- Group: **14**
- Student pace: **Part-time**
- Scheduled project review date/time: **13/02/2024**
- Instructor name:
- Blog post URL: N/A

Predicting H1N1 Flu Vaccination Status

Overview

As the world struggles to vaccinate the global population against COVID-19, an understanding of how people's backgrounds, opinions, and health behaviors are related to their personal vaccination patterns can provide guidance for future public health efforts. Such findings can guide policymakers and public health professionals develop public health efforts to improve vaccine uptake to mitigate spread of preventable communicable dieases.

This project utilises data from a United States' conducted National 2009 H1N1 Flu Survey to predict whether someone revieved H1N1 flu vaccines. Gaining deeper insights into how these attributes correlate with individual vaccination behaviors can offer valuable direction for upcoming public health initiatives.

Business Understanding

The National 2009 H1N1 Flu Survey data was downloaded from DrivenData and the purpose of this project is to use data to forecast whether or not a person received the H1N1 flu vaccination, using features such as social, economic, and demographic background, opinions on risks of illness and vaccine effectiveness, and behaviors towards mitigating transmission, etcetera. The findings would also be applicable for use by the Kenya's Ministry of Health to more effectively target public health initiatives that boost vaccination rates and localise for other communicable dieases like influenza.

Objectives

1. Our objective is to develop a predictive model to identify individuals who are likely to exhibit vaccine hesitancy. Our goal is to provide insights that can inform targeted vaccination campaigns and interventions aimed at addressing vaccine hesitancy and increasing vaccine uptake rates.
2. Identify common factors associated with increased uptake of vaccines. Understanding these factors can inform the development of targeted interventions and public health strategies aimed at promoting vaccination uptake and improving overall immunization rates
3. Examine the influence of socio-economic factors, such as income and education, on vaccination decisions

Data Description

- h1n1_concern - Level of concern about the H1N1 flu.
    - 0 = Not at all concerned; 1 = Not very concerned; 2 = Somewhat concerned; 3 = Very concerned.
- h1n1_knowledge - Level of knowledge about H1N1 flu.
    - 0 = No knowledge; 1 = A little knowledge; 2 = A lot of knowledge.
- behavioral_antiviral_meds - Has taken antiviral medications. (binary)
- behavioral_avoidance - Has avoided close contact with others with flu-like symptoms. (binary)
- behavioral_face_mask - Has bought a face mask. (binary)
- behavioral_wash_hands - Has frequently washed hands or used hand sanitizer. (binary)
- behavioral_large_gatherings - Has reduced time at large gatherings. (binary)
- behavioral_outside_home - Has reduced contact with people outside of own household. (binary)
- behavioral_touch_face - Has avoided touching eyes, nose, or mouth. (binary)
- doctor_recc_h1n1 - H1N1 flu vaccine was recommended by doctor. (binary)
- doctor_recc_seasonal - Seasonal flu vaccine was recommended by doctor. (binary)
- chronic_med_condition - Has any of the following chronic medical conditions: asthma or an other lung condition, diabetes, a heart condition, a kidney condition, sickle cell anemia or other anemia, a neurological or neuromuscular condition, a liver condition, or a weakened immune system caused by a chronic illness or by medicines taken for a chronic illness. (binary)
- child_under_6_months - Has regular close contact with a child under the age of six months. (binary)
- health_worker - Is a healthcare worker. (binary)
- health_insurance - Has health insurance. (binary)
- opinion_h1n1_vacc_effective - Respondent's opinion about H1N1 vaccine effectiveness.
    - 1 = Not at all effective; 2 = Not very effective; 3 = Don't know; 4 = Somewhat effective; 5 = Very effective.
- opinion_h1n1_risk - Respondent's opinion about risk of getting sick with H1N1 flu without vaccine.

    - 1 = Very Low; 2 = Somewhat low; 3 = Don't know; 4 = Somewhat high; 5 = Very high.
- opinion_h1n1_sick_from_vacc - Respondent's worry of getting sick from taking H1N1 vaccine.
    - 1 = Not at all worried; 2 = Not very worried; 3 = Don't know; 4 = Somewhat worried; 5 = Very worried.
- opinion_seas_vacc_effective - Respondent's opinion about seasonal flu vaccine effectiveness.
    - 1 = Not at all effective; 2 = Not very effective; 3 = Don't know; 4 = Somewhat effective; 5 = Very effective.
- opinion_seas_risk - Respondent's opinion about risk of getting sick with seasonal flu without vaccine.
    - 1 = Very Low; 2 = Somewhat low; 3 = Don't know; 4 = Somewhat high; 5 = Very high.
- opinion_seas_sick_from_vacc - Respondent's worry of getting sick from taking seasonal flu vaccine.
    - 1 = Not at all worried; 2 = Not very worried; 3 = Don't know; 4 = Somewhat worried; 5 = Very worried.
- age_group - Age group of respondent.
- education - Self-reported education level.
- race - Race of respondent.
- sex - Sex of respondent.
- income_poverty - Household annual income of respondent with respect to 2008 Census poverty thresholds.
- marital_status - Marital status of respondent.
- rent_or_own - Housing situation of respondent.
- employment_status - Employment status of respondent.
- hhs_geo_region - Respondent's residence using a 10-region geographic classification defined by the U.S. Dept. of Health and Human Services. Values are represented as short random character strings.
- census_msa - Respondent's residence within metropolitan statistical areas (MSA) as defined by the U.S. Census.
- household_adults - Number of other adults in household, top-coded to 3.
- household_children - Number of children in household, top-coded to 3.
- employment_industry - Type of industry respondent is employed in. Values are represented as short random character strings.
- employment_occupation - Type of occupation of respondent. Values are represented as short random character strings.resented as short random character strings.

Import Libraries

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from sklearn.preprocessing import OneHotEncoder, StandardScaler, MinMaxScaler
from sklearn.model_selection import train_test_split, cross_validate
from imblearn.over_sampling import SMOTE
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_curve, roc_auc_score
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.naive_bayes import GaussianNB
from sklearn.feature_selection import RFE, mutual_info_classif
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import GridSearchCV
from xgboost import XGBClassifier
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier
from sklearn.pipeline import Pipeline
import matplotlib.pyplot as plt
import seaborn as sns
plt.style.use('seaborn-v0_8-darkgrid')
```

Load Data

In [2]:
```
# Loading data [original data from 'DrivenData' was seperated into training and testing sets]
train_features_df = pd.read_csv("Data/training_set_features.csv", index_col="respondent_id")

train_labels_df = pd.read_csv("Data/training_set_labels.csv",index_col="respondent_id")

test_validation_df = pd.read_csv("Data/test_set_features.csv",index_col="respondent_id")
```

In [3]:
```
# check first 5 rows of features_df
train_features_df.head()
```

Out[3]:

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

5 rows × 35 columns

In [4]:
```
# check first 5 rows of labels_df
train_labels_df.head()
```

Out[4]:

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

In [5]:
```
# check first 5 rows of test_validation_df
test_validation_df.head()
```

Out[5]:

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_hands	bel
respondent_id							
26707	2.0	2.0	0.0	1.0	0.0	1.0	
26708	1.0	1.0	0.0	0.0	0.0	0.0	
26709	2.0	2.0	0.0	0.0	1.0	1.0	
26710	1.0	1.0	0.0	0.0	0.0	0.0	
26711	3.0	1.0	1.0	1.0	0.0	1.0	

5 rows × 35 columns

In [6]:
```
# Double-check that the rows between the features and the labels match up
np.testing.assert_array_equal(train_features_df.index.values, train_labels_df.index.values)
```

In [7]:
```
## Merge the features and labels data
merged_df = pd.concat([train_features_df, train_labels_df], axis =1)
merged_df
```

Out[7]:

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_hands	bel
respondent_id							
0	1.0	0.0	0.0	0.0	0.0	0.0	
1	3.0	2.0	0.0	1.0	0.0	1.0	
2	1.0	1.0	0.0	1.0	0.0	0.0	
3	1.0	1.0	0.0	1.0	0.0	1.0	
4	2.0	1.0	0.0	1.0	0.0	1.0	
...	...	...	...	...	...	...	
26702	2.0	0.0	0.0	1.0	0.0	0.0	
26703	1.0	2.0	0.0	1.0	0.0	1.0	
26704	2.0	2.0	0.0	1.0	1.0	1.0	
26705	1.0	1.0	0.0	0.0	0.0	0.0	
26706	0.0	0.0	0.0	1.0	0.0	0.0	

26707 rows × 37 columns

In [8]:
```
merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 26707 entries, 0 to 26706
Data columns (total 37 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   h1n1_concern                 26615 non-null  float64
 1   h1n1_knowledge               26591 non-null  float64
 2   behavioral_antiviral_meds    26636 non-null  float64
 3   behavioral_avoidance         26499 non-null  float64
 4   behavioral_face_mask         26688 non-null  float64
 5   behavioral_wash_hands        26665 non-null  float64
 6   behavioral_large_gatherings  26620 non-null  float64
 7   behavioral_outside_home      26625 non-null  float64
 8   behavioral_touch_face        26579 non-null  float64
 9   doctor_recc_h1n1             24547 non-null  float64
 10  doctor_recc_seasonal         24547 non-null  float64
 11  chronic_med_condition        25736 non-null  float64
 12  child_under_6_months         25887 non-null  float64
 13  health_worker                25903 non-null  float64
 14  health_insurance             14433 non-null  float64
 15  opinion_h1n1_vacc_effective  26316 non-null  float64
 16  opinion_h1n1_risk            26319 non-null  float64
 17  opinion_h1n1_sick_from_vacc  26312 non-null  float64
 18  opinion_seas_vacc_effective  26245 non-null  float64
 19  opinion_seas_risk            26193 non-null  float64
 20  opinion_seas_sick_from_vacc  26170 non-null  float64
 21  age_group                    26707 non-null  object 
 22  education                    25300 non-null  object 
 23  race                         26707 non-null  object 
 24  sex                          26707 non-null  object 
 25  income_poverty               22284 non-null  object 
 26  marital_status               25299 non-null  object 
 27  rent_or_own                  24665 non-null  object 
 28  employment_status            25244 non-null  object 
 29  hhs_geo_region               26707 non-null  object 
 30  census_msa                   26707 non-null  object 
 31  household_adults             26458 non-null  float64
 32  household_children           26458 non-null  float64
 33  employment_industry          13377 non-null  object 
 34  employment_occupation        13237 non-null  object 
 35  h1n1_vaccine                 26707 non-null  int64  
```

