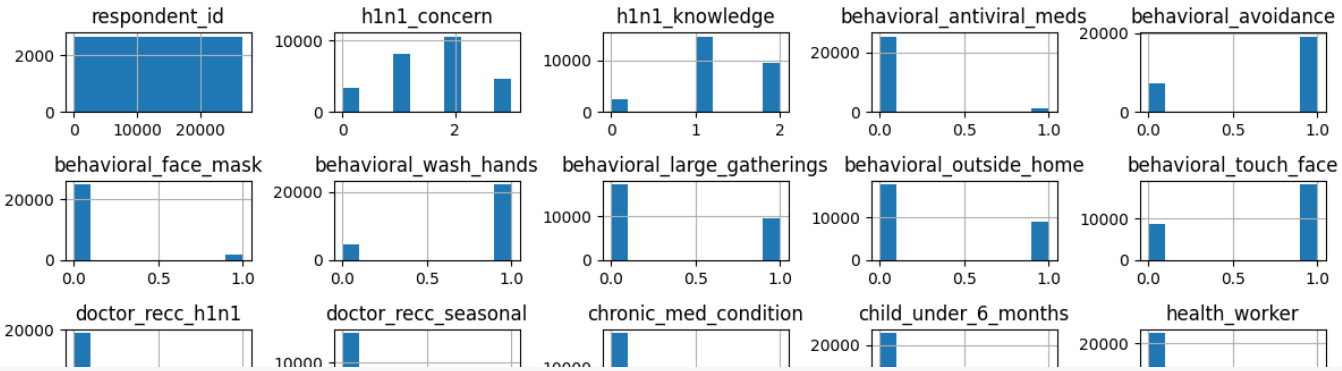
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26707 entries, 0 to 26706
Data columns (total 38 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   respondent_id                26707 non-null  int64
 1   h1n1_concern                 26615 non-null  float64
 2   h1n1_knowledge               26591 non-null  float64
 3   behavioral_antiviral_meds    26636 non-null  float64
 4   behavioral_avoidance         26499 non-null  float64
 5   behavioral_face_mask         26688 non-null  float64
 6   behavioral_wash_hands        26665 non-null  float64
 7   behavioral_large_gatherings  26620 non-null  float64
 8   behavioral_outside_home      26625 non-null  float64
 9   behavioral_touch_face        26579 non-null  float64
 10  doctor_recc_h1n1             24547 non-null  float64
 11  doctor_recc_seasonal         24547 non-null  float64
 12  chronic_med_condition        25736 non-null  float64
 13  child_under_6_months         25887 non-null  float64
 14  health_worker                25903 non-null  float64
 15  health_insurance             14433 non-null  float64
 16  opinion_h1n1_vacc_effective  26316 non-null  float64
 17  opinion_h1n1_risk            26319 non-null  float64
 18  opinion_h1n1_sick_from_vacc  26312 non-null  float64
 19  opinion_seas_vacc_effective  26245 non-null  float64
 20  opinion_seas_risk            26193 non-null  float64
 21  opinion_seas_sick_from_vacc  26170 non-null  float64
 22  age_group                    26707 non-null  object
 23  education                    25300 non-null  object
```

```
 24  race                         26707 non-null  object
 25  sex                          26707 non-null  object
 26  income_poverty               22284 non-null  object
 27  marital_status               25299 non-null  object
 28  rent_or_own                  24665 non-null  object
 29  employment_status            25244 non-null  object
 30  hhs_geo_region               26707 non-null  object
 31  census_msa                   26707 non-null  object
 32  household_adults             26458 non-null  float64
 33  household_children           26458 non-null  float64
 34  employment_industry          13377 non-null  object
 35  employment_occupation        13237 non-null  object
 36  h1n1_vaccine                 26707 non-null  int64
 37  seasonal_vaccine             26707 non-null  int64
dtypes: float64(23), int64(3), object(12)
memory usage: 7.9+ MB
```

EDA

```
#Data distribution
import seaborn as sns
import matplotlib.pyplot as plt

# Plot histogram for each numerical variable
merged_df.hist(figsize=(12, 8))
plt.tight_layout()
plt.show()

# Plot countplot for each categorical variable
categorical_cols = merged_df.select_dtypes(include='object').columns
for col in categorical_cols:
    sns.countplot(data=merged_df, x=col)
```

Creating a copy...




```
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26707 entries, 0 to 26706
Data columns (total 38 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   respondent_id                26707 non-null  int64  
 1   h1n1_concern                 26615 non-null  float64
 2   h1n1_knowledge               26591 non-null  float64
 3   behavioral_antiviral_meds    26636 non-null  float64
 4   behavioral_avoidance         26499 non-null  float64
 5   behavioral_face_mask         26688 non-null  float64
 6   behavioral_wash_hands        26665 non-null  float64
 7   behavioral_large_gatherings  26620 non-null  float64
 8   behavioral_outside_home      26625 non-null  float64
 9   behavioral_touch_face        26579 non-null  float64
 10  doctor_recc_h1n1             24547 non-null  float64
 11  doctor_recc_seasonal         24547 non-null  float64
 12  chronic_med_condition        25736 non-null  float64
 13  child_under_6_months         25887 non-null  float64
                                  25903 non-null  float64
                                  14433 non-null  float64
                                  26316 non-null  float64
 17  opinion_h1n1_risk            26319 non-null  float64
 18  opinion_h1n1_sick_from_vacc  26312 non-null  float64
 19  opinion_seas_vacc_effective  26245 non-null  float64
 20  opinion_seas_risk            26193 non-null  float64
 21  opinion_seas_sick_from_vacc  26170 non-null  float64
 22  age_group                    26707 non-null  object 
 23  education                    25300 non-null  object 
 24  race                         26707 non-null  object 
 25  sex                          26707 non-null  object 
 26  income_poverty               22284 non-null  object 
 27  marital_status               25299 non-null  object 
 28  rent_or_own                  24665 non-null  object 
 29  employment_status            25244 non-null  object 
 30  hhs_geo_region               26707 non-null  object 
 31  census_msa                   26707 non-null  object 
 32  household_adults             26458 non-null  float64
 33  household_children           26458 non-null  float64
 34  employment_industry          13377 non-null  object 
 35  employment_occupation        13237 non-null  object 
 36  h1n1_vaccine                 26707 non-null  int64  
 37  seasonal_vaccine             26707 non-null  int64  
dtypes: float64(23), int64(3), object(12)
memory usage: 7.9+ MB
```

Creating a copy...

Demographic information Distribution

```
merged_df['age_group'].value_counts()
```

```
65+ Years        6843
55 - 64 Years    5563
45 - 54 Years    5238
18 - 34 Years    5215
35 - 44 Years    3848
Name: age_group, dtype: int64
```

```
merged_df['race'].value_counts()
```

```
White               21222
Black                2118
Hispanic             1755
Other or Multiple    1612
Name: race, dtype: int64
```

```
merged_df['sex'].value_counts()
```

```
Female    15858
Male      10849
Name: sex, dtype: int64
```

```
merged_df['education'].value_counts()
```

```
College Graduate    10097
Some College         7043
12 Years             5797
< 12 Years           2363
Name: education, dtype: int64
```

```
merged_df['marital_status'].value_counts()
```

```
Married        13555
Not Married    11744
Name: marital_status, dtype: int64
```

```
target['h1n1_vaccine'].value_counts(normalize=True)
```

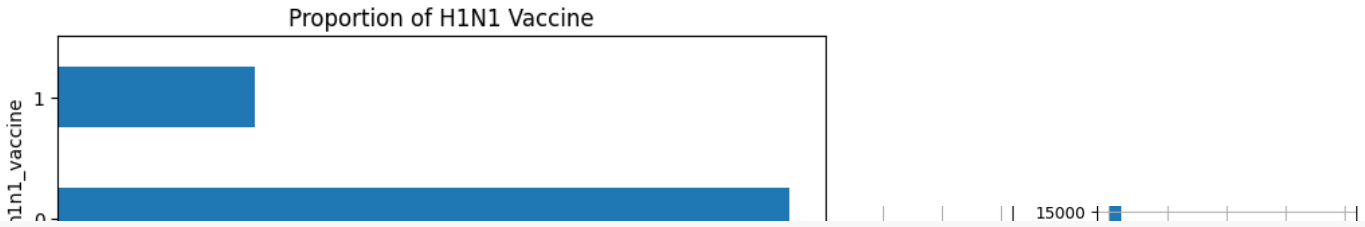
```
0    0.787546
1    0.212454
Name: h1n1_vaccine, dtype: float64
```

```
target['seasonal_vaccine'].value_counts(normalize=True)
```

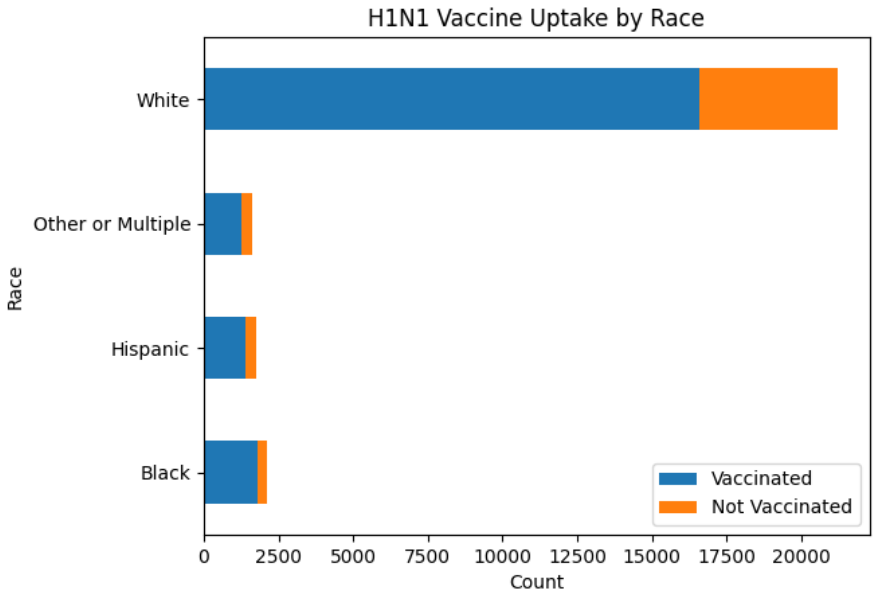
Creating a copy...

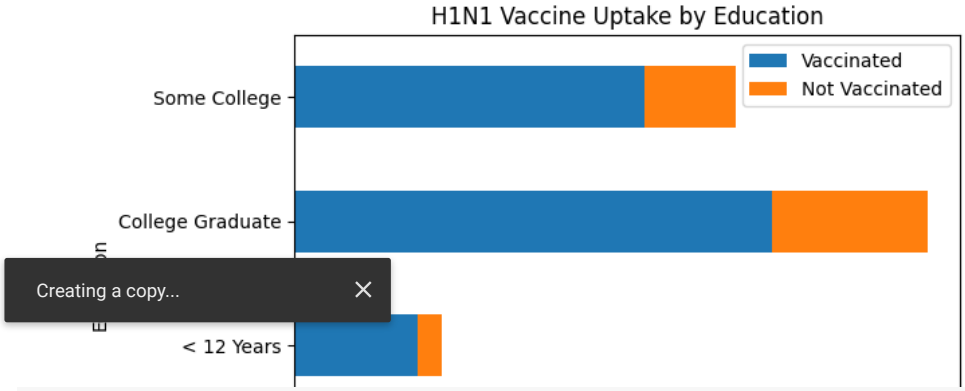
```
Name: seasonal_vaccine, dtype: float64
```