```
 36  seasonal_vaccine             26707 non-null  int64
dtypes: float64(23), int64(2), object(12)
memory usage: 7.7+ MB
```

Additionally the datatypes consist of 23 columns of float type, 2 interger(int64) columns and 12 columns of object datatype.

In [9]:
```
merged_df.describe()
```

Out[9]:

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_hands	behavioral_
count	26615.000000	26591.000000	26636.000000	26499.000000	26688.000000	26665.000000	
mean	1.618486	1.262532	0.048844	0.725612	0.068982	0.825614	
std	0.910311	0.618149	0.215545	0.446214	0.253429	0.379448	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	1.000000	0.000000	0.000000	0.000000	1.000000	
50%	2.000000	1.000000	0.000000	1.000000	0.000000	1.000000	
75%	2.000000	2.000000	0.000000	1.000000	0.000000	1.000000	
max	3.000000	2.000000	1.000000	1.000000	1.000000	1.000000	

8 rows × 25 columns

Inference

- **Target Variable**
  - `h1n1_vaccine` : The sample popluation show that 21.24% received the vacccine, therefore 78.76% during the survey year (2009)

Data Cleaning

In [10]:
```
merged_df.isna().sum()
```

Out[10]:
```
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
sex                               0
income_poverty                 4423
marital_status                 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
```

In [11]:
```
missing = [[column, round(sum(merged_df[column].isna())/len(merged_df[column]),2)] for column in merged_df.columns]
pd.DataFrame(missing, columns= ['column name', 'missing proportion']).sort_values(by='missing proportion', ascending=
```

Out[11]:

	column name	missing proportion
34	employment_occupation	0.50
33	employment_industry	0.50
14	health_insurance	0.46
25	income_poverty	0.17
27	rent_or_own	0.08
9	doctor_recc_h1n1	0.08
10	doctor_recc_seasonal	0.08
26	marital_status	0.05
22	education	0.05
28	employment_status	0.05
11	chronic_med_condition	0.04
13	health_worker	0.03
12	child_under_6_months	0.03
19	opinion_seas_risk	0.02
20	opinion_seas_sick_from_vacc	0.02
18	opinion_seas_vacc_effective	0.02
31	household_adults	0.01
15	opinion_h1n1_vacc_effective	0.01
16	opinion_h1n1_risk	0.01
17	opinion_h1n1_sick_from_vacc	0.01
32	household_children	0.01
3	behavioral_avoidance	0.01
30	census_msa	0.00
29	hhs_geo_region	0.00
35	h1n1_vaccine	0.00

	column name	missing proportion
0	h1n1_concern	0.00
24	sex	0.00
23	race	0.00
21	age_group	0.00
1	h1n1_knowledge	0.00
8	behavioral_touch_face	0.00
7	behavioral_outside_home	0.00
6	behavioral_large_gatherings	0.00
5	behavioral_wash_hands	0.00
4	behavioral_face_mask	0.00
2	behavioral_antiviral_meds	0.00
36	seasonal_vaccine	0.00

- We will use 40% as the threshold for null frequency in the columns to decide whether to consider the column for analysis or not.
- Sometimes columns with greater null percentage have more semantic meaning and thus they cannot be ignored.
- Here we can see `health_insurance` , `employment_industry` and `employment_occupation` columns with approximately **46%, 50% and 50%** missing values percentages respectively, and thus they cannot be used for analysis as nearly half of the data is missing in those columns.

In [12]:
```
# Drop columns with high missing values percentages
merged_df.drop(columns=['health_insurance', 'employment_industry', 'employment_occupation'], inplace=True)
```

In [13]:
```
# Out target variable is h1n1_vaccine so drop seasonal_vaccine
# Drop columns with seasonal information
merged_df.drop(columns=['doctor_recc_seasonal','opinion_seas_vacc_effective',  'opinion_seas_risk',
                        'opinion_seas_sick_from_vacc', 'seasonal_vaccine'
                       ], inplace = True)
```

In [14]:
```
X = merged_df.drop(columns= 'h1n1_vaccine')
y = merged_df['h1n1_vaccine']
```

In [15]:
```
# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state= 40)
```

Impute missing values

In [16]:
```
# Categorical columns of X_train
categorical_X_train = X_train.select_dtypes(include=['object'])
categorical_X_train.columns
```

Out[16]:
```
Index(['age_group', 'education', 'race', 'sex', 'income_poverty',
       'marital_status', 'rent_or_own', 'employment_status', 'hhs_geo_region',
       'census_msa'],
      dtype='object')
```

In [17]:
```
# Categorical columns of X_test
categorical_X_test = X_test.select_dtypes(include=['object'])
categorical_X_test.columns
```

Out[17]:
```
Index(['age_group', 'education', 'race', 'sex', 'income_poverty',
       'marital_status', 'rent_or_own', 'employment_status', 'hhs_geo_region',
       'census_msa'],
      dtype='object')
```

In [18]:
```
# Numerical columns of X_train
numerical_X_train = X_train.select_dtypes(exclude=['object'])
numerical_X_train.columns
```

Out[18]:
```
Index(['h1n1_concern', 'h1n1_knowledge', 'behavioral_antiviral_meds',
       'behavioral_avoidance', 'behavioral_face_mask', 'behavioral_wash_hands',
       'behavioral_large_gatherings', 'behavioral_outside_home',
       'behavioral_touch_face', 'doctor_recc_h1n1', 'chronic_med_condition',
       'child_under_6_months', 'health_worker', 'opinion_h1n1_vacc_effective',
       'opinion_h1n1_risk', 'opinion_h1n1_sick_from_vacc', 'household_adults',
       'household_children'],
      dtype='object')
```

In [19]:
```
# Numerical columns of X_test
numerical_X_test = X_test.select_dtypes(exclude=['object'])
numerical_X_test.columns
```

Out[19]:
```
Index(['h1n1_concern', 'h1n1_knowledge', 'behavioral_antiviral_meds',
       'behavioral_avoidance', 'behavioral_face_mask', 'behavioral_wash_hands',
       'behavioral_large_gatherings', 'behavioral_outside_home',
       'behavioral_touch_face', 'doctor_recc_h1n1', 'chronic_med_condition',
       'child_under_6_months', 'health_worker', 'opinion_h1n1_vacc_effective',
       'opinion_h1n1_risk', 'opinion_h1n1_sick_from_vacc', 'household_adults',
       'household_children'],
      dtype='object')
```

In [20]:
```
# Imputation of mising values on train set data [for numerical data]
# Instantiate imputer
imputer = IterativeImputer()

# Fit and tranform X_train
imputed_numerical_X_train = imputer.fit_transform(numerical_X_train)
imputed_numerical_X_train = pd.DataFrame(np.round(numerical_X_train, 0), columns = numerical_X_train.columns)
imputed_numerical_X_train
```

Out[20]:

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_hands	bel
respondent_id							
7191	1.0	1.0	0.0	1.0	0.0	1.0	
23784	3.0	1.0	0.0	1.0	0.0	1.0	
316	2.0	1.0	0.0	1.0	0.0	1.0	
521	2.0	1.0	0.0	1.0	0.0	1.0	
21647	2.0	2.0	0.0	1.0	0.0	1.0	
...	...	...	...	...	...	...	
21810	2.0	1.0	0.0	1.0	0.0	0.0	
23992	1.0	0.0	0.0	0.0	0.0	0.0	
14501	2.0	1.0	0.0	1.0	0.0	1.0	
14555	2.0	1.0	0.0	0.0	0.0	1.0	
11590	1.0	2.0	0.0	1.0	0.0	1.0	

20030 rows × 18 columns

In [21]:
```
# Tranform X_test
imputed_numerical_X_test = imputer.transform(numerical_X_test)
imputed_numerical_X_test = pd.DataFrame(np.round(numerical_X_test, 0), columns = numerical_X_test.columns)
imputed_numerical_X_test
```

Out[21]:

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_hands	bel
respondent_id							
6458	1.0	0.0	0.0	1.0	0.0	1.0	
12839	2.0	1.0	0.0	1.0	0.0	1.0	
4377	3.0	2.0	0.0	0.0	0.0	1.0	
2731	2.0	1.0	0.0	1.0	0.0	1.0	
4982	3.0	2.0	0.0	1.0	0.0	1.0	
...	...	...	...	...	...	...	
18368	1.0	1.0	0.0	1.0	0.0	1.0	
7212	2.0	0.0	0.0	1.0	0.0	1.0	
13165	2.0	0.0	0.0	0.0	0.0	1.0	
17397	3.0	2.0	1.0	1.0	1.0	1.0	
20852	3.0	2.0	0.0	1.0	0.0	1.0	

6677 rows × 18 columns

In [22]:
```
# Encode categorical variables
# Instatiate encoder class
encoder = OneHotEncoder(drop= 'first', handle_unknown = 'ignore', sparse_output= False)

# Fit and transform X_train data
encoded_categorical_X_train = encoder.fit_transform(categorical_X_train)
encoded_categorical_X_train = pd.DataFrame(encoded_categorical_X_train, columns = encoder.get_feature_names_out(),
                                           index= categorical_X_train.index)
encoded_categorical_X_train
```

Out[22]:

	age_group_35 - 44 Years	age_group_45 - 54 Years	age_group_55 - 64 Years	age_group_65+ Years	education_< 12 Years	education_College Graduate	education_Some College	education_nan	race
respondent_id									
7191	0.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	
23784	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	
316	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	
521	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	
21647	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	
21810	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	
23992	0.0	1.0	0.0	0.0	0.0	0.0	0.0	1.0	
14501	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	
14555	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	
11590	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	

20030 rows × 33 columns

In [23]:
```
# Check for columns with all zeros to drop
pd.DataFrame([[column, encoded_categorical_X_train[column].sum() == 0] for column in encoded_categorical_X_train.colum
```

Out[23]:

	0	1
0	age_group_35 - 44 Years	False
1	age_group_45 - 54 Years	False
2	age_group_55 - 64 Years	False
3	age_group_65+ Years	False
4	education_< 12 Years	False
5	education_College Graduate	False
6	education_Some College	False
7	education_nan	False
8	race_Hispanic	False
9	race_Other or Multiple	False
10	race_White	False
11	sex_Male	False
12	income_poverty_> $75,000	False
13	income_poverty_Below Poverty	False
14	income_poverty_nan	False
15	marital_status_Not Married	False
16	marital_status_nan	False
17	rent_or_own_Rent	False
18	rent_or_own_nan	False
19	employment_status_Not in Labor Force	False
20	employment_status_Unemployed	False
21	employment_status_nan	False
22	hhs_geo_region_bhuqouqj	False
23	hhs_geo_region_dqpwygqj	False
24	hhs_geo_region_fpwskwrf	False

	0	1
25	hhs_geo_region_kbazzjca	False
26	hhs_geo_region_lrircsnp	False
27	hhs_geo_region_lzgpxyit	False
28	hhs_geo_region_mlyzmhmf	False
29	hhs_geo_region_oxchjgsf	False
30	hhs_geo_region_qufhixun	False
31	census_msa_MSA, Principle City	False
32	census_msa_Non-MSA	False

In [24]:
```
# Transform X_test data [encoder]
encoded_categorical_X_test = encoder.transform(categorical_X_test)
encoded_categorical_X_test = pd.DataFrame(encoded_categorical_X_test, columns = encoder.get_feature_names_out(),
                                          index = categorical_X_test.index)
encoded_categorical_X_test
```

Out[24]:

	age_group_35 - 44 Years	age_group_45 - 54 Years	age_group_55 - 64 Years	age_group_65+ Years	education_< 12 Years	education_College Graduate	education_Some College	education_nan	race
respondent_id									
6458	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	
12839	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	
4377	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	
2731	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	
4982	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	
...	...	...	...	...	...	...	...	...	
18368	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
7212	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
13165	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	
17397	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	
20852	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	

6677 rows × 33 columns

In [25]:
```
# Check for columns with all zeros to drop
pd.DataFrame([[column, encoded_categorical_X_test[column].sum() == 0] for column in encoded_categorical_X_test.columns
```

Out[25]:

	0	1
0	age_group_35 - 44 Years	False
1	age_group_45 - 54 Years	False
2	age_group_55 - 64 Years	False
3	age_group_65+ Years	False
4	education_< 12 Years	False
5	education_College Graduate	False
6	education_Some College	False
7	education_nan	False
8	race_Hispanic	False
9	race_Other or Multiple	False
10	race_White	False
11	sex_Male	False
12	income_poverty_> $75,000	False
13	income_poverty_Below Poverty	False
14	income_poverty_nan	False
15	marital_status_Not Married	False
16	marital_status_nan	False
17	rent_or_own_Rent	False
18	rent_or_own_nan	False
19	employment_status_Not in Labor Force	False
20	employment_status_Unemployed	False
21	employment_status_nan	False
22	hhs_geo_region_bhuqouqj	False
23	hhs_geo_region_dqpwygqj	False
24	hhs_geo_region_fpwskwrf	False

	0	1
25	hhs_geo_region_kbazzjca	False
26	hhs_geo_region_lrircsnp	False
27	hhs_geo_region_lzgpxyit	False
28	hhs_geo_region_mlyzmhmf	False
29	hhs_geo_region_oxchjgsf	False
30	hhs_geo_region_qufhixun	False
31	census_msa_MSA, Principle City	False
32	census_msa_Non-MSA	False

In [26]:
```
# Back concatenate numerical and categorical columns for both training and test data sets
# Training data set
X_train_clean = pd.concat([imputed_numerical_X_train, encoded_categorical_X_train], axis = 1)
```

In [27]:
```
# Test data set
X_test_clean = pd.concat([imputed_numerical_X_test, encoded_categorical_X_test], axis = 1)
```

In [28]:
```
X_train_clean.isna().sum()
```

Out[28]:
```
h1n1_concern                          68
h1n1_knowledge                        88
behavioral_antiviral_meds             52
behavioral_avoidance                 159
behavioral_face_mask                  18
behavioral_wash_hands                 35
behavioral_large_gatherings           60
behavioral_outside_home               59
behavioral_touch_face                 99
doctor_recc_h1n1                    1627
chronic_med_condition                706
child_under_6_months                 602
health_worker                        587
opinion_h1n1_vacc_effective          276
opinion_h1n1_risk                    269
opinion_h1n1_sick_from_vacc          278
household_adults                     171
household_children                   171
age_group_35 - 44 Years                0
age_group_45 - 54 Years                0
age_group_55 - 64 Years                0
age_group_65+ Years                    0
education_< 12 Years                   0
education_College Graduate             0
education_Some College                 0
education_nan                          0
race_Hispanic                          0
race_Other or Multiple                 0
race_White                             0
sex_Male                               0
income_poverty_> $75,000               0
income_poverty_Below Poverty           0
income_poverty_nan                     0
marital_status_Not Married             0
marital_status_nan                     0
rent_or_own_Rent                       0
rent_or_own_nan                        0
employment_status_Not in Labor Force   0
employment_status_Unemployed           0
employment_status_nan                  0
hhs_geo_region_bhuqouqj                0
```

```
hhs_geo_region_dqpwygqj              0
hhs_geo_region_fpwskwrf              0
hhs_geo_region_kbazzjca              0
hhs_geo_region_lrircsnp              0
hhs_geo_region_lzgpxyit              0
hhs_geo_region_mlyzmhmf              0
hhs_geo_region_oxchjgsf              0
hhs_geo_region_qufhixun              0
census_msa_MSA, Principle City       0
census_msa_Non-MSA                   0
dtype: int64
```

In [29]:
```
X_test_clean.isna().sum()
```

Out[29]:
```
h1n1_concern                              24
h1n1_knowledge                            28
behavioral_antiviral_meds                 19
behavioral_avoidance                      49
behavioral_face_mask                       1
behavioral_wash_hands                      7
behavioral_large_gatherings               27
behavioral_outside_home                   23
behavioral_touch_face                     29
doctor_recc_h1n1                         533
chronic_med_condition                    265
child_under_6_months                     218
health_worker                            217
opinion_h1n1_vacc_effective              115
opinion_h1n1_risk                        119
opinion_h1n1_sick_from_vacc              117
household_adults                          78
household_children                        78
age_group_35 - 44 Years                    0
age_group_45 - 54 Years                    0
age_group_55 - 64 Years                    0
age_group_65+ Years                        0
education_< 12 Years                       0
education_College Graduate                 0
education_Some College                     0
education_nan                              0
race_Hispanic                              0
race_Other or Multiple                     0
race_White                                 0
sex_Male                                   0
income_poverty_> $75,000                   0
income_poverty_Below Poverty               0
income_poverty_nan                         0
marital_status_Not Married                 0
marital_status_nan                         0
rent_or_own_Rent                           0
rent_or_own_nan                            0
employment_status_Not in Labor Force       0
employment_status_Unemployed               0
employment_status_nan                      0
hhs_geo_region_bhuqouqj                    0
```