```
fig, ax = plt.subplots(2, 1, sharex=True)

n_obs = target.shape[0]

(target['h1n1_vaccine']
    .value_counts()
    .div(n_obs)
    .plot.barh(title="Proportion of H1N1 Vaccine", ax=ax[0])
)
ax[0].set_ylabel("h1n1_vaccine")

(target['seasonal_vaccine']
    .value_counts()
    .div(n_obs)
    .plot.barh(title="Proportion of Seasonal Vaccine", ax=ax[1])
)
ax[1].set_ylabel("seasonal_vaccine")

fig.tight_layout()
```




```
import matplotlib.pyplot as plt

# Calculate counts of respondents by demographic category and vaccine status
race_vaccine_counts = merged_df.groupby(['race', 'h1n1_vaccine']).size().unstack()
education_vaccine_counts = merged_df.groupby(['education', 'h1n1_vaccine']).size().unstack()
age_vaccine_counts = merged_df.groupby(['age_group', 'h1n1_vaccine']).size().unstack()
sex_vaccine_counts = merged_df.groupby(['sex', 'h1n1_vaccine']).size().unstack()
marital_status_vaccine_counts = merged_df.groupby(['marital_status', 'h1n1_vaccine']).size().unstack()
income_vaccine_counts = merged_df.groupby(['income_poverty', 'h1n1_vaccine']).size().unstack()

# Plot the counts for each demographic category
race_vaccine_counts.plot(kind='barh', stacked=True)
plt.xlabel('Count')
plt.ylabel('Race')
plt.title('H1N1 Vaccine Uptake by Race')
plt.legend(['Vaccinated', 'Not Vaccinated'])
plt.show()

education_vaccine_counts.plot(kind='barh', stacked=True)
plt.xlabel('Count')
plt.ylabel('Education')
plt.title('H1N1 Vaccine Uptake by Education')
plt.legend(['Vaccinated', 'Not Vaccinated'])
plt.show()

                                                    ', stacked=True)
plt.ylabel('Age Group')
plt.title('H1N1 Vaccine Uptake by Age')
plt.legend(['Vaccinated', 'Not Vaccinated'])
plt.show()

sex_vaccine_counts.plot(kind='barh', stacked=True)
plt.xlabel('Count')
plt.ylabel('Sex')
plt.title('H1N1 Vaccine Uptake by Sex')
plt.legend(['Vaccinated', 'Not Vaccinated'])
plt.show()

marital_status_vaccine_counts.plot(kind='barh', stacked=True)
plt.xlabel('Count')
plt.ylabel('Marital Status')
plt.title('H1N1 Vaccine Uptake by Marital Status')
plt.legend(['Vaccinated', 'Not Vaccinated'])
plt.show()

income_vaccine_counts.plot(kind='barh', stacked=True)
plt.xlabel('Count')
plt.ylabel('income_poverty')
plt.title('H1N1 Vaccine Uptake by Income')
plt.legend(['Vaccinated', 'Not Vaccinated'])
plt.show()
```

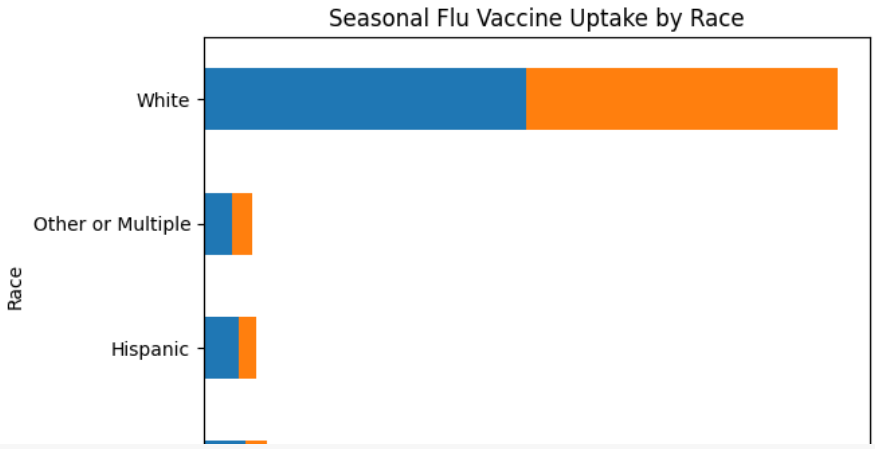




Creating a copy...

```
import matplotlib.pyplot as plt

# Calculate counts of respondents by demographic category and vaccine status
race_seasonal_counts = merged_df.groupby(['race', 'seasonal_vaccine']).size().unstack()
race_h1n1_counts = merged_df.groupby(['race', 'h1n1_vaccine']).size().unstack()

education_seasonal_counts = merged_df.groupby(['education', 'seasonal_vaccine']).size().unstack()
education_h1n1_counts = merged_df.groupby(['education', 'h1n1_vaccine']).size().unstack()

age_seasonal_counts = merged_df.groupby(['age_group', 'seasonal_vaccine']).size().unstack()
age_h1n1_counts = merged_df.groupby(['age_group', 'h1n1_vaccine']).size().unstack()

sex_seasonal_counts = merged_df.groupby(['sex', 'seasonal_vaccine']).size().unstack()
sex_h1n1_counts = merged_df.groupby(['sex', 'h1n1_vaccine']).size().unstack()

marital_status_seasonal_counts = merged_df.groupby(['marital_status', 'seasonal_vaccine']).size().unstack()
marital_status_h1n1_counts = merged_df.groupby(['marital_status', 'h1n1_vaccine']).size().unstack()

income_seasonal_counts = merged_df.groupby(['income_poverty', 'seasonal_vaccine']).size().unstack()
income_h1n1_counts = merged_df.groupby(['income_poverty', 'h1n1_vaccine']).size().unstack()

# Plot the counts for each demographic category and vaccine status
race_seasonal_counts.plot(kind='barh', stacked=True)
plt.xlabel('Count')
plt.ylabel('Race')
plt.title('Seasonal Flu Vaccine Uptake by Race')
plt.legend(['Not Vaccinated', 'Vaccinated'])
plt.show()

race_h1n1_counts.plot(kind='barh', stacked=True)
plt.xlabel('Count')
plt.ylabel('Race')
plt.title('H1N1 Vaccine Uptake by Race')
plt.legend(['Not Vaccinated', 'Vaccinated'])
plt.show()
```

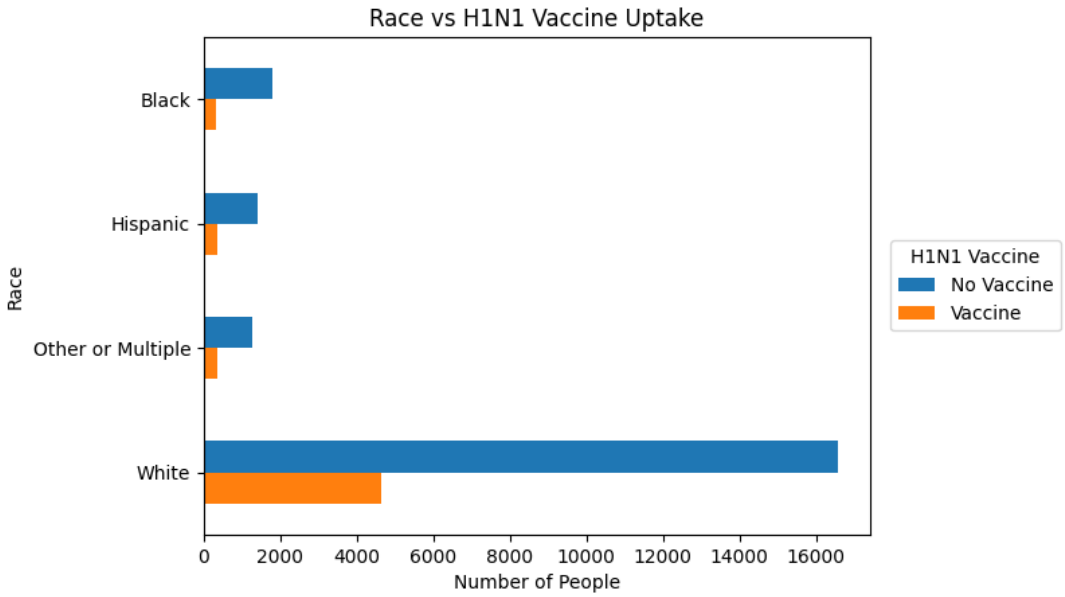
```
education_seasonal_counts.plot(kind='barh', stacked=True)
plt.xlabel('Count')
plt.ylabel('Education')
plt.title('Seasonal Flu Vaccine Uptake by Education')
plt.legend(['Not Vaccinated', 'Vaccinated'])
plt.show()

education_h1n1_counts.plot(kind='barh', stacked=True)
plt.xlabel('Count')
plt.ylabel('Education')
plt.title('H1N1 Vaccine Uptake by Education')
plt.legend(['Not Vaccinated', 'Vaccinated'])
plt.show()

age_seasonal_counts.plot(kind='barh', stacked=True)
plt.xlabel('Count')
plt.ylabel('Age')
plt.title('Seasonal Flu Vaccine Uptake by Age')
plt.legend(['Not Vaccinated', 'Vaccinated'])
plt.show()

age_h1n1_counts.plot(kind='barh', stacked=True)
plt.xlabel('Count')
plt.ylabel('Age')
plt.title('H1N1 Vaccine Uptake by Age')
plt.legend(['Not Vaccinated', 'Vaccinated'])
plt.show()

sex_seasonal_counts.plot(kind='barh', stacked=True)
plt.xlabel('Count')
plt.ylabel('Sex')
plt.title('Seasonal Flu Vaccine Uptake by Sex')
plt.legend(['Not Vaccinated', 'Vaccinated'])
plt.show()