```
hhs_geo_region_dqpwygqj          0
hhs_geo_region_fpwskwrf          0
hhs_geo_region_kbazzjca          0
hhs_geo_region_lrircsnp          0
hhs_geo_region_lzgpxyit          0
hhs_geo_region_mlyzmhmf          0
hhs_geo_region_oxchjgsf          0
hhs_geo_region_qufhixun          0
census_msa_MSA, Principle City   0
census_msa_Non-MSA               0
dtype: int64
```

In [30]:
```
# Impute more missing values on X_train data set
X_train = imputer.fit_transform(X_train_clean)
X_train = pd.DataFrame(np.round(X_train, 0), columns = X_train_clean.columns, index = X_train_clean.index)
X_train
```

Out[30]:

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_hands	bel
respondent_id							
7191	1.0	1.0	0.0	1.0	0.0	1.0	
23784	3.0	1.0	0.0	1.0	0.0	1.0	
316	2.0	1.0	0.0	1.0	0.0	1.0	
521	2.0	1.0	0.0	1.0	0.0	1.0	
21647	2.0	2.0	0.0	1.0	0.0	1.0	
...	...	...	...	...	...	...	
21810	2.0	1.0	0.0	1.0	0.0	0.0	
23992	1.0	0.0	0.0	0.0	0.0	0.0	
14501	2.0	1.0	0.0	1.0	0.0	1.0	
14555	2.0	1.0	0.0	0.0	0.0	1.0	
11590	1.0	2.0	0.0	1.0	0.0	1.0	

20030 rows × 51 columns

In [31]:
```
# Impute more missing values on X_test data set
X_test = imputer.fit_transform(X_test_clean)
X_test = pd.DataFrame(np.round(X_test, 0), columns = X_test_clean.columns, index= X_test_clean.index)
X_test
```

Out[31]:

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_wash_hands	bel
respondent_id							
6458	1.0	0.0	0.0	1.0	0.0	1.0	
12839	2.0	1.0	0.0	1.0	0.0	1.0	
4377	3.0	2.0	0.0	0.0	0.0	1.0	
2731	2.0	1.0	0.0	1.0	0.0	1.0	
4982	3.0	2.0	0.0	1.0	0.0	1.0	
...	...	...	...	...	...	...	
18368	1.0	1.0	0.0	1.0	0.0	1.0	
7212	2.0	0.0	0.0	1.0	0.0	1.0	
13165	2.0	0.0	0.0	0.0	0.0	1.0	
17397	3.0	2.0	1.0	1.0	1.0	1.0	
20852	3.0	2.0	0.0	1.0	0.0	1.0	

6677 rows × 51 columns

In [32]:
```
X_train.isna().sum()
```

Out[32]:
```
h1n1_concern                            0
h1n1_knowledge                          0
behavioral_antiviral_meds               0
behavioral_avoidance                    0
behavioral_face_mask                    0
behavioral_wash_hands                   0
behavioral_large_gatherings             0
behavioral_outside_home                 0
behavioral_touch_face                   0
doctor_recc_h1n1                        0
chronic_med_condition                   0
child_under_6_months                    0
health_worker                           0
opinion_h1n1_vacc_effective             0
opinion_h1n1_risk                       0
opinion_h1n1_sick_from_vacc             0
household_adults                        0
household_children                      0
age_group_35 - 44 Years                 0
age_group_45 - 54 Years                 0
age_group_55 - 64 Years                 0
age_group_65+ Years                     0
education_< 12 Years                    0
education_College Graduate              0
education_Some College                  0
education_nan                           0
race_Hispanic                           0
race_Other or Multiple                  0
race_White                              0
sex_Male                                0
income_poverty_> $75,000                0
income_poverty_Below Poverty            0
income_poverty_nan                      0
marital_status_Not Married              0
marital_status_nan                      0
rent_or_own_Rent                        0
rent_or_own_nan                         0
employment_status_Not in Labor Force    0
employment_status_Unemployed            0
employment_status_nan                   0
hhs_geo_region_bhuqouqj                 0
```

```
hhs_geo_region_dqpwygqj               0
hhs_geo_region_fpwskwrf               0
hhs_geo_region_kbazzjca               0
hhs_geo_region_lrircsnp               0
hhs_geo_region_lzgpxyit               0
hhs_geo_region_mlyzmhmf               0
hhs_geo_region_oxchjgsf               0
hhs_geo_region_qufhixun               0
census_msa_MSA, Principle City        0
census_msa_Non-MSA                    0
dtype: int64
```

In [33]:
```
X_test.isna().sum()
```

Out[33]:
```
h1n1_concern                              0
h1n1_knowledge                            0
behavioral_antiviral_meds                 0
behavioral_avoidance                      0
behavioral_face_mask                      0
behavioral_wash_hands                     0
behavioral_large_gatherings               0
behavioral_outside_home                   0
behavioral_touch_face                     0
doctor_recc_h1n1                          0
chronic_med_condition                     0
child_under_6_months                      0
health_worker                             0
opinion_h1n1_vacc_effective               0
opinion_h1n1_risk                         0
opinion_h1n1_sick_from_vacc               0
household_adults                          0
household_children                        0
age_group_35 - 44 Years                   0
age_group_45 - 54 Years                   0
age_group_55 - 64 Years                   0
age_group_65+ Years                       0
education_< 12 Years                      0
education_College Graduate                0
education_Some College                    0
education_nan                             0
race_Hispanic                             0
race_Other or Multiple                    0
race_White                                0
sex_Male                                  0
income_poverty_> $75,000                  0
income_poverty_Below Poverty              0
income_poverty_nan                        0
marital_status_Not Married                0
marital_status_nan                        0
rent_or_own_Rent                          0
rent_or_own_nan                           0
employment_status_Not in Labor Force      0
employment_status_Unemployed              0
employment_status_nan                     0
hhs_geo_region_bhuqouqj                   0
```

```
hhs_geo_region_dqpwygqj              0
hhs_geo_region_fpwskwrf              0
hhs_geo_region_kbazzjca              0
hhs_geo_region_lrircsnp              0
hhs_geo_region_lzgpxyit              0
hhs_geo_region_mlyzmhmf              0
hhs_geo_region_oxchjgsf              0
hhs_geo_region_qufhixun              0
census_msa_MSA, Principle City       0
census_msa_Non-MSA                   0
dtype: int64
```

Feature Engineering

i) behavior_score

- Create a variable that represents how much an individual has done behaviorally to avoid the flu, aside from getting vaccinated, by summing up all behavioral variables. These are all binary columns with **1** representing **YES**, meaning the person has engaged in a behavior that reduces the risk of contracting the flu. By taking the sum across these columns, a higher score represents a more cautious, flu-conscious individual.

In [34]:
```
# Get the columns with `behavior` attributes
behavior_cols = [col for col in X_train.columns if 'behavioral' in col]
behavior_cols
```

Out[34]:
```
['behavioral_antiviral_meds',
 'behavioral_avoidance',
 'behavioral_face_mask',
 'behavioral_wash_hands',
 'behavioral_large_gatherings',
 'behavioral_outside_home',
 'behavioral_touch_face']
```

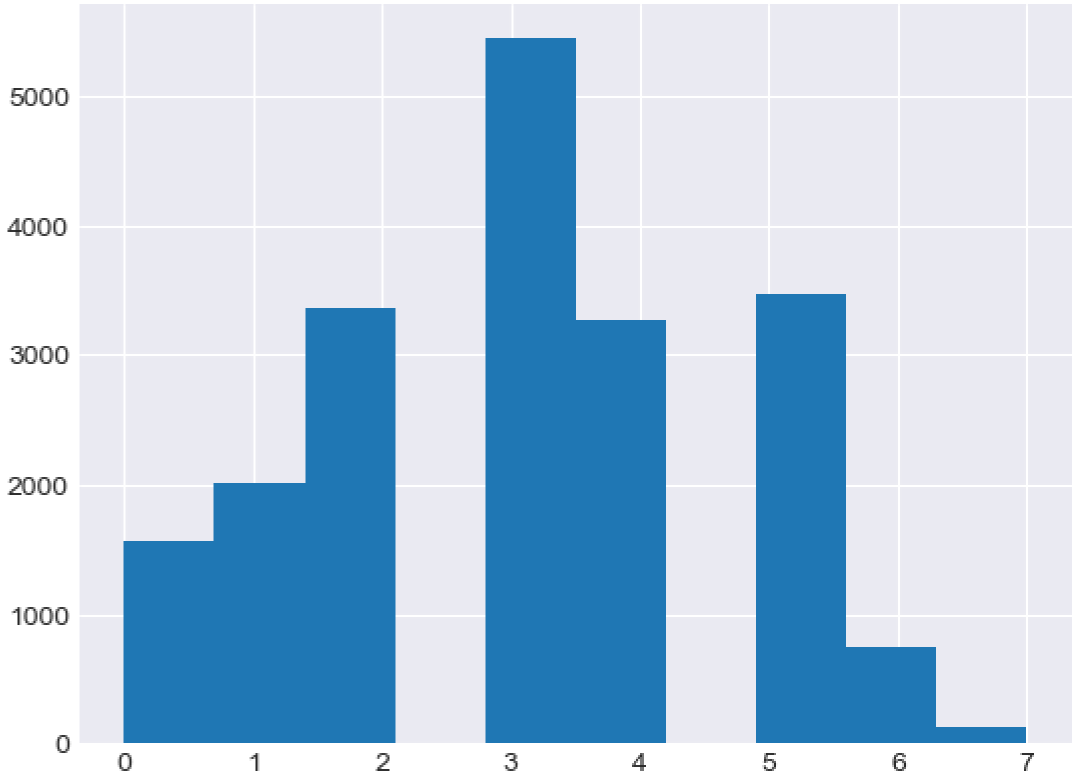
In [35]:
```
# Create the `behavior_score` variable for X_train data set
X_train['behavior_score'] = X_train[behavior_cols].sum(axis=1)
```

In [36]:
```
# Create the `behavior_score` variable for X_test data set
X_test['behavior_score'] = X_test[behavior_cols].sum(axis=1)
```

In [37]:
```
X_test.columns
```

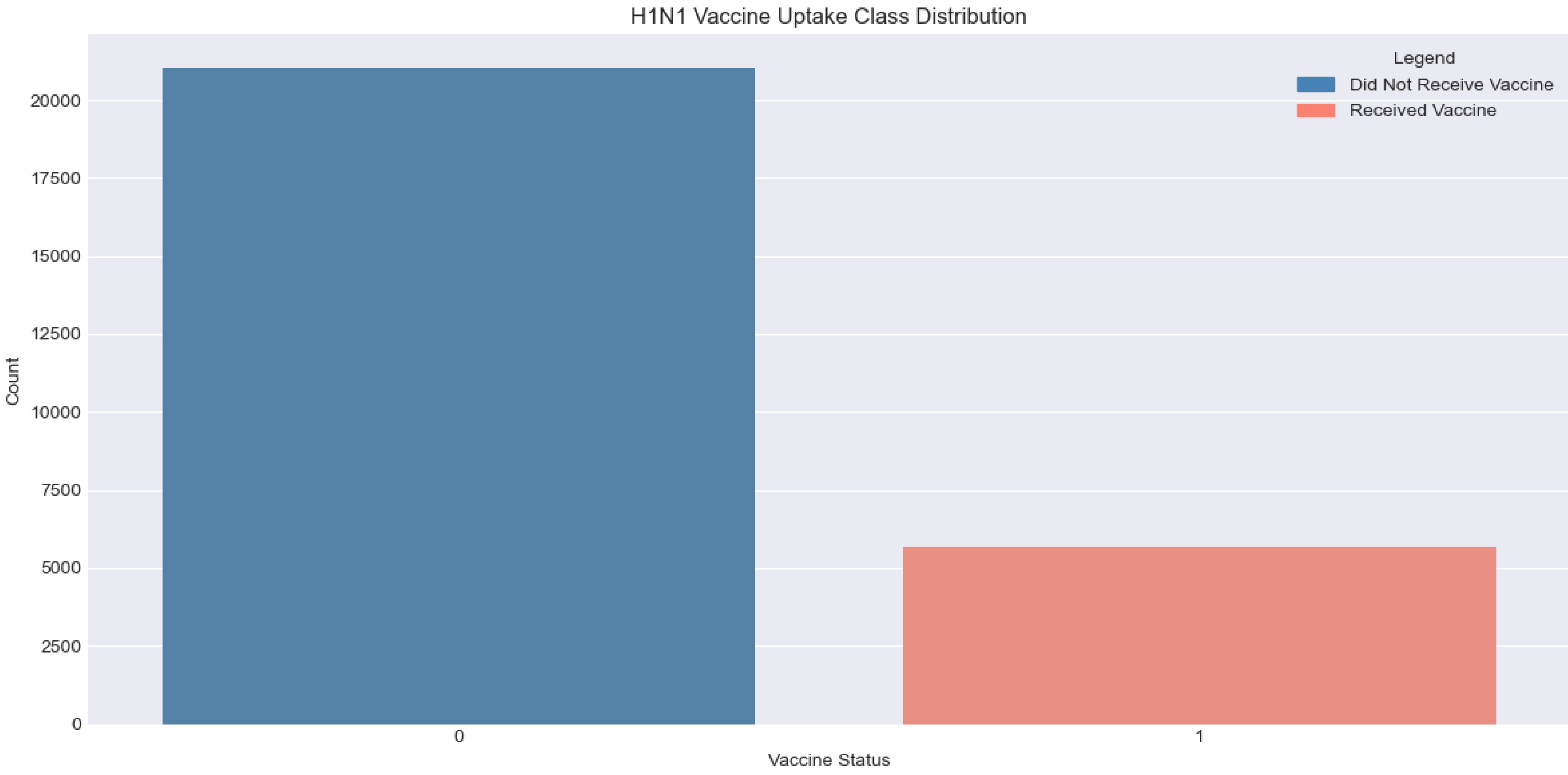
Out[37]:
```
Index(['h1n1_concern', 'h1n1_knowledge', 'behavioral_antiviral_meds',
       'behavioral_avoidance', 'behavioral_face_mask', 'behavioral_wash_hands',
       'behavioral_large_gatherings', 'behavioral_outside_home',
       'behavioral_touch_face', 'doctor_recc_h1n1', 'chronic_med_condition',
       'child_under_6_months', 'health_worker', 'opinion_h1n1_vacc_effective',
       'opinion_h1n1_risk', 'opinion_h1n1_sick_from_vacc', 'household_adults',
       'household_children', 'age_group_35 - 44 Years',
       'age_group_45 - 54 Years', 'age_group_55 - 64 Years',
       'age_group_65+ Years', 'education_< 12 Years',
       'education_College Graduate', 'education_Some College', 'education_nan',
       'race_Hispanic', 'race_Other or Multiple', 'race_White', 'sex_Male',
       'income_poverty_> $75,000', 'income_poverty_Below Poverty',
       'income_poverty_nan', 'marital_status_Not Married',
       'marital_status_nan', 'rent_or_own_Rent', 'rent_or_own_nan',
       'employment_status_Not in Labor Force', 'employment_status_Unemployed',
       'employment_status_nan', 'hhs_geo_region_bhuqouqj',
       'hhs_geo_region_dqpwygqj', 'hhs_geo_region_fpwskwrf',
       'hhs_geo_region_kbazzjca', 'hhs_geo_region_lrircsnp',
       'hhs_geo_region_lzgpxyit', 'hhs_geo_region_mlyzmhmf',
       'hhs_geo_region_oxchjgsf', 'hhs_geo_region_qufhixun',
       'census_msa_MSA, Principle City', 'census_msa_Non-MSA',
       'behavior_score'],
      dtype='object')
```

In [38]:
```
# Plot the distribution of behavior score variable we created
plt.hist(X_train['behavior_score']);
```



Class Imbalance

In [39]:
```
# Checking for class distribution
fig, ax = plt.subplots(figsize=(12, 6))
sns.countplot(x='h1n1_vaccine', data=merged_df, ax=ax, palette=["steelblue", "salmon"])

ax.set_title('H1N1 Vaccine Uptake Class Distribution')
ax.set_xlabel('Vaccine Status')
ax.set_ylabel('Count')

# Add separate legend labels for each class
legend_labels = ['Did Not Receive Vaccine', "Received Vaccine"]
colors = ["steelblue", "salmon"]
legend_handles = [plt.Rectangle((0, 0), 1, 1, color=color) for color in colors]
ax.legend(legend_handles, legend_labels, title='Legend')

plt.tight_layout()
plt.savefig('Visualization1')
```



- This plot shows the uptake distribution between those who received the vaccine and those who did not receive the vaccine

In [40]:
```
# Checking class imbalance for h1n1_vaccine [target variable]
y.value_counts()
```

Out[40]:
```
h1n1_vaccine
0    21033
1     5674
Name: count, dtype: int64
```

Presence of class imbalance

In [41]:
```
# Address class imbalance [only uses training set]
smote_df = pd.concat([X_train, y_train], axis = 1)

# Instantiate SMOTE class
smote = SMOTE()

# Fit and transform data
X_train_resample, y_train_resample = smote.fit_resample(X_train, y_train)
y_train_resample.value_counts()
```

Out[41]:
```
h1n1_vaccine
1    15779
0    15779
Name: count, dtype: int64
```

Exploratory Data Analysis

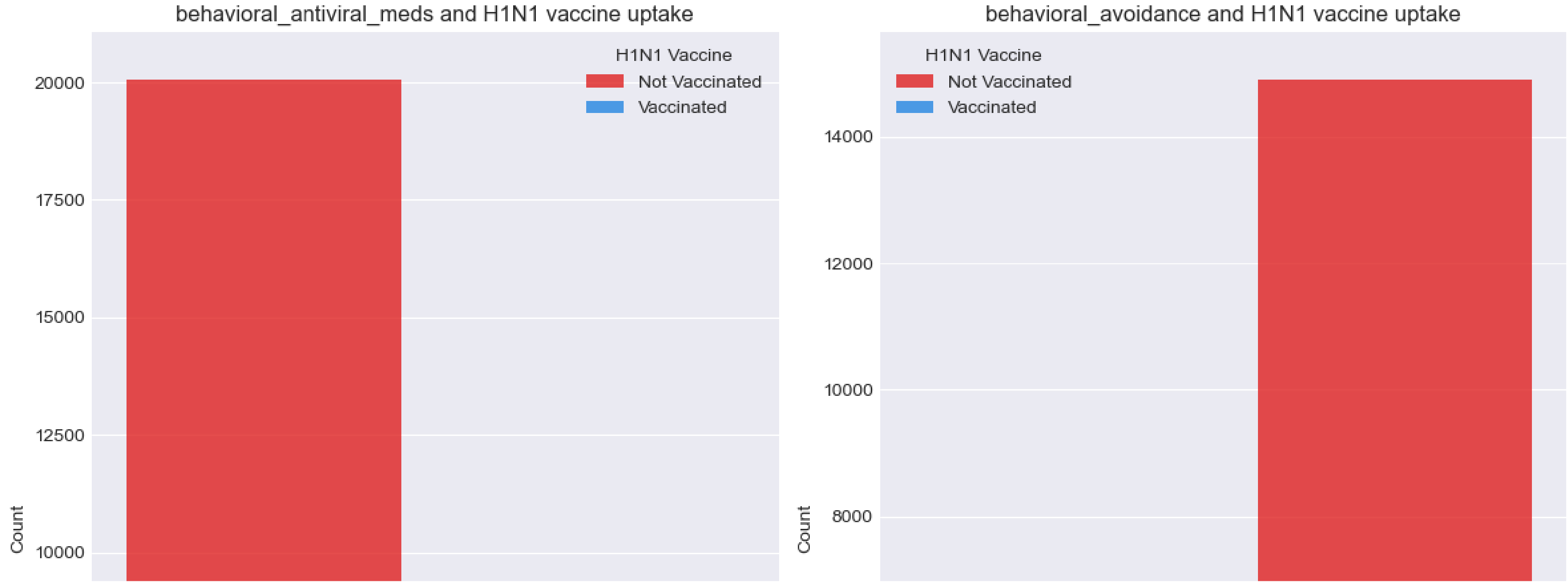
Checking the relationshop between our target variable **h1n1_vaccine** and the features.

In [42]:
```
print(merged_df['h1n1_vaccine'].unique())
```

```
[0 1]
```

In [43]:
```
# List of columns to plot
columns = ['behavioral_antiviral_meds', 'behavioral_avoidance',
           'behavioral_face_mask', 'behavioral_wash_hands', 'behavioral_large_gatherings',
           'behavioral_outside_home', 'behavioral_touch_face',
           'doctor_recc_h1n1', 'chronic_med_condition', 'child_under_6_months',
            'health_worker',
           'opinion_h1n1_vacc_effective', 'opinion_h1n1_risk', 'opinion_h1n1_sick_from_vacc',
            'age_group', 'education', 'race', 'sex','income_poverty', 'marital_status',
            'rent_or_own', 'employment_status', 'household_adults', 'household_children']

# Select columns for plotting
columns_to_plot = columns[:25]
# Determine the number of rows and columns for subplots
num_rows = (len(columns_to_plot) + 1) // 2
num_cols = 2
# Create subplots
fig, axes = plt.subplots(num_rows, num_cols, figsize=(12, 8 * num_rows))
axes = axes.flatten()
# Iterate over the columns and create count plots
for i, column in enumerate(columns_to_plot):
    # Check if the 'h1n1_vaccine' column is present in the DataFrame
    if 'h1n1_vaccine' in merged_df.columns:
        unique_values = merged_df[column].unique()
        if len(unique_values) > 1:  # Proceed only if there are multiple unique values
            sns.countplot(x=column, data=merged_df[merged_df['h1n1_vaccine'] == 0], ax=axes[i], color='red', label='No
            sns.countplot(x=column, data=merged_df[merged_df['h1n1_vaccine'] == 1], ax=axes[i], color='dodgerblue', la
            axes[i].set_title(f"{column} and H1N1 vaccine uptake")
            axes[i].set_xlabel('')
            axes[i].set_ylabel('Count')
            axes[i].legend(title='H1N1 Vaccine', loc='best')
        else:
            axes[i].set_title(f"{column} (only one value)")
            axes[i].set_xlabel('')
            axes[i].set_ylabel('Count')
# Remove any empty subplots
if len(columns_to_plot) % 2 == 1:
    fig.delaxes(axes[-1])
# Adjust spacing between subplots
plt.tight_layout()
# Display the plot
```

```
plt.show()
```



Modeling

Logistic Regression

In [44]:
```
# Baseline model

# Instantiate classifier
baseline_logreg = LogisticRegression(C= 1e12, random_state=40, solver='liblinear')

# Fit model to train set
baseline_logreg.fit(X_train_resample, y_train_resample)
```

Out[44]:
```
LogisticRegression
LogisticRegression(C=1000000000000.0, random_state=40, solver='liblinear')
```

In [45]:
```
# Accuracy on training data set
baseline_preds = baseline_logreg.predict(X_train_resample)

print(f"accuracy score: {accuracy_score(y_train_resample, baseline_preds)}")
print(f"f1 score: {f1_score(y_train_resample, baseline_preds)}")
print(f"precision score: {precision_score(y_train_resample, baseline_preds)}")
print(f"recall score: {recall_score(y_train_resample, baseline_preds)}")
```

```
accuracy score: 0.7672222574307624
f1 score: 0.7606698377533068
precision score: 0.7827019778746228
recall score: 0.7398440965840675
```

In [46]:
```
# Accuracy on test data set
baseline_preds = baseline_logreg.predict(X_test)

print(f"accuracy score: {accuracy_score(y_test, baseline_preds)}")
print(f"f1 score: {f1_score(y_test, baseline_preds)}")
print(f"precision score: {precision_score(y_test, baseline_preds)}")
print(f"recall score: {recall_score(y_test, baseline_preds)}")
```

```
accuracy score: 0.7744496031151715
f1 score: 0.5764904386951631
precision score: 0.4805438349742147
recall score: 0.7203092059030218
```

In [47]:
```
# Model2

# Instantiate classifier
logreg_2 = LogisticRegression(penalty = 'l1', C= 1e12, random_state=40, solver='liblinear')

# Fit model to train set
logreg_2.fit(X_train_resample, y_train_resample)
```

Out[47]:
```
LogisticRegression

LogisticRegression(C=1000000000000.0, penalty='l1', random_state=40,
                   solver='liblinear')
```

In [48]:
```
# Accuracy on training data set
logreg2_preds = logreg_2.predict(X_train_resample)

print(f"accuracy score: {accuracy_score(y_train_resample, logreg2_preds)}")
print(f"f1 score: {f1_score(y_train_resample, logreg2_preds)}")
print(f"precision score: {precision_score(y_train_resample, logreg2_preds)}")
print(f"recall score: {recall_score(y_train_resample, logreg2_preds)}")
```

```
accuracy score: 0.7672222574307624
f1 score: 0.7606854313265573
precision score: 0.7826640745458202
recall score: 0.7399074719563977
```

In [49]:
```
# Accuracy on test data set
logreg2_preds = logreg_2.predict(X_test)

print(f"accuracy score: {accuracy_score(y_test, logreg2_preds)}")
print(f"f1 score: {f1_score(y_test, logreg2_preds)}")
print(f"precision score: {precision_score(y_test, logreg2_preds)}")
print(f"recall score: {recall_score(y_test, logreg2_preds)}")
```

```
accuracy score: 0.7744496031151715
f1 score: 0.5764904386951631
precision score: 0.4805438349742147
recall score: 0.7203092059030218
```

In [50]:
```
# Model 3

# Instantiate classifier
logreg_3 = LogisticRegression(penalty = 'l2', random_state=40, solver='lbfgs')

# Fit model to train set
logreg_3.fit(X_train_resample, y_train_resample)
```

```
C:\Users\Richard.LAPTOP-2O23AAHO\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarnin
g: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/preprocessin
g.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (https://scikit-learn.org/stable/mo
dules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
```

Out[50]:
```
▾ LogisticRegression
LogisticRegression(random_state=40)
```

In [51]:
```
# Accuracy on training data set
logreg3_preds = logreg_3.predict(X_train_resample)

print(f"accuracy score: {accuracy_score(y_train_resample, logreg3_preds)}")
print(f"f1 score: {f1_score(y_train_resample, logreg3_preds)}")
print(f"precision score: {precision_score(y_train_resample, logreg3_preds)}")
print(f"recall score: {recall_score(y_train_resample, logreg3_preds)}")
```