                                                stacked=True)
plt.ylabel('Sex')
plt.title('H1N1')
```

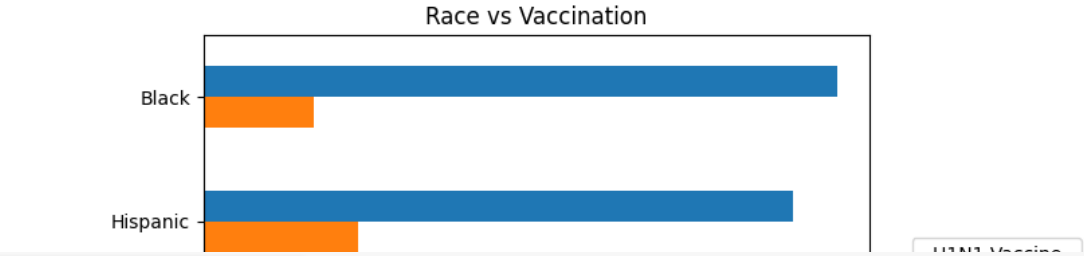



```
import matplotlib.pyplot as plt

# Calculate counts of respondents by race and H1N1 vaccine uptake
race_counts = merged_df.groupby(['race', 'h1n1_vaccine']).size().unstack()

# Plot the counts
ax = race_counts.plot.barh()
ax.invert_yaxis()
ax.legend(['No Vaccine', 'Vaccine'], loc='center right', bbox_to_anchor=(1.3, 0.5), title='H1N1 Vaccine')
ax.set_ylabel('Race')
ax.set_xlabel('Number of People')
ax.set_title('Race vs H1N1 Vaccine Uptake')
plt.savefig('race.png', bbox_inches='tight', dpi=300)

# Calculate proportions of vaccine uptake by race
race_totals = race_counts.sum(axis='columns')
                                  _totals, axis='index')
```



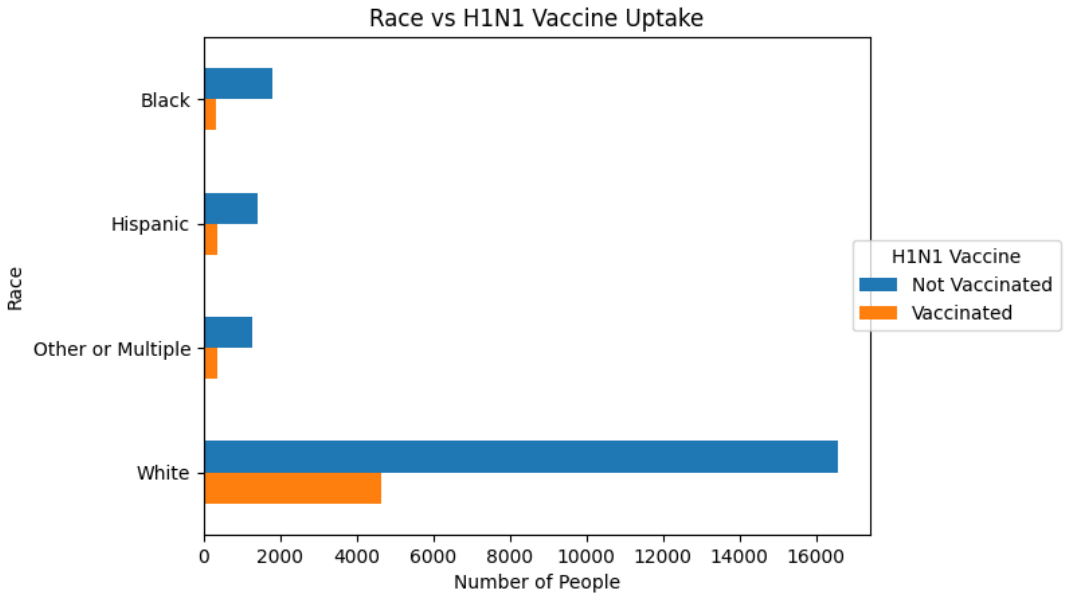
```
ax = proportions.plot.barh()
ax.invert_yaxis()
ax.legend(['No Vaccine', 'Vaccine'], loc='center left', bbox_to_anchor=(1.05, 0.5), title='H1N1 Vaccine')
ax.set_ylabel('Race')
ax.set_xlabel('Proportion')
ax.set_title('Race vs H1N1 Vaccine Uptake')
plt.title('Race vs Vaccination')  # Update the title
plt.show()

# Plot the stacked proportions
ax = proportions.plot.barh(stacked=True)
ax.invert_yaxis()
ax.legend(['No Vaccine', 'Vaccine'], loc='center left', bbox_to_anchor=(1.05, 0.5), title='H1N1 Vaccine')
ax.set_ylabel('Race')
ax.set_xlabel('Proportion')
ax.set_title('Race vs H1N1 Vaccine Uptake')
plt.title('Race vs Vaccination')  # Update the title
plt.show()
```

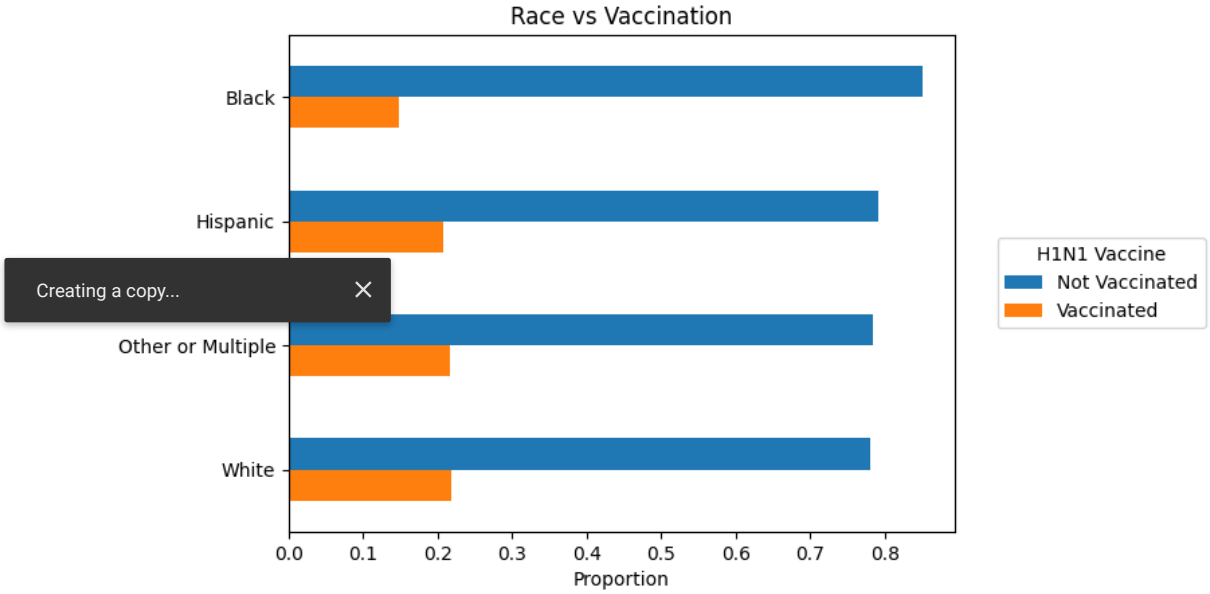


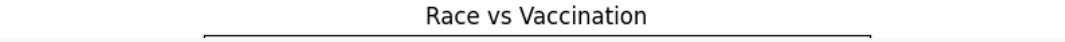


Creating a copy...

```
# Calculate counts of respondents by race and H1N1 vaccine uptake
race_counts = merged_df.groupby(['race', 'h1n1_vaccine']).size().unstack(fill_value=0)

# Plot the counts
ax = race_counts.plot.barh()
ax.invert_yaxis()
ax.legend(['Not Vaccinated', 'Vaccinated'], loc='center right', bbox_to_anchor=(1.3, 0.5), title='H1N1 Vaccine')
ax.set_ylabel('Race')
ax.set_xlabel('Number of People')
ax.set_title('Race vs H1N1 Vaccine Uptake')
plt.savefig('race.png', bbox_inches='tight', dpi=300)

# Calculate proportions of vaccine uptake by race
race_totals = race_counts.sum(axis='columns')
proportions = race_counts.div(race_totals, axis='index')

# Plot the proportions
ax = proportions.plot.barh()
ax.invert_yaxis()
ax.legend(['Not Vaccinated', 'Vaccinated'], loc='center left', bbox_to_anchor=(1.05, 0.5), title='H1N1 Vaccine')
ax.set_ylabel('Race')
ax.set_xlabel('Proportion')
ax.set_title('Race vs H1N1 Vaccine Uptake')
plt.title('Race vs Vaccination')  # Update the title
plt.show()

# Plot the stacked proportions
ax = proportions.plot.barh(stacked=True)
ax.invert_yaxis()
ax.legend(['Not Vaccinated', 'Vaccinated'], loc='center left', bbox_to_anchor=(1.05, 0.5), title='H1N1 Vaccine')
ax.set_ylabel('Race')
ax.set_xlabel('Proportion')
ax.set_title('Race vs H1N1 Vaccine Uptake')
plt.title('Race vs Vaccination')  # Update the title
plt.show()
```