```
accuracy score: 0.7678560111540655
f1 score: 0.7613058777531603
precision score: 0.7834104472607792
recall score: 0.7404144749350402
```

In [52]:
```
# Accuracy on test data set
logreg3_preds = logreg_3.predict(X_test)

print(f"accuracy score: {accuracy_score(y_test, logreg3_preds)}")
print(f"f1 score: {f1_score(y_test, logreg3_preds)}")
print(f"precision score: {precision_score(y_test, logreg3_preds)}")
print(f"recall score: {recall_score(y_test, logreg3_preds)}")
```

```
accuracy score: 0.7742998352553542
f1 score: 0.5763283666010683
precision score: 0.4803186504217432
recall score: 0.7203092059030218
```

In [53]:
```
# ROC curve for the best Logistic regression model
fpr_logreg, tpr_logreg, _ = roc_curve(y_test, logreg_3.predict_proba(X_test)[:,1])
```

K-Nearest Neighbours

In [54]:
```
# Baseline model

# Instantiate classifier
baseline_KNN_clf = KNeighborsClassifier()

# Fit model to train set
baseline_KNN_clf.fit(X_train_resample, y_train_resample)
```

Out[54]:
```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

In [55]:
```
# Accuracy on training data set
baseline_preds = baseline_KNN_clf.predict(X_train_resample)

print(f"accuracy score: {accuracy_score(y_train_resample, baseline_preds)}")
print(f"f1 score: {f1_score(y_train_resample, baseline_preds)}")
print(f"precision score: {precision_score(y_train_resample, baseline_preds)}")
print(f"recall score: {recall_score(y_train_resample, baseline_preds)}")
```

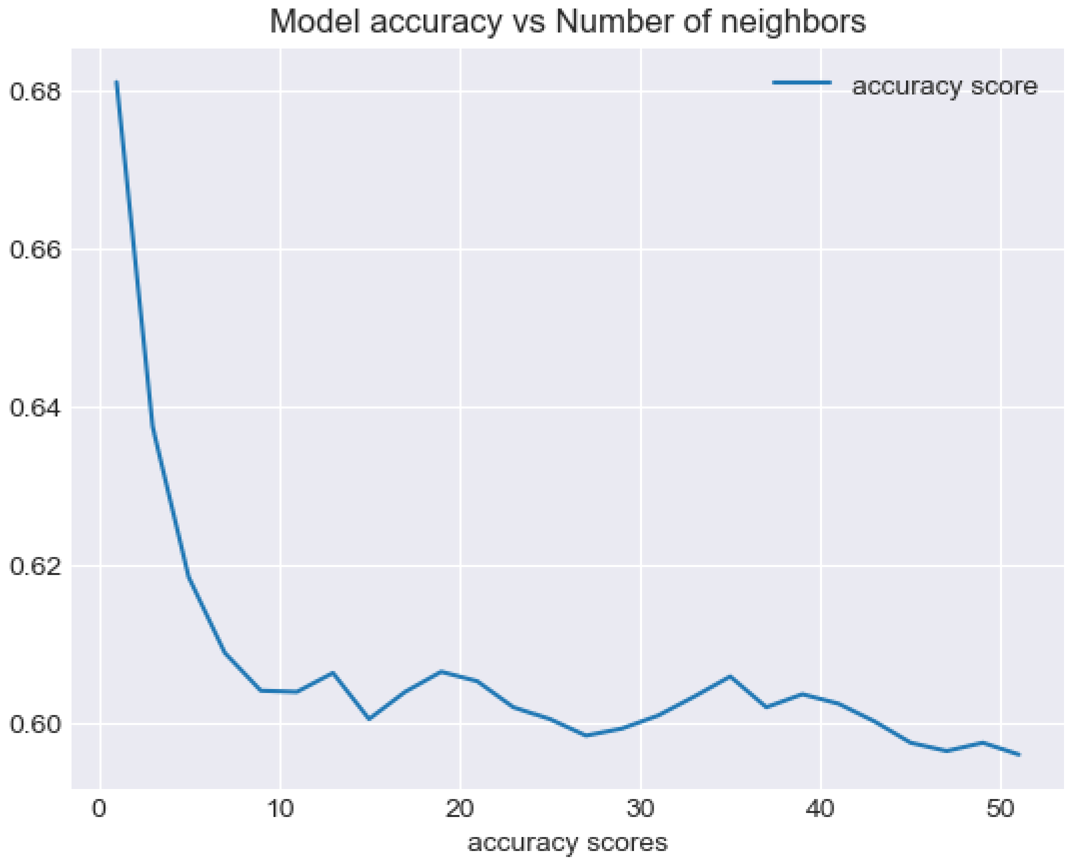
```
accuracy score: 0.845649280689524
f1 score: 0.8652670594418167
precision score: 0.7676941199568077
recall score: 0.9912541986184169
```

In [56]:
```
# Accuracy on test data set
baseline_preds = baseline_KNN_clf.predict(X_test)

print(f"accuracy score: {accuracy_score(y_test, baseline_preds)}")
print(f"f1 score: {f1_score(y_test, baseline_preds)}")
print(f"precision score: {precision_score(y_test, baseline_preds)}")
print(f"recall score: {recall_score(y_test, baseline_preds)}")
```

```
accuracy score: 0.6185412610453797
f1 score: 0.45143226362265776
precision score: 0.32546583850931676
recall score: 0.7364722417427969
```

In [57]:
```
# Find best n_neighbors parameter
n_neighbors_params = []
accuracy_scores = []

for n in np.arange(1, 52, 2):
    n_neighbors_params.append(n)

    clf_model = KNeighborsClassifier(n_neighbors = n)
    clf_model.fit(X_train_resample, y_train_resample)
    acc = accuracy_score(y_test, clf_model.predict(X_test))
    accuracy_scores.append(acc)
```

In [58]:
```
plt.plot(n_neighbors_params, accuracy_scores, label ='accuracy score')
plt.xlabel('n_neighbors params values')
plt.xlabel('accuracy scores')
plt.title('Model accuracy vs Number of neighbors')
plt.legend();
```



In [59]:
```
# Scale training and test data sets
scaler = StandardScaler()

X_train_resample_scaled = scaler.fit_transform(X_train_resample)
X_test_scaled = scaler.transform(X_test)
```

In [60]:
```
# Model Iteration

# Instantiate classifier
KNN_clf2 = KNeighborsClassifier()

# Fit model to train set
KNN_clf2.fit(X_train_resample_scaled, y_train_resample)

# Accuracy of model on train set
print(f"accuracy score: {accuracy_score(y_train_resample, KNN_clf2.predict(X_train_resample_scaled))}")
print(f"f1 score: {f1_score(y_train_resample, KNN_clf2.predict(X_train_resample_scaled))}")
print(f"precision score: {precision_score(y_train_resample, KNN_clf2.predict(X_train_resample_scaled))}")
print(f"recall score: {recall_score(y_train_resample, KNN_clf2.predict(X_train_resample_scaled))}")
```

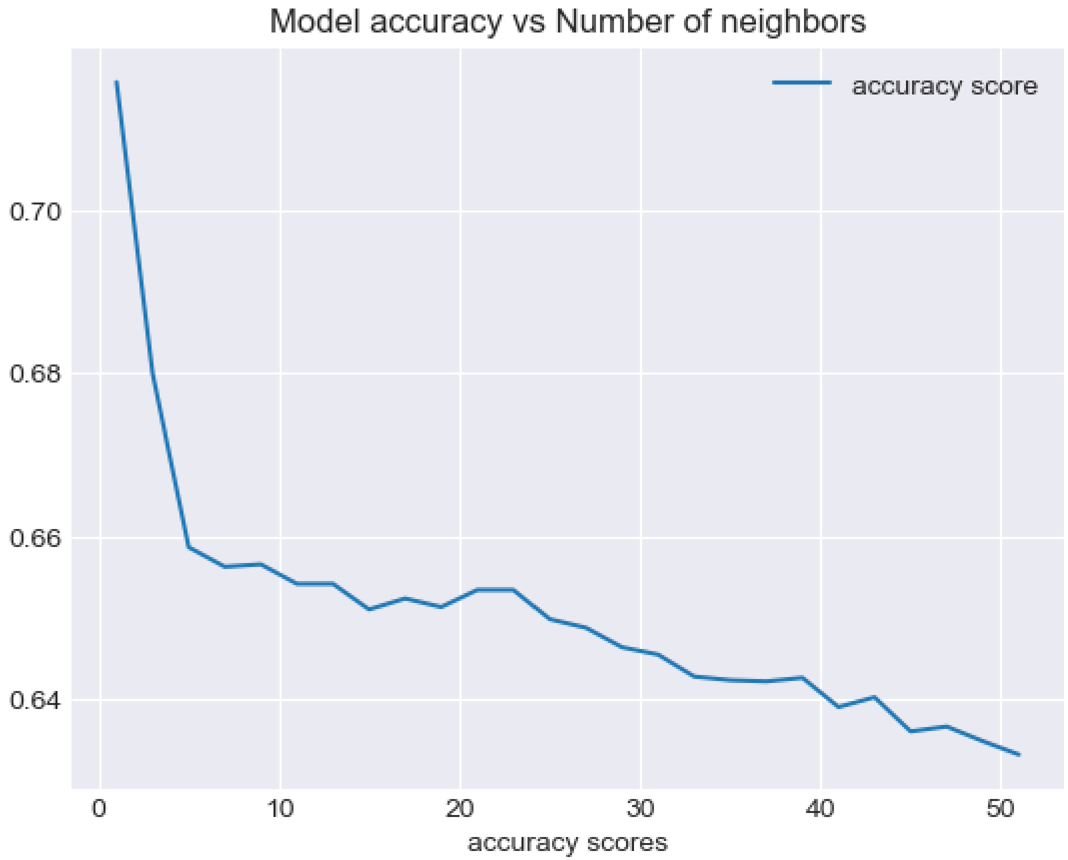
```
accuracy score: 0.8823753089549401
f1 score: 0.8932658577261487
precision score: 0.8175693457550397
recall score: 0.9844096584067431
```

In [61]:
```
# Accuracy of model on test set
print(f"accuracy score: {accuracy_score(y_test, KNN_clf2.predict(X_test_scaled))}")
print(f"f1 score: {f1_score(y_test, KNN_clf2.predict(X_test_scaled))}")
print(f"precision score: {precision_score(y_test, KNN_clf2.predict(X_test_scaled))}")
print(f"recall score: {recall_score(y_test, KNN_clf2.predict(X_test_scaled))}")
```

```
accuracy score: 0.6586790474764116
f1 score: 0.4278182274667337
precision score: 0.3328125
recall score: 0.5987350667603655
```

In [62]:
```
# Find best n_neighbors parameter
n_neighbors_params = []
accuracy_scores = []

for n in np.arange(1, 52, 2):
    n_neighbors_params.append(n)

    clf_model = KNeighborsClassifier(n_neighbors = n)
    clf_model.fit(X_train_resample_scaled, y_train_resample)
    acc = accuracy_score(y_test, clf_model.predict(X_test_scaled))
    accuracy_scores.append(acc)
```

In [63]:
```
plt.plot(n_neighbors_params, accuracy_scores, label ='accuracy score')
plt.xlabel('n_neighbors params values')
plt.xlabel('accuracy scores')
plt.title('Model accuracy vs Number of neighbors')
plt.legend();
```



Feature selection

In [64]:
```
# Define a custom function to compute feature importances
def custom_importance_getter_knn(estimator):
    # Extract the distances to the nearest neighbors
    distances, indices = estimator.kneighbors()
    # Compute the mean distance for each feature
    feature_importances = distances.mean(axis=0)
    return feature_importances

# Initialize RFE with the classifier and desired number of features to select
rfe = RFE(estimator= KNN_clf2, n_features_to_select= .8, step= 1, importance_getter= custom_importance_getter_knn)  # 

# Fit RFE on train data set
rfe.fit(X_train_resample_scaled, y_train_resample)

print(X_train_resample.columns)
print(rfe.ranking_)
print(rfe.support_)
```

```
Index(['h1n1_concern', 'h1n1_knowledge', 'behavioral_antiviral_meds',
       'behavioral_avoidance', 'behavioral_face_mask', 'behavioral_wash_hands',
       'behavioral_large_gatherings', 'behavioral_outside_home',
       'behavioral_touch_face', 'doctor_recc_h1n1', 'chronic_med_condition',
       'child_under_6_months', 'health_worker', 'opinion_h1n1_vacc_effective',
       'opinion_h1n1_risk', 'opinion_h1n1_sick_from_vacc', 'household_adults',
       'household_children', 'age_group_35 - 44 Years',
       'age_group_45 - 54 Years', 'age_group_55 - 64 Years',
       'age_group_65+ Years', 'education_< 12 Years',
       'education_College Graduate', 'education_Some College', 'education_nan',
       'race_Hispanic', 'race_Other or Multiple', 'race_White', 'sex_Male',
       'income_poverty_> $75,000', 'income_poverty_Below Poverty',
       'income_poverty_nan', 'marital_status_Not Married',
       'marital_status_nan', 'rent_or_own_Rent', 'rent_or_own_nan',
       'employment_status_Not in Labor Force', 'employment_status_Unemployed',
       'employment_status_nan', 'hhs_geo_region_bhuqouqj',
       'hhs_geo_region_dqpwygqj', 'hhs_geo_region_fpwskwrf',
       'hhs_geo_region_kbazzjca', 'hhs_geo_region_lrircsnp',
       'hhs_geo_region_lzgpxyit', 'hhs_geo_region_mlyzmhmf',
       'hhs_geo_region_oxchjgsf', 'hhs_geo_region_qufhixun',
       'census_msa_MSA, Principle City', 'census_msa_Non-MSA',
       'behavior_score'],
      dtype='object')
[12 11 10  9  8  7  6  5  4  3  2  1  1  1  1  1  1  1  1  1  1  1  1  1
  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1
  1  1  1  1]
[False False False False False False False False False False False  True
  True  True  True  True  True  True  True  True  True  True  True  True
  True  True  True  True  True  True  True  True  True  True  True  True
  True  True  True  True  True  True  True  True  True  True  True  True
  True  True  True  True]
```