```
test_df=merged_df[['race', 'h1n1_vaccine']]
test_df
```

	race	h1n1_vaccine
0	White	0
1	White	0
2	White	0
3	White	0
4	White	0
...	...	...
26702	White	0
26703	White	0
26704	White	0
26705	Hispanic	0
26706	White	0

26707 rows × 2 columns

```
#arragning the values  from the higest to the smallest
test_df1 = test_df.value_counts().to_frame('values').reset_index()
test_df1
```

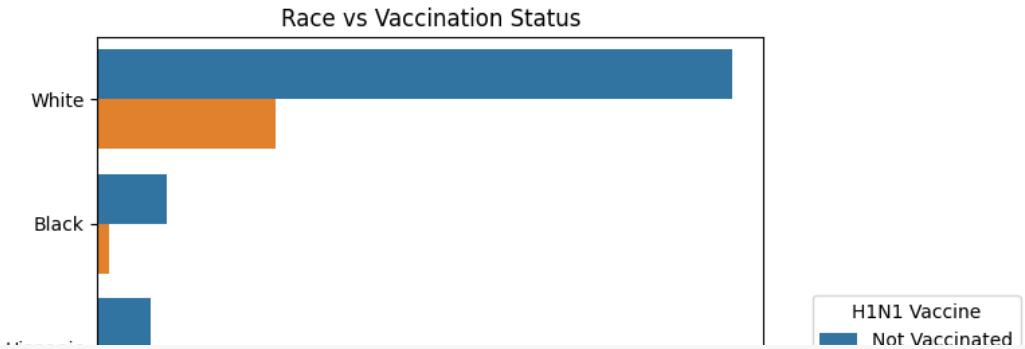
	race	h1n1_vaccine	values
0	White	0	16577
1	White	1	4645
2	Black	0	1803
3	Hispanic	0	1390
4	Other or Multiple	0	1263
5	Hispanic	1	365
6	Other or Multiple	1	349
7	Black	1	315

```
test_df=merged_df[['race', 'h1n1_vaccine']]
test_df
```

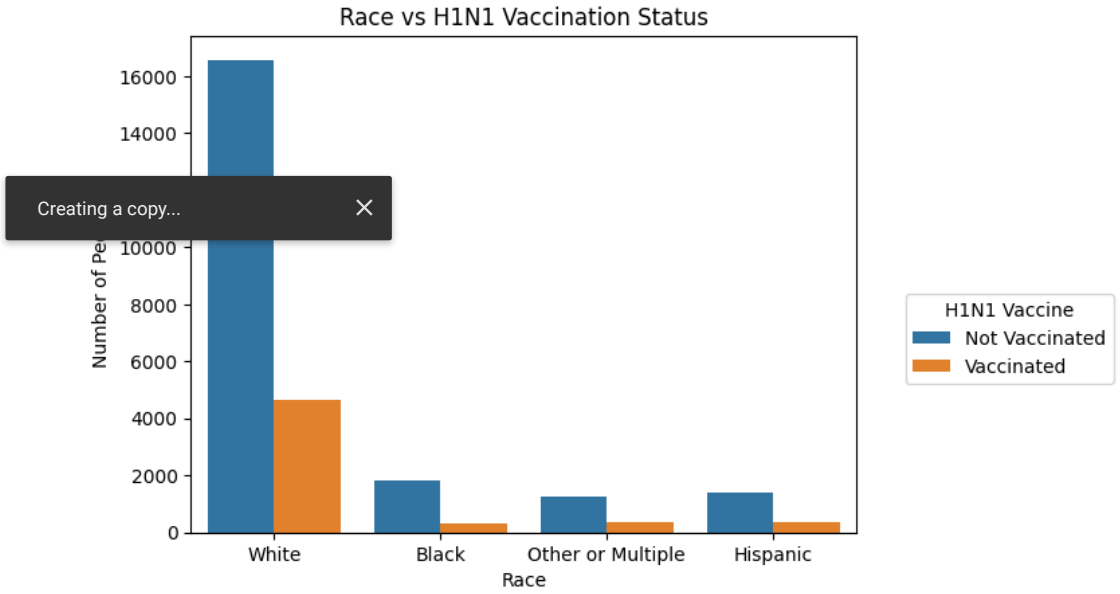
	race	h1n1_vaccine
0	White	0
1	White	0
2	White	0
3	White	0
...	...	...
26702	White	0
26703	White	0
26704	White	0
26705	Hispanic	0
26706	White	0

26707 rows × 2 columns


```
ax=sns.barplot(data=test_df1, x='values', y='race', hue='h1n1_vaccine', palette= 'tab10')
ax.set_ylabel('')
ax.set_xlabel('Number of People')
ax.set_title('Race vs Vaccination Status')

#ax.legend(['Not Vaccinated', 'Vaccinated'], title = 'H1N1 Vaccine',
#         bbox_to_anchor=(1.4, 0.5));

labels=['Not Vaccinated', 'Vaccinated']
h, l = ax.get_legend_handles_labels()
ax.legend(h, labels, title='H1N1 Vaccine', bbox_to_anchor=(1.4, 0.5));
plt.savefig('race.png', bbox_inches='tight', dpi=300)
```

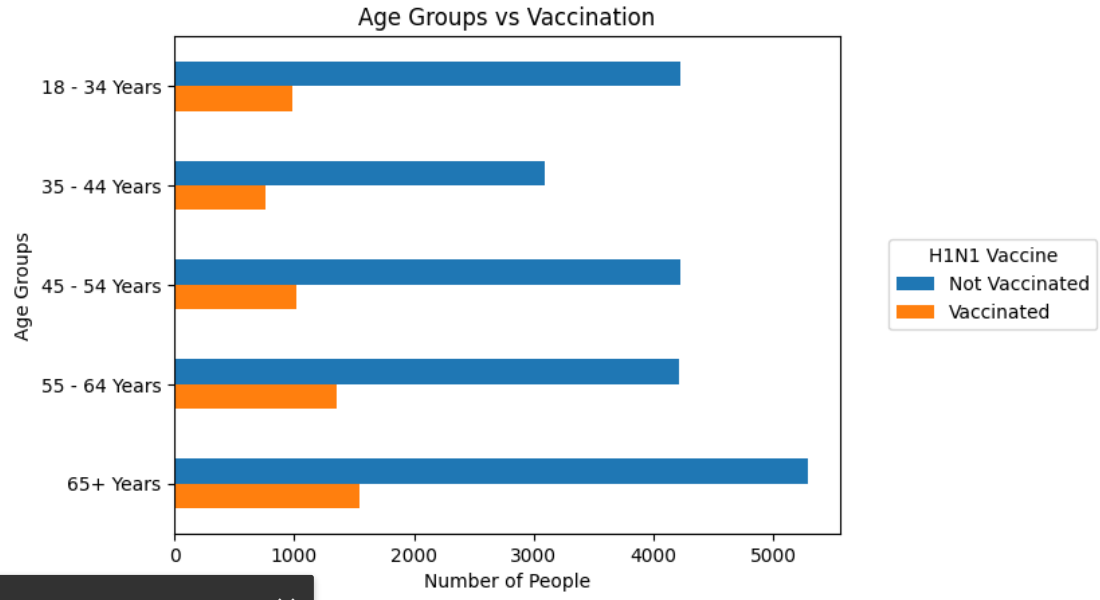



```
ax = sns.countplot(data=test_df, x='race', hue='h1n1_vaccine', palette='tab10')
ax.set_ylabel('Number of People')
ax.set_xlabel('Race')
ax.set_title('Race vs H1N1 Vaccination Status')

labels = ['Not Vaccinated', 'Vaccinated']
h, _ = ax.get_legend_handles_labels()
ax.legend(h, labels, title='H1N1 Vaccine', bbox_to_anchor=(1.4, 0.5))

plt.savefig('race.png', bbox_inches='tight', dpi=300)
plt.show()
```




```
import matplotlib.pyplot as plt

counts3 = merged_df.groupby(['age_group', 'h1n1_vaccine']).size().unstack('h1n1_vaccine')

# Plotting the bar plot
ax = counts3.plot(kind='barh')
ax.invert_yaxis()

# Customizing the plot
ax.legend(['Not Vaccinated', 'Vaccinated'], loc='center right', bbox_to_anchor=(1.4, 0.5), title='H1N1 Vaccine')
ax.set_ylabel('Age Groups')
ax.set_xlabel('Number of People')
ax.set_title('Age Groups vs Vaccination')

# Saving the plot
plt.savefig('ages.png', bbox_inches='tight', dpi=300)
plt.show()

# Calculate the proportion of vaccinated and not vaccinated individuals within each age group
age_group_totals = counts3.sum(axis=1)
age_group_proportions = counts3.divide(age_group_totals, axis='index')

# Plotting the stacked bar plot
```

```
ax = age_group_proportions.plot(kind='barh', stacked=True)
ax.invert_yaxis()

# Customizing the plot
ax.legend(['Not Vaccinated', 'Vaccinated'], loc='center left', bbox_to_anchor=(1.05, 0.5), title='H1N1 Vaccine')
ax.set_ylabel('Age Groups')
ax.set_xlabel('Proportion of People')
ax.set_title('Age Groups vs Vaccination')

plt.show()
```



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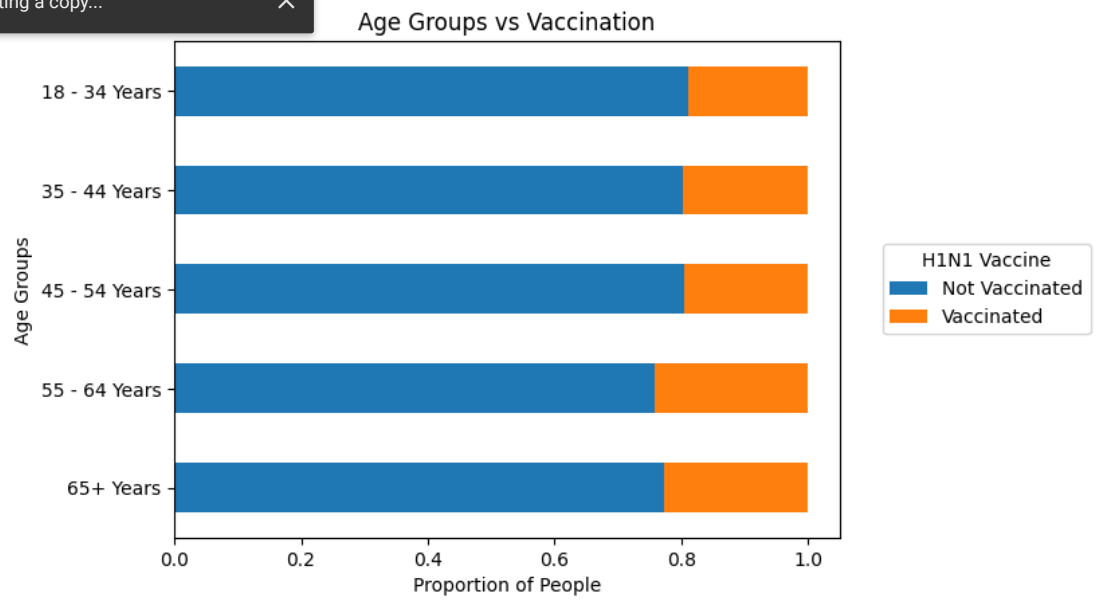
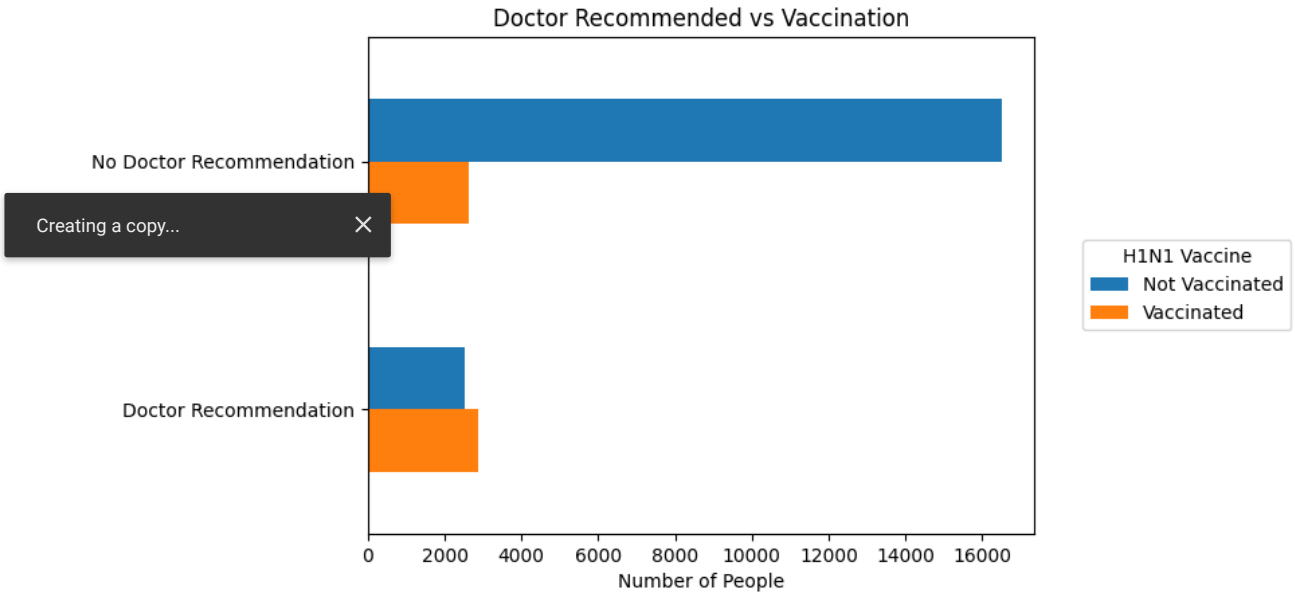



```
import matplotlib.pyplot as plt

# Counting the number of vaccinated and not vaccinated individuals for each doctor recommendation
counts4 = (merged_df[['doctor_recc_h1n1', 'h1n1_vaccine']]
              .groupby(['doctor_recc_h1n1', 'h1n1_vaccine'])
              .size()
              .unstack('h1n1_vaccine'))

# Plotting the bar plot
ax = counts4.plot.barh()
ax.invert_yaxis()

# Customizing the plot
ax.legend(['Not Vaccinated', 'Vaccinated'], loc='center right', bbox_to_anchor=(1.4, 0.5), title='H1N1 Vaccine')
ax.set_yticklabels(['No Doctor Recommendation', 'Doctor Recommendation'])
```

```
ax.set_ylabel('')
ax.set_xlabel('Number of People')
ax.set_title('Doctor Recommended vs Vaccination')

# Saving the plot
plt.savefig('docrec2.png', bbox_inches='tight', dpi=300)

# Calculating the proportion of vaccinated and not vaccinated individuals for each doctor recommendation
h_ins = counts4.sum(axis='columns')
ins = counts4.div(h_ins, axis='index')

# Plotting the stacked bar plot
ax = ins.plot.barh(stacked=True)
ax.invert_yaxis()

# Customizing the plot
ax.legend(['Not Vaccinated', 'Vaccinated'], loc='center left', bbox_to_anchor=(1.05, 0.5), title='H1N1 Vaccine')
ax.set_yticklabels(['No Doctor Recommendation', 'Doctor Recommendation'])
ax.set_ylabel('')
ax.set_xlabel('Proportion of People')
ax.set_title('Doctor Recommended vs Vaccination')

# Saving the plot
plt.savefig('docrec.png', bbox_inches='tight', dpi=300)
```



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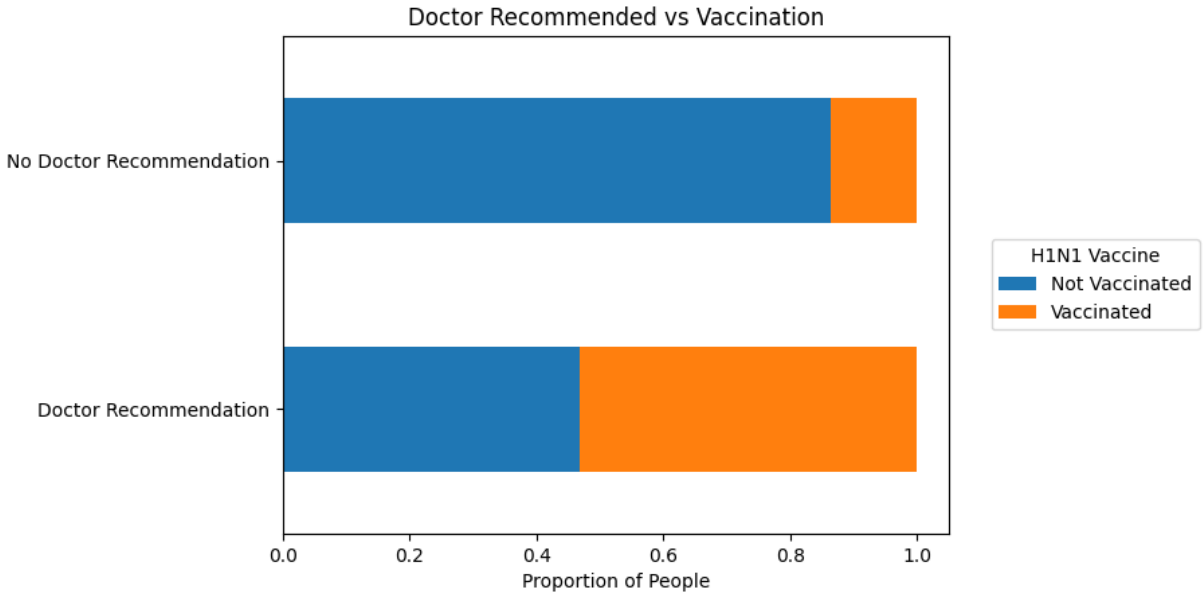
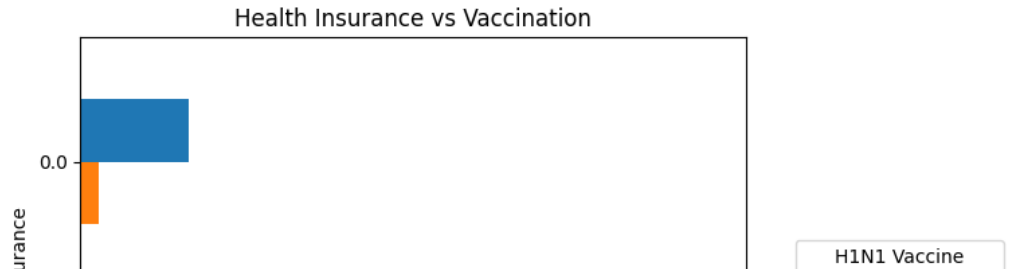


```
import matplotlib.pyplot as plt

# Counting the number of vaccinated and not vaccinated individuals for each health insurance status
counts5 = (merged_df[['health_insurance', 'h1n1_vaccine']]
              .groupby(['health_insurance', 'h1n1_vaccine'])
              .size()
              .unstack('h1n1_vaccine'))

# Plotting the bar plot
ax = counts5.plot.barh()
ax.invert_yaxis()

# Customizing the plot
ax.legend(['Not Vaccinated', 'Vaccinated'], loc='center right', bbox_to_anchor=(1.4, 0.5), title='H1N1 Vaccine')
ax.set_ylabel('Health Insurance')
ax.set_xlabel('Number of People')
ax.set_title('Health Insurance vs Vaccination')

# Saving the plot
plt.savefig('income.png', bbox_inches='tight', dpi=300)

# Calculating the proportion of vaccinated and not vaccinated individuals for each health insurance status
income = counts5.sum(axis='columns')
p_income = counts5.div(income, axis='index')

# Plotting the stacked bar plot
ax = p_income.plot.barh(stacked=True)
ax.invert_yaxis()

# Customizing the plot
ax.legend(['Not Vaccinated', 'Vaccinated'], loc='center left', bbox_to_anchor=(1.05, 0.5), title='H1N1 Vaccine')
ax.set_ylabel('Health Insurance')
ax.set_xlabel('Proportion of People')
ax.set_title('Health Insurance vs Vaccination')

Creating a copy...                                                                    ', bbox_inches='tight', dpi=300)
```



Modeling