In [65]:
```
masked_columns = X_train_resample.columns[rfe.get_support(indices= True)]
```

In [66]:
```
X_train_rfe = X_train_resample_scaled[:,0:11]
X_test_rfe = X_test_scaled[:,0:11]
```

In [67]:
```
# Instantiate classifier
KNN_clf3 = KNeighborsClassifier()

# Fit model to train set
KNN_clf3.fit(X_train_rfe, y_train_resample)
```

Out[67]:
```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

In [68]:
```
# Accuracy of model on train set
print(f"accuracy score: {accuracy_score(y_train_resample, KNN_clf3.predict(X_train_rfe))}")
print(f"f1 score: {f1_score(y_train_resample, KNN_clf3.predict(X_train_rfe))}")
print(f"precision score: {precision_score(y_train_resample, KNN_clf3.predict(X_train_rfe))}")
print(f"recall score: {recall_score(y_train_resample, KNN_clf3.predict(X_train_rfe))}")
```

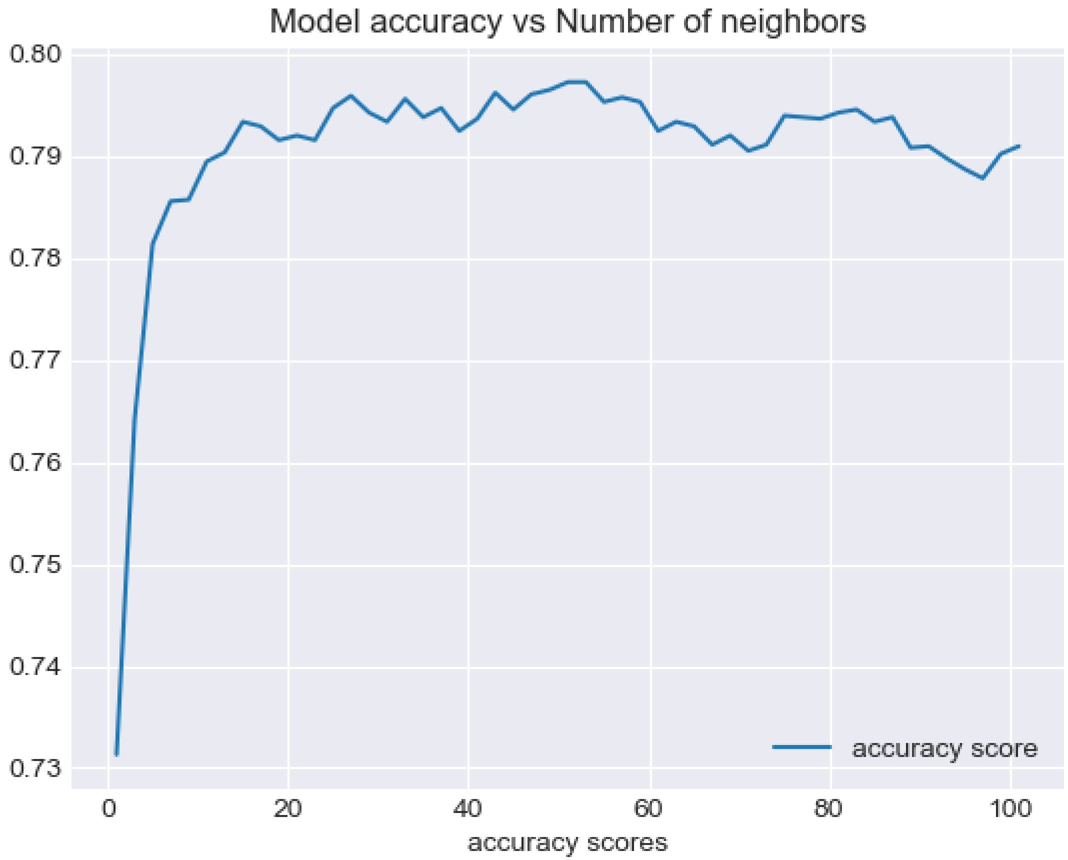
```
accuracy score: 0.8212497623423538
f1 score: 0.8028656299143806
precision score: 0.894904954814584
recall score: 0.727992901958299
```

In [69]:
```
# Accuracy of model on test set
print(f"accuracy score: {accuracy_score(y_test, KNN_clf3.predict(X_test_rfe))}")
print(f"f1 score: {f1_score(y_test, KNN_clf3.predict(X_test_rfe))}")
print(f"precision score: {precision_score(y_test, KNN_clf3.predict(X_test_rfe))}")
print(f"recall score: {recall_score(y_test, KNN_clf3.predict(X_test_rfe))}")
```

```
accuracy score: 0.7813389246667665
f1 score: 0.4089068825910931
precision score: 0.48233046800382046
recall score: 0.35488404778636684
```

In [70]:
```
# Find best n_neighbors parameter
n_neighbors_params = []
accuracy_scores = []

for n in np.arange(1, 102, 2):
    n_neighbors_params.append(n)

    clf_model = KNeighborsClassifier(n_neighbors = n)
    clf_model.fit(X_train_rfe, y_train_resample)
    acc = accuracy_score(y_test, clf_model.predict(X_test_rfe))
    accuracy_scores.append(acc)
```

In [71]:
```
plt.plot(n_neighbors_params, accuracy_scores, label ='accuracy score')
plt.xlabel('n_neighbors params values')
plt.xlabel('accuracy scores')
plt.title('Model accuracy vs Number of neighbors')
plt.legend();
```



In [72]:
```
# Best n_neighbors parameter is 51
index = accuracy_scores.index(max(accuracy_scores))
n_neighbors_params[index]
```

Out[72]:
```
51
```

In [73]:
```
# Instantiate classifier
KNN_clf_final = KNeighborsClassifier(n_neighbors = 51)

# Fit model to train set
KNN_clf_final.fit(X_train_rfe, y_train_resample)
```

Out[73]:
```
KNeighborsClassifier
KNeighborsClassifier(n_neighbors=51)
```

In [74]:
```
# Accuracy of model on train set
print(f"accuracy score on train set: {accuracy_score(y_train_resample, KNN_clf_final.predict(X_train_rfe))}")
print(f"f1 score on train set: {f1_score(y_train_resample, KNN_clf_final.predict(X_train_rfe))}")
print(f"precision score on train set: {precision_score(y_train_resample, KNN_clf_final.predict(X_train_rfe))}")
print(f"recall score on train set: {recall_score(y_train_resample, KNN_clf_final.predict(X_train_rfe))}")
print("\n------------------------------------------------------------\n")

# Accuracy of model on test set
print(f"accuracy score on test set: {accuracy_score(y_test, KNN_clf_final.predict(X_test_rfe))}")
print(f"f1 score on test set: {f1_score(y_test, KNN_clf_final.predict(X_test_rfe))}")
print(f"precision score on test set: {precision_score(y_test, KNN_clf_final.predict(X_test_rfe))}")
print(f"recall score on test set: {recall_score(y_test, KNN_clf_final.predict(X_test_rfe))}")
```

```
accuracy score on train set: 0.7479244565561822
f1 score on train set: 0.7073538608689255
precision score on train set: 0.8430375306909856
recall score on train set: 0.6092908295836238

------------------------------------------------------------

accuracy score on test set: 0.7972143178073985
f1 score on test set: 0.4970282317979197
precision score on test set: 0.5271867612293144
recall score on test set: 0.4701335207308503
```

Cross validation

In [75]:
```
results = cross_validate(KNeighborsClassifier(n_neighbors = 51), X_train_rfe, y_train_resample,
              scoring = ['f1', 'accuracy', 'precision', 'recall'])
```

In [76]:
```
print(f"test f1 score with cross validation: {np.mean(results['test_f1'])}")
print(f"test accuracy with cross validation: {np.mean(results['test_accuracy'])}")
print(f"test precision with cross validation: {np.mean(results['test_precision'])}")
print(f"test recall with cross validation: {np.mean(results['test_recall'])}")
```

```
test f1 score with cross validation: 0.6855375126532584
test accuracy with cross validation: 0.7323037923002044
test precision with cross validation: 0.8220560610454491
test recall with cross validation: 0.5917382632432074
```

In [77]:
```
# ROC curve for the best KNN model
fpr_knn, tpr_knn, _ = roc_curve(y_test, KNN_clf_final.predict_proba(X_test_rfe)[:,1])
```

Naive Bayes

In [78]:
```
# Instantiate NB classifier
baseline_nbayes_clf = GaussianNB()

# Fit model
baseline_nbayes_clf.fit(X_train_resample_scaled, y_train_resample)
```

Out[78]:
```
▾ GaussianNB
GaussianNB()
```

In [79]:
```
# Accuracy in training data
print(f"accuracy score: {accuracy_score(y_train_resample, baseline_nbayes_clf.predict(X_train_resample_scaled))}")
print(f"f1 score: {f1_score(y_train_resample, baseline_nbayes_clf.predict(X_train_resample_scaled))}")
print(f"precision score: {precision_score(y_train_resample, baseline_nbayes_clf.predict(X_train_resample_scaled))}")
print(f"recall score: {recall_score(y_train_resample, baseline_nbayes_clf.predict(X_train_resample_scaled))}")
```

```
accuracy score: 0.6933899486659484
f1 score: 0.7117664581471552
precision score: 0.6715193075150357
recall score: 0.7571455732302427
```

In [80]:
```
# Accuracy in testing data
print(f"accuracy score: {accuracy_score(y_test, baseline_nbayes_clf.predict(X_test_scaled))}")
print(f"f1 score: {f1_score(y_test, baseline_nbayes_clf.predict(X_test_scaled))}")
print(f"precision score: {precision_score(y_test, baseline_nbayes_clf.predict(X_test_scaled))}")
print(f"recall score: {recall_score(y_test, baseline_nbayes_clf.predict(X_test_scaled))}")
```

```
accuracy score: 0.6350157256252809
f1 score: 0.43964129684985054
precision score: 0.3267259056732741
recall score: 0.6718200983836964
```

Feature Selection

In [81]:
```
def custom_importance_getter_gnb(estimator, X_train, y_train):
    # Fit the Gaussian Naive Bayes estimator
    estimator.fit(X_train, y_train)
    # Compute mutual information between each feature and the target variable
    feature_importances = mutual_info_classif(X_train, y_train)
    return feature_importances
```

In [82]:
```
n_bayes_clf = GaussianNB()
custom_importance_getter_gnb(n_bayes_clf, X_train_resample_scaled, y_train_resample)
```

Out[82]:
```
array([0.1196517 , 0.10429541, 0.01636836, 0.04490508, 0.02711308,
       0.03356308, 0.02870022, 0.03539581, 0.04275712, 0.15892905,
       0.07112501, 0.0310447 , 0.05806617, 0.17394533, 0.14835401,
       0.07969732, 0.08064103, 0.06042524, 0.0273831 , 0.03893174,
       0.03873633, 0.03625291, 0.02520077, 0.05433004, 0.05218689,
       0.00333946, 0.01647591, 0.02505719, 0.04590719, 0.07056339,
       0.0516445 , 0.02708794, 0.03731297, 0.05104169, 0.00554979,
       0.05065674, 0.01009066, 0.04923573, 0.02179269, 0.00321481,
       0.03574412, 0.02035769, 0.03809774, 0.03808411, 0.03089951,
       0.04791079, 0.0291331 , 0.04109341, 0.04205457, 0.0624955 ,
       0.05978115, 0.10178605])
```

In [83]:
```
# Fit the Gaussian Naive Bayes estimator
estimator = GaussianNB()

# Compute feature importances using the custom function
feature_importances = custom_importance_getter_gnb(estimator, X_train_resample_scaled, y_train_resample)

# Get the indices of features sorted by importance
sorted_indices = feature_importances.argsort()[::-1]

# Get feature names
feature_names = X_train_resample.columns

# Get feature names and their rankings
feature_rankings = [[feature_names[i], rank + 1] for rank, i in enumerate(sorted_indices)]

print("Feature rankings:")
pd.DataFrame(feature_rankings, columns=['Feature', 'Rank'])
```