```
### This is formatted as code
```

```
X = merged_df.drop(['seasonal_vaccine', 'h1n1_vaccine'], axis=1)
y = merged_df['h1n1_vaccine']
X.head()
```

	respondent_id	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_
0	0	1.0	0.0	0.0	0.0	0.0	
1	1	3.0	2.0	0.0	1.0	0.0	
2	2	1.0	1.0	0.0	1.0	0.0	
3	3	1.0	1.0	0.0	1.0	0.0	
			1.0	0.0	1.0	0.0	

Creating a copy...

5 rows × 36 columns

```
y.describe()
```

```
count    26707.000000
mean         0.212454
std          0.409052
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          1.000000
Name: h1n1_vaccine, dtype: float64
```

```
# Train test Split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=1337)
X_train.shape
```

```
(20030, 36)
```

```
X_test.shape
```

```
(6677, 36)
```

```
y_train.describe()
```

```
count    20030.000000
mean         0.210984
std          0.408017
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
```

```
max          1.000000
Name: h1n1_vaccine, dtype: float64
```

```
y_train.value_counts(normalize=True)
```

```
0    0.789016
1    0.210984
Name: h1n1_vaccine, dtype: float64
```

e notice that the target data is imbalanced, with 79% not getting the vaccine and 21% receiving the vaccine. We want to utilze SMOTE in order to over sample the vaccine class. Can utilize this after encoding for the categorical data.

One-Hot-Encode the categorical data

```
# Selecting all of the columns that contain 'objects' to One Hot Encode.
X_train_cat = X_train.select_dtypes('object')

ohe = OneHotEncoder(sparse=False)

dums = ohe.fit_transform(X_train_cat)
dums_df = pd.DataFrame(dums,
                       columns=ohe.get_feature_names_out(input_features=X_train_cat.columns),
                       index=X_train_cat.index)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_encoders.py:868: FutureWarning: `sparse` was renamed to `sparse_ou
  warnings.warn(
```

```
#check the information about the dums_df
dums_df.info()
```

Creating a copy...

```
aFrame'>
620 to 3223
Data columns (total 89 columns):
 #   Column                                     Non-Null Count  Dtype
---  ------                                     --------------  -----
 0   age_group_18 - 34 Years                    20030 non-null  float64
 1   age_group_35 - 44 Years                    20030 non-null  float64
 2   age_group_45 - 54 Years                    20030 non-null  float64
 3   age_group_55 - 64 Years                    20030 non-null  float64
 4   age_group_65+ Years                        20030 non-null  float64
 5   education_12 Years                         20030 non-null  float64
 6   education_< 12 Years                       20030 non-null  float64
 7   education_College Graduate                 20030 non-null  float64
 8   education_Some College                     20030 non-null  float64
 9   education_nan                              20030 non-null  float64
 10  race_Black                                 20030 non-null  float64
 11  race_Hispanic                              20030 non-null  float64
 12  race_Other or Multiple                     20030 non-null  float64
 13  race_White                                 20030 non-null  float64
 14  sex_Female                                 20030 non-null  float64
 15  sex_Male                                   20030 non-null  float64
 16  income_poverty_<= $75,000, Above Poverty   20030 non-null  float64
 17  income_poverty_> $75,000                   20030 non-null  float64
 18  income_poverty_Below Poverty               20030 non-null  float64
 19  income_poverty_nan                         20030 non-null  float64
 20  marital_status_Married                     20030 non-null  float64
 21  marital_status_Not Married                 20030 non-null  float64
 22  marital_status_nan                         20030 non-null  float64
 23  rent_or_own_Own                            20030 non-null  float64
 24  rent_or_own_Rent                           20030 non-null  float64
 25  rent_or_own_nan                            20030 non-null  float64
 26  employment_status_Employed                 20030 non-null  float64
 27  employment_status_Not in Labor Force       20030 non-null  float64
 28  employment_status_Unemployed               20030 non-null  float64
 29  employment_status_nan                      20030 non-null  float64
 30  hhs_geo_region_atmpeygn                    20030 non-null  float64
 31  hhs_geo_region_bhuqouqj                    20030 non-null  float64
 32  hhs_geo_region_dqpwygqj                    20030 non-null  float64
 33  hhs_geo_region_fpwskwrf                    20030 non-null  float64
 34  hhs_geo_region_kbazzjca                    20030 non-null  float64
 35  hhs_geo_region_lrircsnp                    20030 non-null  float64
 36  hhs_geo_region_lzgpxyit                    20030 non-null  float64
 37  hhs_geo_region_mlyzmhmf                    20030 non-null  float64
 38  hhs_geo_region_oxchjgsf                    20030 non-null  float64
 39  hhs_geo_region_qufhixun                    20030 non-null  float64
```

```
 40  census_msa_MSA, Not Principle  City       20030 non-null  float64
 41  census_msa_MSA, Principle City            20030 non-null  float64
 42  census_msa_Non-MSA                        20030 non-null  float64
 43  employment_industry_arjwrbjb              20030 non-null  float64
 44  employment_industry_atmlpfrs              20030 non-null  float64
 45  employment_industry_cfqqtusy              20030 non-null  float64
 46  employment_industry_dotnnunm              20030 non-null  float64
 47  employment_industry_fcxhlnwr              20030 non-null  float64
 48  employment_industry_haxffmxo              20030 non-null  float64
 49  employment_industry_ldnlellj              20030 non-null  float64
 50  employment_industry_mcubkhph              20030 non-null  float64
 51  employment_industry_mfikgejo              20030 non-null  float64
 52  employment_industry_msuufmds              20030 non-null  float64
```

```
dums_df.head()
```

	age_group_18 - 34 Years	age_group_35 - 44 Years	age_group_45 - 54 Years	age_group_55 - 64 Years	age_group_65+ Years	education_12 Years	education_< 12 Years	education_College Graduate	educat
24620	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	
5457	0.0	0.0	0.0	1.0	0.0	1.0	0.0	0.0	
1936	0.0	0.0	0.0	0.0	1.0	1.0	0.0	0.0	
19956	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	
2502	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

5 rows × 89 columns

```
X_train_nums = X_train.select_dtypes('float64')

ss = StandardScaler()
```

Creating a copy...

```
nums_df = pd.DataFrame(ss.transform(X_train_nums), columns=X_train_nums.columns, index=X_train_nums.index)
```

```
#combine the standardized numerical columns (nums_df) and the one-hot encoded categorical columns (dums_df) into a single Dataframe
X_train_clean = pd.concat([nums_df, dums_df], axis=1)
X_train_clean.head()
```

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_hands
24620	0.420121	-0.419285	-0.226384	0.617385	-0.274045	0.456855
5457	0.420121	-0.419285	4.417275	0.617385	-0.274045	0.456855
1936	-1.780802	-0.419285	-0.226384	0.617385	-0.274045	0.456855
19956	-0.680340	-0.419285	-0.226384	-1.619735	-0.274045	-2.188880
2502	-0.680340	-2.037583	4.417275	-1.619735	-0.274045	0.456855

5 rows × 112 columns

```
X_train_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20030 entries, 24620 to 3223
Columns: 112 entries, h1n1_concern to employment_occupation_nan
dtypes: float64(112)
memory usage: 17.3 MB
```

```
X_test_cat = X_test.select_dtypes('object')

ohe = OneHotEncoder(sparse=False)
test_dums = ohe.fit_transform(X_test_cat)
test_dums_df = pd.DataFrame(test_dums,
                            columns=ohe.get_feature_names_out(X_test_cat.columns),
```

```
                            index=X_test_cat.index)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_encoders.py:868: FutureWarning: `sparse` was renamed to `sparse_ou
  warnings.warn(
```

```
#performe standard scaling on the numerical columns of X_test and stored the transformed data in test_nums_df
X_test_nums = X_test.select_dtypes('float64')

test_nums = ss.transform(X_test_nums)
test_nums_df = pd.DataFrame(test_nums,
                            columns=X_test_nums.columns,
                            index=X_test_nums.index)
```

```
#concatenate it with test_dums_df to create the final cleaned test dataset:
X_test_clean = pd.concat([test_nums_df, test_dums_df], axis=1)
X_test_clean.head()
```

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_hands
762	0.420121	-0.419285	4.417275	0.617385	3.649034	0.456855
2299	-0.680340	1.199012	-0.226384	-1.619735	-0.274045	0.456855
9680	1.520583	-0.419285	-0.226384	0.617385	-0.274045	0.456855
15632	0.420121	-0.419285	-0.226384	0.617385	-0.274045	0.456855
13735	0.420121	-0.419285	-0.226384	0.617385	-0.274045	0.456855

5 rows × 112 columns

Creating a copy...

Double click (or enter) to edit

```
X_test_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 6677 entries, 762 to 8220
Columns: 112 entries, h1n1_concern to employment_occupation_nan
dtypes: float64(112)
memory usage: 5.8 MB
```

Utilizing SMOTE

```
# Drop samples with missing values from the training and test data
X_train_clean_dropped = X_train_clean.dropna()
y_train_dropped = y_train.loc[X_train_clean_dropped.index]

X_test_clean_dropped = X_test_clean.dropna()
y_test_dropped = y_test.loc[X_test_clean_dropped.index]

# Apply SMOTE to the dropped training data
X_train_resampled, y_train_resampled = smote.fit_resample(X_train_clean_dropped, y_train_dropped)
```

```
from sklearn.impute import SimpleImputer

# Create an instance of SimpleImputer to impute missing values
imputer = SimpleImputer(strategy='mean')

# Fit the imputer on the training data
imputer.fit(X_train_clean)

# Transform the training and test data with the imputer
X_train_imputed = imputer.transform(X_train_clean)
```

```
X_test_imputed = imputer.transform(X_test_clean)

# Apply SMOTE to the imputed training data
X_train_resampled, y_train_resampled = smote.fit_resample(X_train_imputed, y_train)
```

```
# View the first few rows of the DataFrame
X_train_clean.head()
```

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_hands
24620	0.420121	-0.419285	-0.226384	0.617385	-0.274045	0.456855
5457	0.420121	-0.419285	4.417275	0.617385	-0.274045	0.456855
1936	-1.780802	-0.419285	-0.226384	0.617385	-0.274045	0.456855
19956	-0.680340	-0.419285	-0.226384	-1.619735	-0.274045	-2.188880
2502	-0.680340	-2.037583	4.417275	-1.619735	-0.274045	0.456855

5 rows × 112 columns

```
# View the summary statistics of y_train_resampled
y_train_resampled.describe()
```

```
count    31608.000000
mean         0.500000
std          0.500008
min          0.000000
max          1.000000
Name: h1n1_vaccine, dtype: float64
```

Creating a copy...

```
y_train_resampled.value_counts()
```

```
0    15804
1    15804
Name: h1n1_vaccine, dtype: int64
```

Models. Descision trees

```
from sklearn.tree import DecisionTreeClassifier

# Create the decision tree model
tree_model = DecisionTreeClassifier(max_depth=2)

# Fit the model to the resampled training data
tree_model.fit(X_train_resampled, y_train_resampled)

# Get the feature importances
feature_importances = tree_model.feature_importances_

# Create a dataframe to display the feature importances
importance_df = pd.DataFrame({'Feature': X_train_clean.columns, 'Importance': feature_importances})
importance_df = importance_df.sort_values(by='Importance', ascending=False)

# Display the feature importances
print(importance_df)
```

```
                          Feature  Importance
9               doctor_recc_h1n1     0.61464
14              health_insurance     0.38536
70   employment_industry_fcxhlnwr     0.00000
82   employment_industry_vjjrobsf     0.00000
```

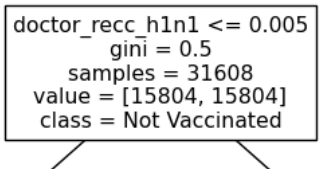
```
81   employment_industry_saaquncn     0.00000
..                            ...         ...
35         race_Other or Multiple     0.00000
34                 race_Hispanic     0.00000
33                    race_Black     0.00000
32                 education_nan     0.00000
111     employment_occupation_nan     0.00000

[112 rows x 2 columns]
```

```
from sklearn.tree import DecisionTreeClassifier

from sklearn.tree import DecisionTreeClassifier

# Decision Tree with max_depth of 2 and a random_state of 1337.
tree_clf = DecisionTreeClassifier(max_depth=2, random_state=1337)
tree_clf.fit(X_train_resampled, y_train_resampled)

importance = tree_clf.feature_importances_
feature_names = X_train_clean.columns

# Create a dataframe to display the feature importance
feature_importance_df = pd.DataFrame({'Feature': feature_names, 'Importance': importance})
feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)

# Display the feature importance
print(feature_importance_df)
```

```
                          Feature  Importance
9               doctor_recc_h1n1     0.61464
14              health_insurance     0.38536
70   employment_industry_fcxhlnwr     0.00000
82   employment_industry_vjjrobsf     0.00000
81   employment_industry_saaquncn     0.00000
                             ...         ...
                            iple     0.00000
                            anic     0.00000
33                    race_Black     0.00000
32                 education_nan     0.00000
111     employment_occupation_nan     0.00000

[112 rows x 2 columns]
```



```
from sklearn import tree
import matplotlib.pyplot as plt

# Plot the decision tree
plt.figure(figsize=(12, 8))
tree.plot_tree(tree_clf, feature_names=X_train_clean.columns, filled=True, class_names=['Not Vaccinated', 'Vaccinated'])
plt.show()
```



the descsion tree shows that the two important fetures is the doctors reccomendation and insurance

```
from sklearn.impute import SimpleImputer

# Create the imputer with a strategy (e.g., mean, median, mode)
imputer = SimpleImputer(strategy='mean')

# Apply imputation to the selected features
X_train_imputed = imputer.fit_transform(X_train_selected)
X_test_imputed = imputer.transform(X_test_selected)

# Create a logistic regression model
logreg = LogisticRegression()

# Fit the model to the imputed training data
logreg.fit(X_train_imputed, y_train_selected)

# Make predictions on the imputed testing data
y_pred_imputed = logreg.predict(X_test_imputed)

# Evaluate the performance of the model
accuracy_imputed = accuracy_score(y_test_selected, y_pred_imputed)
precision_imputed = precision_score(y_test_selected, y_pred_imputed)
                                    st_selected, y_pred_imputed)
                                    ted, y_pred_imputed)

# Print the evaluation metrics
print("Accuracy (with imputation):", accuracy_imputed)
print("Precision (with imputation):", precision_imputed)
print("Recall (with imputation):", recall_imputed)
print("F1-score (with imputation):", f1_imputed)
```



```
Accuracy (with imputation): 0.8085063897763578
Precision (with imputation): 0.5604963805584281
Recall (with imputation): 0.5037174721189591
F1-score (with imputation): 0.5305922662750857
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# Create a logistic regression model
logreg = LogisticRegression()

# Fit the model to the training data
logreg.fit(X_train_imputed, y_train_selected)

# Predict the labels for training and testing data
y_train_pred = logreg.predict(X_train_imputed)
y_test_pred = logreg.predict(X_test_imputed)

# Calculate accuracy scores
train_accuracy = accuracy_score(y_train_selected, y_train_pred)
test_accuracy = accuracy_score(y_test_selected, y_test_pred)

# Print the accuracy scores
print("Training Accuracy:", train_accuracy)
print("Testing Accuracy:", test_accuracy)
```

```
Training Accuracy: 0.8016242843829051
Testing Accuracy: 0.8085063897763578
```

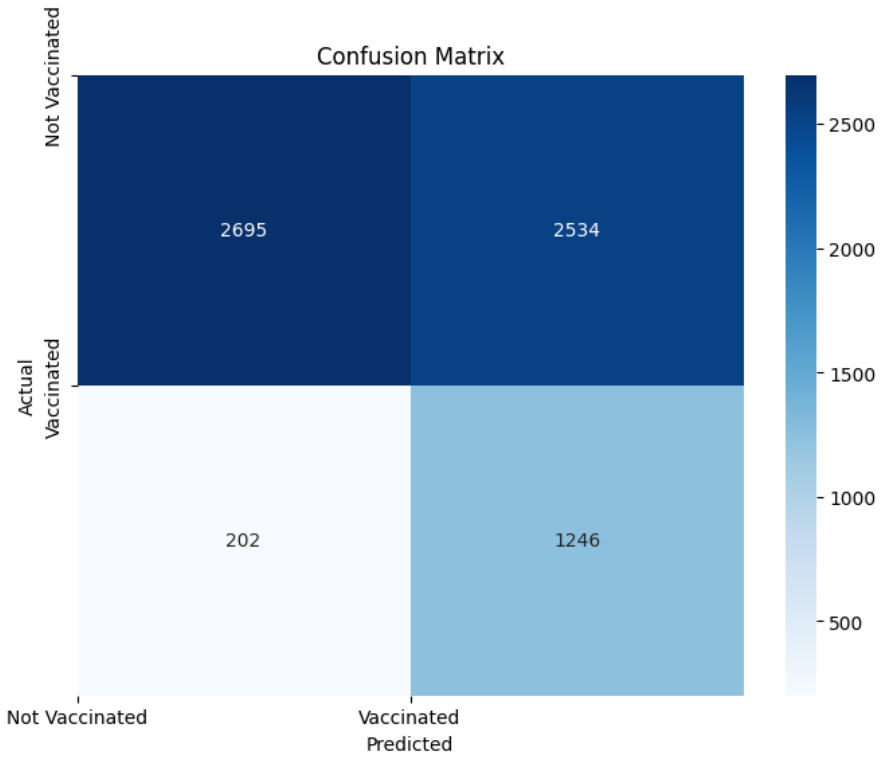
our accuracy on the training data is 80% and the Test data is 81%

```
from sklearn.impute import SimpleImputer

#calculate the confusion matrix for the predictions made by the decision tree model
# Create an instance of SimpleImputer to fill missing values with a strategy (e.g., mean, median)
imputer = SimpleImputer(strategy='mean')

# Fit the imputer on the training data and transform both training and testing data
X_train_imputed = imputer.fit_transform(X_train_clean)
X_test_imputed = imputer.transform(X_test_clean)

# Make predictions on the test data using the decision tree model
y_pred = tree_clf.predict(X_test_imputed)

# Calculate the confusion matrix
cm = confusion_matrix(y_test, y_pred)

print(cm)
```

```
[[2695 2534]
 [ 202 1246]]
```

```
import matplotlib.pyplot as plt
import seaborn as sns

# Create a confusion matrix heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')

# Add labels, title, and axis ticks
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.xticks([0, 1], ['Not Vaccinated', 'Vaccinated'])
plt.yticks([0, 1], ['Not Vaccinated', 'Vaccinated'])

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

Creating a copy...



```
from sklearn.metrics import precision_score

# Calculate the precision score for the test predictions
precision = precision_score(y_test, y_pred)

print("Precision:", precision)
```

```
Precision: 0.3296296296296296
```

Second model.

```
from sklearn.impute import SimpleImputer

# Impute missing values in numerical features with mean imputation
imputer = SimpleImputer(strategy='mean')
X_train_clean_imputed = imputer.fit_transform(X_train_clean)

# Impute missing values in categorical features with mode imputation
imputer = SimpleImputer(strategy='most_frequent')
X_train_clean_imputed = imputer.fit_transform(X_train_clean)
```

```
print("X_train_clean shape:", X_train_clean.shape)
print("y_train_resampled shape:", y_train_resampled.shape)
```