```
Feature rankings:
```

Out[83]:

	Feature	Rank
0	opinion_h1n1_vacc_effective	1
1	doctor_recc_h1n1	2
2	opinion_h1n1_risk	3
3	h1n1_concern	4
4	behavior_score	5
5	h1n1_knowledge	6
6	opinion_h1n1_sick_from_vacc	7
7	household_adults	8
8	sex_Male	9
9	chronic_med_condition	10
10	census_msa_MSA, Principle City	11
11	census_msa_Non-MSA	12
12	marital_status_Not Married	13
13	employment_status_Not in Labor Force	14
14	household_children	15
15	health_worker	16
16	education_College Graduate	17
17	rent_or_own_Rent	18
18	income_poverty_> $75,000	19
19	race_White	20
20	education_Some College	21
21	hhs_geo_region_lzgpxyit	22
22	behavioral_touch_face	23
23	age_group_45 - 54 Years	24
24	hhs_geo_region_bhuqouqj	25

	Feature	Rank
25	behavioral_avoidance	26
26	hhs_geo_region_fpwskwrf	27
27	hhs_geo_region_oxchjgsf	28
28	child_under_6_months	29
29	age_group_55 - 64 Years	30
30	hhs_geo_region_kbazzjca	31
31	hhs_geo_region_qufhixun	32
32	behavioral_wash_hands	33
33	age_group_65+ Years	34
34	hhs_geo_region_mlyzmhmf	35
35	behavioral_large_gatherings	36
36	income_poverty_nan	37
37	hhs_geo_region_lrircsnp	38
38	age_group_35 - 44 Years	39
39	behavioral_outside_home	40
40	income_poverty_Below Poverty	41
41	behavioral_face_mask	42
42	race_Hispanic	43
43	education_< 12 Years	44
44	race_Other or Multiple	45
45	behavioral_antiviral_meds	46
46	hhs_geo_region_dqpwygqj	47
47	employment_status_Unemployed	48
48	rent_or_own_nan	49
49	education_nan	50
50	marital_status_nan	51

	Feature	Rank
51	employment_status_nan	52

In [84]:

```
feature_rankings = pd.DataFrame(feature_rankings, columns=['Feature', 'Rank'])

select_columns = feature_rankings['Feature'][0:10]
X_train_resample[select_columns]
```

Out[84]:

	opinion_h1n1_vacc_effective	doctor_recc_h1n1	opinion_h1n1_risk	h1n1_concern	behavior_score	h1n1_knowledge	opinion_h1n1_sick_from_
0	4.000000	0.0	2.000000	1.000000	5.0	1.0	4.0
1	4.000000	1.0	4.000000	3.000000	3.0	1.0	4.0
2	3.000000	0.0	3.000000	2.000000	4.0	1.0	2.0
3	4.000000	0.0	2.000000	2.000000	4.0	1.0	4.0
4	5.000000	0.0	2.000000	2.000000	3.0	2.0	2.0
...	...	...	...	...	...	...	
31553	5.000000	0.0	4.000000	2.543444	4.0	0.0	5.0
31554	5.000000	0.0	4.000000	2.124890	4.0	2.0	5.0
31555	5.000000	0.0	1.000000	1.829397	3.0	2.0	1.1
31556	5.000000	0.0	4.000000	2.000000	3.0	1.0	4.5
31557	4.071783	1.0	4.071783	1.071783	3.0	1.0	2.0

31558 rows × 10 columns

In [85]:

```
X_train_resample_scaled_select_columns = scaler.fit_transform(X_train_resample[select_columns])
X_test_scaled_select_columns = scaler.transform(X_test[select_columns])
```

In [86]:
```
n_bayes_clf2 = GaussianNB()

# Fit model
n_bayes_clf2.fit(X_train_resample_scaled_select_columns, y_train_resample)
```

Out[86]:
```
▾ GaussianNB
GaussianNB()
```

In [87]:
```
# Accuracy in training data
print(f"accuracy score: {accuracy_score(y_train_resample, n_bayes_clf2.predict(X_train_resample_scaled_select_columns)
print(f"f1 score: {f1_score(y_train_resample, n_bayes_clf2.predict(X_train_resample_scaled_select_columns))}")
print(f"precision score: {precision_score(y_train_resample, n_bayes_clf2.predict(X_train_resample_scaled_select_column
print(f"recall score: {recall_score(y_train_resample, n_bayes_clf2.predict(X_train_resample_scaled_select_columns))}")
```

```
accuracy score: 0.7455161924076303
f1 score: 0.7401054982039417
precision score: 0.756183044570824
recall score: 0.7246973825971228
```

In [88]:
```
# Accuracy in testing data
print(f"accuracy score: {accuracy_score(y_test, n_bayes_clf2.predict(X_test_scaled_select_columns))}")
print(f"f1 score: {f1_score(y_test, n_bayes_clf2.predict(X_test_scaled_select_columns))}")
print(f"precision score: {precision_score(y_test, n_bayes_clf2.predict(X_test_scaled_select_columns))}")
print(f"recall score: {recall_score(y_test, n_bayes_clf2.predict(X_test_scaled_select_columns))}")
```

```
accuracy score: 0.7531825670211173
f1 score: 0.5555555555555556
precision score: 0.45076586433260396
recall score: 0.7238229093464511
```

Cross validate

In [89]:
```
results = cross_validate(GaussianNB(), X_train_resample_scaled_select_columns, y_train_resample,
              scoring = ['f1', 'accuracy', 'precision', 'recall'])
```

In [90]:
```
print(f"test f1 score with cross validation: {np.mean(results['test_f1'])}")
print(f"test accuracy with cross validation: {np.mean(results['test_accuracy'])}")
print(f"test precision with cross validation: {np.mean(results['test_precision'])}")
print(f"test recall with cross validation: {np.mean(results['test_recall'])}")
```

```
test f1 score with cross validation: 0.7387037395746147
test accuracy with cross validation: 0.7443121622194254
test precision with cross validation: 0.7553095105542178
test recall with cross validation: 0.7229233176461609
```

In [91]:
```
# ROC curve for the best Gausssian Naive Bayes model
fpr_gnbayes, tpr_gnbayes, _ = roc_curve(y_test, n_bayes_clf2.predict_proba(X_test_scaled_select_columns)[:,1])
```

Decision Tree

In [92]:
```
# Initialize Decision Tree classifier
dt_classifier = DecisionTreeClassifier(random_state=40)

# Train the model
dt_classifier.fit(X_train_resample, y_train_resample)

# Make predictions on the testing set
y_pred = dt_classifier.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)

# Classification report
print("Classification Report:")
print(classification_report(y_test, y_pred))

# Confusion matrix
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

```
Accuracy: 0.7486895312265988
Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.82      0.84      5254
           1       0.42      0.48      0.45      1423

    accuracy                           0.75      6677
   macro avg       0.64      0.65      0.64      6677
weighted avg       0.76      0.75      0.75      6677

Confusion Matrix:
[[4322  932]
 [ 746  677]]
```

In [93]:
```
# Define the hyperparameters grid
param_grid = {
    'criterion': ['gini', 'entropy'],
    'max_depth': [None, 10, 20, 30, 40, 50],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Initialize the decision tree classifier
dt_classifier = DecisionTreeClassifier(random_state=40)

# Initialize GridSearchCV
grid_search = GridSearchCV(estimator=dt_classifier, param_grid=param_grid, cv=5, scoring='accuracy')

# Perform grid search
grid_search.fit(X_train_resample, y_train_resample)

# Get the best parameters and best score
best_params = grid_search.best_params_
best_score = grid_search.best_score_

print("Best Parameters:", best_params)
print("Best Score:", best_score)
```

```
Best Parameters: {'criterion': 'gini', 'max_depth': 10, 'min_samples_leaf': 4, 'min_samples_split': 10}
Best Score: 0.8464134784678972
```

In [94]:
```
# Initialize the decision tree classifier with best parameters
best_dt_classifier = DecisionTreeClassifier(criterion='entropy', max_depth=20, min_samples_leaf=4, min_samples_split=2

# Train the model with best parameters
best_dt_classifier.fit(X_train_resample, y_train_resample)

# Make predictions on the testing set
y_pred_best = best_dt_classifier.predict(X_test)

# Evaluate the model with best parameters
accuracy_best = accuracy_score(y_test, y_pred_best)
print("Accuracy with best parameters:", accuracy_best)

# Classification report
print("Classification Report with best parameters:")
print(classification_report(y_test, y_pred_best))

# Confusion matrix
print("Confusion Matrix with best parameters:")
print(confusion_matrix(y_test, y_pred_best))
```

```
Accuracy with best parameters: 0.7918226748539763
Classification Report with best parameters:
              precision    recall  f1-score   support

           0       0.85      0.89      0.87      5254
           1       0.51      0.43      0.47      1423

    accuracy                           0.79      6677
   macro avg       0.68      0.66      0.67      6677
weighted avg       0.78      0.79      0.78      6677

Confusion Matrix with best parameters:
[[4681  573]
 [ 817  606]]
```

Feature selection

In [95]:
```
# Initialize RFE with the classifier and desired number of features to select
rfe = RFE(estimator= best_dt_classifier, n_features_to_select= .8, step= 1)  # Select top 80% features

# Fit RFE on train data set
rfe.fit(X_train_resample, y_train_resample)
print(X_train_resample.columns)
print(rfe.ranking_)
print(rfe.support_)
```

```
Index(['h1n1_concern', 'h1n1_knowledge', 'behavioral_antiviral_meds',
       'behavioral_avoidance', 'behavioral_face_mask', 'behavioral_wash_hands',
       'behavioral_large_gatherings', 'behavioral_outside_home',
       'behavioral_touch_face', 'doctor_recc_h1n1', 'chronic_med_condition',
       'child_under_6_months', 'health_worker', 'opinion_h1n1_vacc_effective',
       'opinion_h1n1_risk', 'opinion_h1n1_sick_from_vacc', 'household_adults',
       'household_children', 'age_group_35 - 44 Years',
       'age_group_45 - 54 Years', 'age_group_55 - 64 Years',
       'age_group_65+ Years', 'education_< 12 Years',
       'education_College Graduate', 'education_Some College', 'education_nan',
       'race_Hispanic', 'race_Other or Multiple', 'race_White', 'sex_Male',
       'income_poverty_> $75,000', 'income_poverty_Below Poverty',
       'income_poverty_nan', 'marital_status_Not Married',
       'marital_status_nan', 'rent_or_own_Rent', 'rent_or_own_nan',
       'employment_status_Not in Labor Force', 'employment_status_Unemployed',
       'employment_status_nan', 'hhs_geo_region_bhuqouqj',
       'hhs_geo_region_dqpwygqj', 'hhs_geo_region_fpwskwrf',
       'hhs_geo_region_kbazzjca', 'hhs_geo_region_lrircsnp',
       'hhs_geo_region_lzgpxyit', 'hhs_geo_region_mlyzmhmf',
       'hhs_geo_region_oxchjgsf', 'hhs_geo_region_qufhixun',
       'census_msa_MSA, Principle City', 'census_msa_Non-MSA',
       'behavior_score'],
      dtype='object')
[ 1  1  4  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1  1
  1  9  7  1  1  1  1  5  1  1 11  1  8  1  6 12  1 10  1  2  3  1  1  1
  1  1  1  1]
[ True  True False  True  True  True  True  True  True  True  True  True
  True  True  True  True  True  True  True  True  True  True  True  True
  True False False  True  True  True  True False  True  True False  True
 False  True False False  True False  True False False  True  True  True
  True  True  True  True]
```

In [96]:
```
masked_columns = X_train_resample.columns[rfe.get_support(indices= True)]
masked_columns
```

Out[96]:
```
Index(['h1n1_concern', 'h1n1_knowledge', 'behavioral_avoidance',
       'behavioral_face_mask', 'behavioral_wash_hands',
       'behavioral_large_gatherings', 'behavioral_outside_home',
       'behavioral_touch_face', 'doctor_recc_h1n1', 'chronic_med_condition',
       'child_under_6_months', 'health_worker', 'opinion_h1n1_vacc_effective',
       'opinion_h1n1_risk', 'opinion_h1n1_sick_from_vacc', 'household_adults',
       'household_children', 'age_group_35 - 44 Years',
       'age_group_45 - 54 Years', 'age_group_55 - 64 Years',
       'age_group_65+ Years', 'education_< 12 Years',
       'education_College Graduate', 'education_Some College',
       'race_Other or Multiple', 'race_White', 'sex_Male',
       'income_poverty_> $75,000', 'income_poverty_nan',
       'marital_status_Not Married', 'rent_or_own_Rent',
       'employment_status_Not in Labor Force', 'hhs_geo_region_bhuqouqj',
       'hhs_geo_region_fpwskwrf', 'hhs_geo_region_lzgpxyit',
       'hhs_geo_region_mlyzmhmf', 'hhs_geo_region_oxchjgsf',
       'hhs_geo_region_qufhixun', 'census_msa_MSA, Principle City',
       'census_msa_Non-MSA', 'behavior_score'],
      dtype='object')
```

In [97]:
```
select_colums = []
for column in X_train_resample.columns:
    if column not in masked_columns:
        select_colums.append(column)

select_colums
```

Out[97]:
```
['behavioral_antiviral_meds',
 'education_nan',
 'race_Hispanic',
 'income_poverty_Below Poverty',
 'marital_status_nan',
 'rent_or_own_nan',
 'employment_status_Unemployed',
 'employment_status_nan',
 'hhs_geo_region_dqpwygqj',
 'hhs_geo_region_kbazzjca',
 'hhs_geo_region_lrircsnp']
```