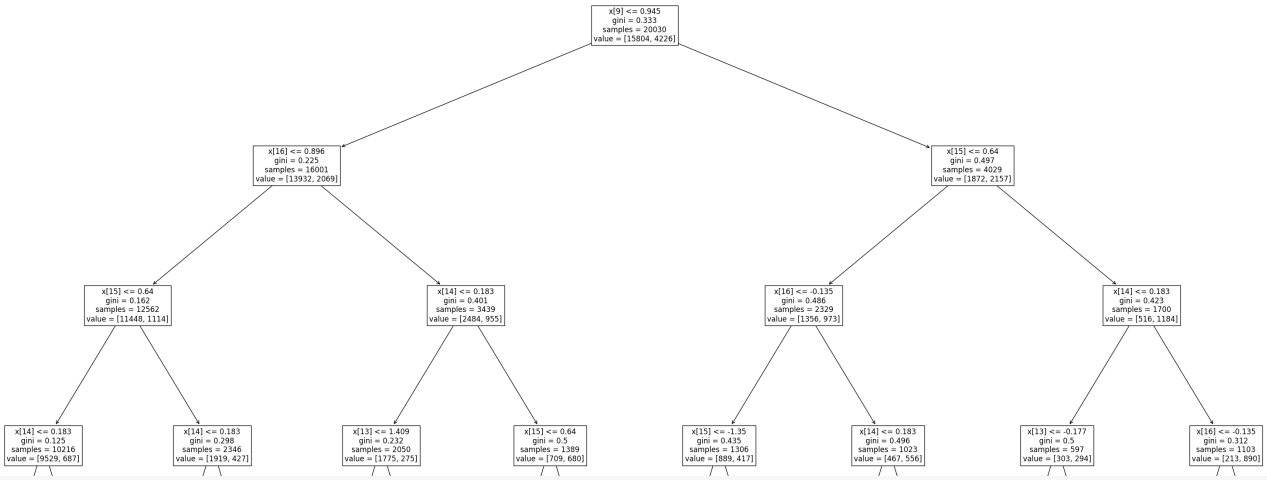
```
X_train_clean shape: (20030, 112)
y_train_resampled shape: (31608,)
```

```
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy='mean')

# Fit the imputer on the training data
imputer.fit(X_train_clean)

# Transform the training data
X_train_clean_imputed = imputer.transform(X_train_clean)

# Create and fit the decision tree classifier
tree_clf_2 = DecisionTreeClassifier(max_depth=5, random_state=1337)
tree_clf_2.fit(X_train_clean_imputed, y_train_resampled_subset)
```



```
DecisionTreeClassifier
DecisionTreeClassifier(max_depth=5, random_state=1337)
```

```
import matplotlib.pyplot as plt
from sklearn import tree

plt.figure(figsize=(40, 25))
tree.plot_tree(tree_clf_2, fontsize=12)
plt.show()
```




```
#calculating the accuracy of the train and test data
# Calculate accuracy on training data
train_accuracy = tree_clf_2.score(X_train_imputed, y_train)

# Calculate accuracy on testing data
test_accuracy = tree_clf_2.score(X_test_imputed, y_test)

print('Training Accuracy:', train_accuracy)
print('Testing Accuracy:', test_accuracy)
```

```
Training Accuracy: 0.8484772840738891
Testing Accuracy: 0.8388497828366033
```

Creating a copy...

```
sing the predicted labels
y_pred_3 = tree_clf_2.predict(X_test_imputed)
cm_3 = confusion_matrix(y_test, y_pred_3)

print("Confusion Matrix:")
print(cm_3)
```

```
Confusion Matrix:
[[5000  229]
 [ 847  601]]
```

```
#calculating the precision within our model
precision = cm_3[1, 1] / (cm_3[1, 1] + cm_3[0, 1])
print("Precision:", precision)
```

```
Precision: 0.7240963855421687
```

```
#calculating the importance
importance_scores = tree_clf_2.feature_importances_
feature_names = X_train_clean.columns

# Create a dictionary to map feature names to importance scores
feature_importances = dict(zip(feature_names, importance_scores))

# Sort the features based on their importance scores in descending order
sorted_features = sorted(feature_importances.items(), key=lambda x: x[1], reverse=True)

# Print the important features and their scores
for feature, score in sorted_features:
    print(f"{feature}: {score}")
```

```
doctor_recc_h1n1: 0.486141788212135
health_insurance: 0.1887583058595066
opinion_h1n1_vacc_effective: 0.13155960019863897
opinion_h1n1_risk: 0.12724764004987707
health_worker: 0.0337973346426029
employment_industry_fcxhlnwr: 0.012545881737271707
```

```
employment_industry_haxffmxo: 0.008284072046023203
education_nan: 0.004265901590055689
age_group_18 - 34 Years: 0.004059641054348122
opinion_seas_vacc_effective: 0.0017704534601999055
race_Black: 0.0015693811493408298
h1n1_concern: 0.0
h1n1_knowledge: 0.0
behavioral_antiviral_meds: 0.0
behavioral_avoidance: 0.0
behavioral_face_mask: 0.0
behavioral_wash_hands: 0.0
behavioral_large_gatherings: 0.0
behavioral_outside_home: 0.0
behavioral_touch_face: 0.0
doctor_recc_seasonal: 0.0
chronic_med_condition: 0.0
child_under_6_months: 0.0
opinion_h1n1_sick_from_vacc: 0.0
opinion_seas_risk: 0.0
opinion_seas_sick_from_vacc: 0.0
household_adults: 0.0
household_children: 0.0
age_group_35 - 44 Years: 0.0
age_group_45 - 54 Years: 0.0
age_group_55 - 64 Years: 0.0
age_group_65+ Years: 0.0
education_12 Years: 0.0
education_< 12 Years: 0.0
education_College Graduate: 0.0
education_Some College: 0.0
race_Hispanic: 0.0
race_Other or Multiple: 0.0
race_White: 0.0
sex_Female: 0.0
sex_Male: 0.0
income_poverty_<= $75,000, Above Poverty: 0.0
income_poverty_> $75,000: 0.0
income_poverty_Below Poverty: 0.0
```

Creating a copy...

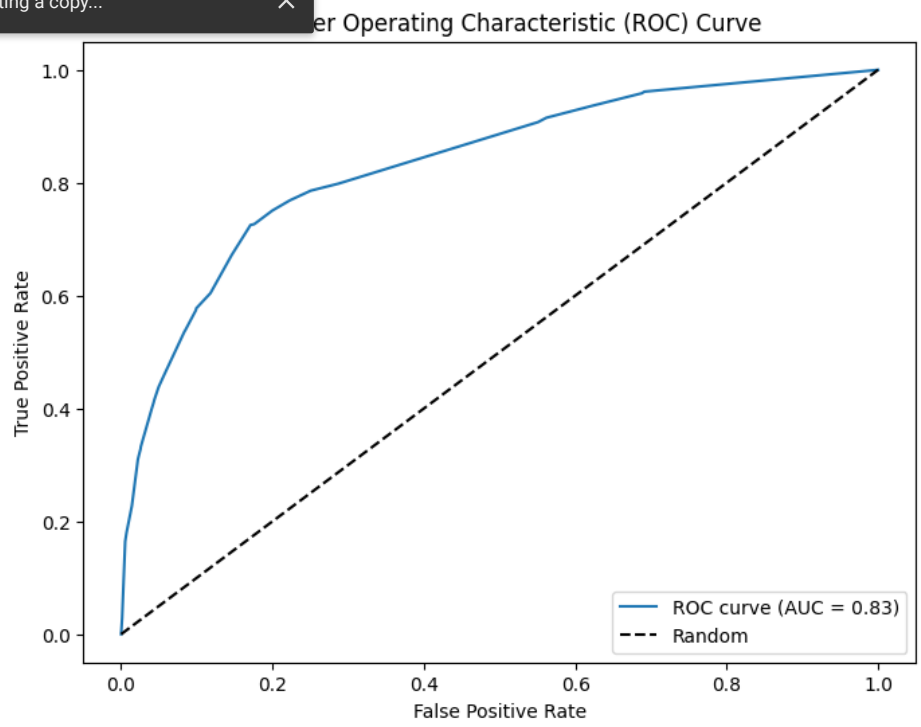
```
.0
marital_status_nan: 0.0
rent_or_own_Own: 0.0
rent_or_own_Rent: 0.0
rent_or_own_nan: 0.0
employment_status_Employed: 0.0
employment_status_Not in Labor Force: 0.0
employment_status_Unemployed: 0.0
employment_status_nan: 0.0
hhs_geo_region_atmpeygn: 0.0
hhs_geo_region_bhuqouqj: 0.0
hhs_geo_region_dqpwygqj: 0.0
```

```
tree_clf_2.feature_importances_
```

```
array([0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.48614179,
       0.        , 0.        , 0.        , 0.03379733, 0.18875831,
       0.1315596 , 0.12724764, 0.        , 0.00177045, 0.        ,
       0.        , 0.        , 0.        , 0.00405964, 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.0042659 , 0.00156938, 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.01254588, 0.00828407, 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        , 0.        , 0.        , 0.        ,
       0.        , 0.        ])
```

Running an ROC curve

```
from sklearn.impute import SimpleImputer
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import roc_curve, roc_auc_score
import matplotlib.pyplot as plt

# Create the imputer with a strategy (e.g., mean, median, mode)
imputer = SimpleImputer(strategy='mean')

# Apply imputation to the training and test datasets
X_train_imputed = imputer.fit_transform(X_train_clean)
X_test_imputed = imputer.transform(X_test_clean)

# Train the decision tree model
tree_clf = DecisionTreeClassifier(max_depth=5, random_state=1337)
tree_clf.fit(X_train_imputed, y_train)

# Make predictions on the test set
y_pred_prob = tree_clf.predict_proba(X_test_imputed)[:, 1]

# Compute the false positive rate, true positive rate, and threshold values for the ROC curve
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)

# Compute the area under the ROC curve (AUC)
auc = roc_auc_score(y_test, y_pred_prob)

# Plot the ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label='ROC curve (AUC = %0.2f)' % auc)
plt.plot([0, 1], [0, 1], 'k--', label='Random')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

The AUC score represents the overall performance of the model. It ranges between 0 and 1, with 0.83 indicating a perfect classifier. A higher AUC score signifies better discrimination between positive and negative classes.

EVALUATION

Based on the results of the National 2009 H1N1 Flu Survey and the ML models developed, the findings suggest that the models had moderate performance in predicting the H1N1 vaccine status. The precision score of 0.81 indicates that a portion of individuals who received the vaccine was correctly identified by the models. However, there is still room for improvement in terms of accuracy.

One limitation of the study is that it only considered data from a single year, which may not capture the full complexity and variability of vaccine uptake over time. Moreover, the presence of imbalanced data and potential inaccuracies in the modeling process could have influenced the performance of the models. It is important to acknowledge that the findings are specific to the dataset and ML models used in this study.

Despite these limitations, the results highlight the potential of ML models in predicting vaccine uptake and informing public health interventions. Further research and refinement of the models are necessary to enhance their accuracy and generalizability. Additionally, considering data from multiple years and incorporating more comprehensive features may provide a more robust understanding of the factors influencing vaccine decisions.


```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```