In [98]:
```
X_train_rfe = X_train_resample[select_colums]
X_test_rfe = X_test[select_colums]
```

In [99]:
```
# Initialize the decision tree classifier with best parameters
best_dt_classifier_with_rfe = DecisionTreeClassifier(criterion='entropy', max_depth=20, min_samples_leaf=4, min_sample

# Train the model with best parameters
best_dt_classifier_with_rfe.fit(X_train_rfe, y_train_resample)

# Make predictions on the testing set
y_pred_best = best_dt_classifier_with_rfe.predict(X_test_rfe)

# Evaluate the model with best parameters
accuracy_best = accuracy_score(y_test, y_pred_best)
print("Accuracy with best parameters:", accuracy_best)

# Classification report
print("Classification Report with best parameters:")
print(classification_report(y_test, y_pred_best))

# Confusion matrix
print("Confusion Matrix with best parameters:")
print(confusion_matrix(y_test, y_pred_best))
```

```
Accuracy with best parameters: 0.7862812640407368
Classification Report with best parameters:
              precision    recall  f1-score   support

           0       0.79      1.00      0.88      5254
           1       0.30      0.00      0.00      1423

    accuracy                           0.79      6677
   macro avg       0.54      0.50      0.44      6677
weighted avg       0.68      0.79      0.69      6677

Confusion Matrix with best parameters:
[[5247    7]
 [1420    3]]
```

In [100]:
```
# ROC curve for the best Decision tree model
fpr_dtree, tpr_dtree, _ = roc_curve(y_test, best_dt_classifier_with_rfe.predict_proba(X_test_rfe)[:,1])
```

Random Forest

In [101]:
```
def create_models(seed=42):
    models =[]
    models.append(('random_forest', RandomForestClassifier(random_state=40)))
    return models
models= create_models()
```

In [102]:
```
# results using default parameters
results= []
names=[]
scoring = 'accuracy'
for name, model in models:
    # fit model with training data
    model.fit(X_train_resample, y_train_resample).predict(X_test)
    # make predictions with testing data
    predictions=model.predict(X_test)
    # calculating accuracy
    accuracy = accuracy_score(y_test, predictions)
    # append model name and accuracy to the lists
    results.append(accuracy)
    names.append(name)
    #print classifier accuracy
    print('classifier:{}, Accuracy score: {})'.format(name, accuracy))
    print(classification_report(y_test, predictions))
```

```
classifier:random_forest, Accuracy score: 0.8340572113224503)
              precision    recall  f1-score   support

           0       0.86      0.94      0.90      5254
           1       0.66      0.45      0.54      1423

    accuracy                           0.83      6677
   macro avg       0.76      0.69      0.72      6677
weighted avg       0.82      0.83      0.82      6677
```

In [103]:
```
def perform_grid_search(classifer, param_grid):
    pipe = Pipeline([
        ('scaler', StandardScaler()),
        ('classifier', RandomForestClassifier())
    ])

    random_search = GridSearchCV(estimator = pipe,
                       param_grid = param_grid,
                       scoring = 'accuracy',
                       cv = 3,
                       verbose =1)
    random_search.fit(X_train_resample, y_train_resample)

    best_params = random_search.best_params_
    print("Best Parameters:",  best_params)

    # Evaluate the model on the test set
    y_pred = random_search.predict(X_test)


    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)



    print("Test Accuracy:", accuracy)
    print("Precision:", precision)
    print("Recall:", recall)
    print("F1 score:", f1)

    # classifiaction reports
    print("Classification Report:")
    print(classification_report(y_test, y_pred))

    return best_params, accuracy
```

In [104]:
```
classifier = RandomForestClassifier()
param_grid = [{'classifier__max_depth': [5,10],
        'classifier__min_samples_split': [4,6]}]
perform_grid_search(classifier, param_grid)
```

```
Fitting 3 folds for each of 4 candidates, totalling 12 fits
Best Parameters: {'classifier__max_depth': 10, 'classifier__min_samples_split': 4}
Test Accuracy: 0.8264190504717688
Precision: 0.594017094017094
Recall: 0.5860857343640197
F1 score: 0.5900247612309869
Classification Report:
              precision    recall  f1-score   support

           0       0.89      0.89      0.89      5254
           1       0.59      0.59      0.59      1423

    accuracy                           0.83      6677
   macro avg       0.74      0.74      0.74      6677
weighted avg       0.83      0.83      0.83      6677
```

Out[104]:
```
({'classifier__max_depth': 10, 'classifier__min_samples_split': 4},
 0.8264190504717688)
```

In [105]:
```
# Final random forest model
# Instantiate classifier
random_forest_final = RandomForestClassifier(max_depth= 10, min_samples_split= 4)

# Fit model
random_forest_final.fit(X_train_resample, y_train_resample)
```

Out[105]:
```
RandomForestClassifier
RandomForestClassifier(max_depth=10, min_samples_split=4)
```

In [106]:
```
# ROC curve for the best Decision tree model
fpr_rforest, tpr_rforest, _ = roc_curve(y_test, random_forest_final.predict_proba(X_test)[:,1])
```

XGBoost

In [107]:
```
# Clean feature names
clean_feature_names = [name.replace('[', '').replace(']', '').replace('<', '') for name in X_train_resample.columns]
X_train_resample.columns = clean_feature_names

X_test.columns = [name.replace('education_< ', 'education_ ') for name in X_test.columns]

# Initialize the XGBoost model
xgboost = XGBClassifier()

# Train the XGBoost model
xgboost.fit(X_train_resample, y_train_resample)

# Make predictions on the training set
y_train_pred = xgboost.predict(X_train_resample)

# Calculate evaluation metrics for training set
train_accuracy = accuracy_score(y_train_resample, y_train_pred)
train_precision = precision_score(y_train_resample, y_train_pred)
train_recall = recall_score(y_train_resample, y_train_pred)
train_f1_score = f1_score(y_train_resample, y_train_pred)

# Make predictions on the test set
y_test_pred = xgboost.predict(X_test)

print("confusion_matrix for XGBoost\n",confusion_matrix(y_test,y_test_pred))


print(classification_report(y_test, y_test_pred))


print("Test Accuracy Score:", accuracy_score(y_test, y_test_pred))
```

```
confusion_matrix for XGBoost
 [[4898  356]
 [ 755  668]]
              precision    recall  f1-score   support

           0       0.87      0.93      0.90      5254
           1       0.65      0.47      0.55      1423

    accuracy                           0.83      6677
   macro avg       0.76      0.70      0.72      6677
weighted avg       0.82      0.83      0.82      6677

Test Accuracy Score: 0.8336079077429983
```

In [108]:
```
# Define the hyperparameters to tune

param_grid = {
    'max_depth': [ 5, 7, 9],
    'learning_rate': [0.1, 0.01],
    'n_estimators': [100, 300],
    'subsample': [0.8, 1.0],
    'colsample_bytree': [0.8, 1.0]
}

grid_clf = GridSearchCV(xgboost, param_grid, scoring='accuracy', cv=None, n_jobs=1)
grid_clf.fit(X_train_resample, y_train_resample)

best_parameters = grid_clf.best_params_

print('Grid Search found the following optimal parameters: ')
for param_name in sorted(best_parameters.keys()):
    print('%s: %r' % (param_name, best_parameters[param_name]))

training_preds = grid_clf.predict(X_train_resample)
test_preds = grid_clf.predict(X_test)
training_accuracy = accuracy_score(y_train_resample, training_preds)
test_accuracy = accuracy_score(y_test, test_preds)

print('')
print('Training Accuracy: {:.4}%'.format(training_accuracy * 100))
print('Validation accuracy: {:.4}%'.format(test_accuracy * 100))
```

```
Grid Search found the following optimal parameters:
colsample_bytree: 0.8
learning_rate: 0.01
max_depth: 9
n_estimators: 300
subsample: 0.8

Training Accuracy: 90.83%
Validation accuracy: 83.9%
```

In [109]:
```
# Final XGBoost Model
# Instantiate Classifer
xgboost_final = XGBClassifier(colsample_bytree= 0.8, learning_rate= 0.01, max_depth= 9, n_estimators= 300, subsample= (

# Fit model
xgboost_final.fit(X_train_resample, y_train_resample)
```

Out[109]:
```
XGBClassifier

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.8, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.01, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=9, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=300, n_jobs=None,
```

In [110]:
```
# ROC curve for the best Decision tree model
fpr_xgboost, tpr_xgboost, _ = roc_curve(y_test, xgboost_final.predict_proba(X_test)[:,1])
```

Summary of all the tuned models using an Accuracy Scores:

1. Logistic Regression - **0.7735**
2. Decision Tree - **0.7814**
3. KNN - **0.7811**
4. Naive Bayes - **0.7528**
5. Random Forest - **0.8288**
6. XGBoost - **0.8405**

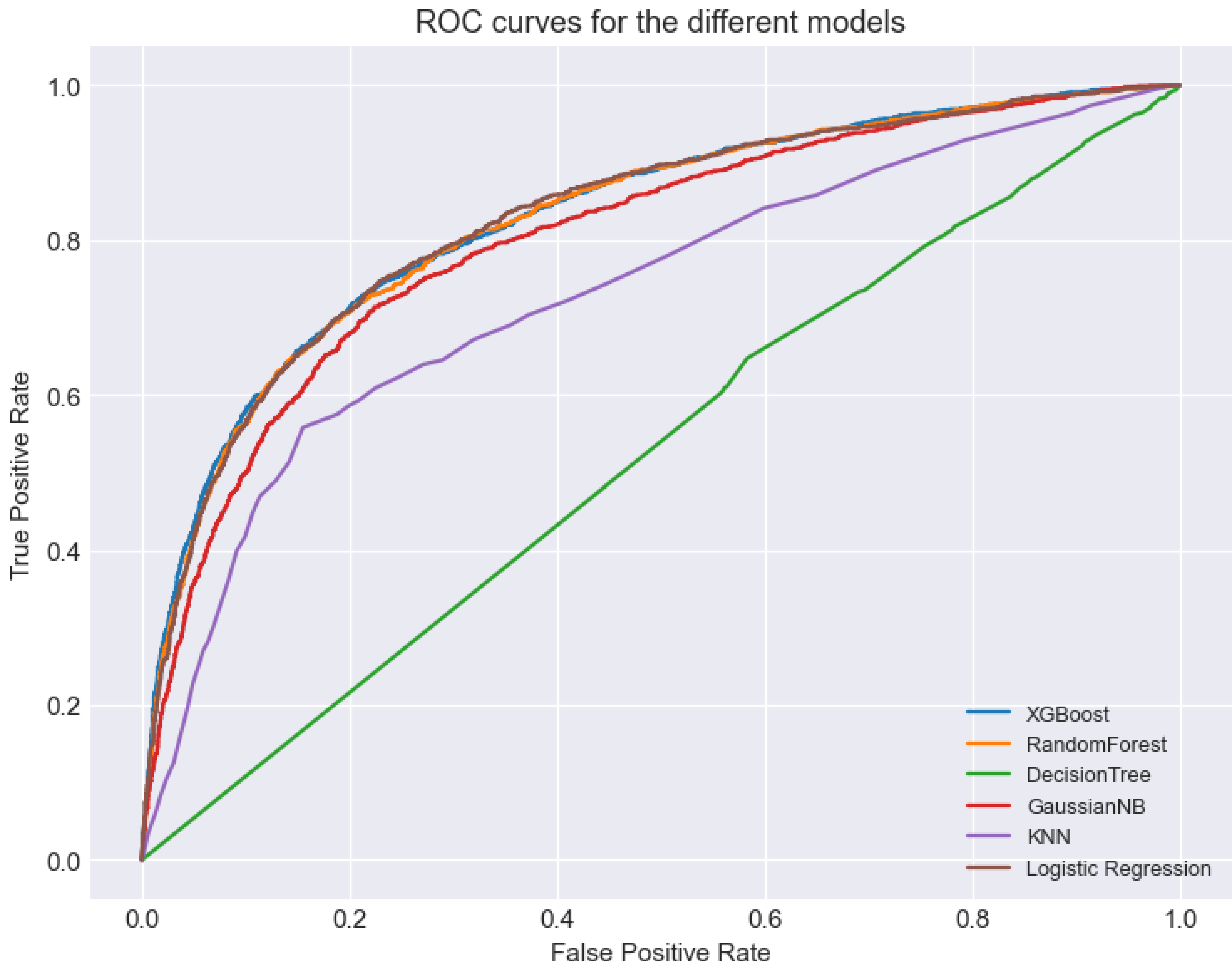
The best model for predicting vaccine uptake:

- XGBoost is therefore our **best and final model** with the best Accuracy of **0.8405**, as compared to all other models

ROC Curve

Summary of all the tuned models using an ROC curve:

In [111]:
```
plt.figure(figsize=(8,6), dpi=110)
plt.plot(fpr_xgboost, tpr_xgboost, label='XGBoost')
plt.plot(fpr_rforest, tpr_rforest, label='RandomForest')
plt.plot(fpr_dtree, tpr_dtree, label='DecisionTree')
plt.plot(fpr_gnbayes, tpr_gnbayes, label='GaussianNB')
plt.plot(fpr_knn, tpr_knn, label='KNN')
plt.plot(fpr_logreg, tpr_logreg, label='Logistic Regression')
plt.title('ROC curves for the different models')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(fontsize= 'small', loc='lower right')
plt.show()
```



Conclusions

Features that were most important in predicting whether someone was vaccinated or not included:

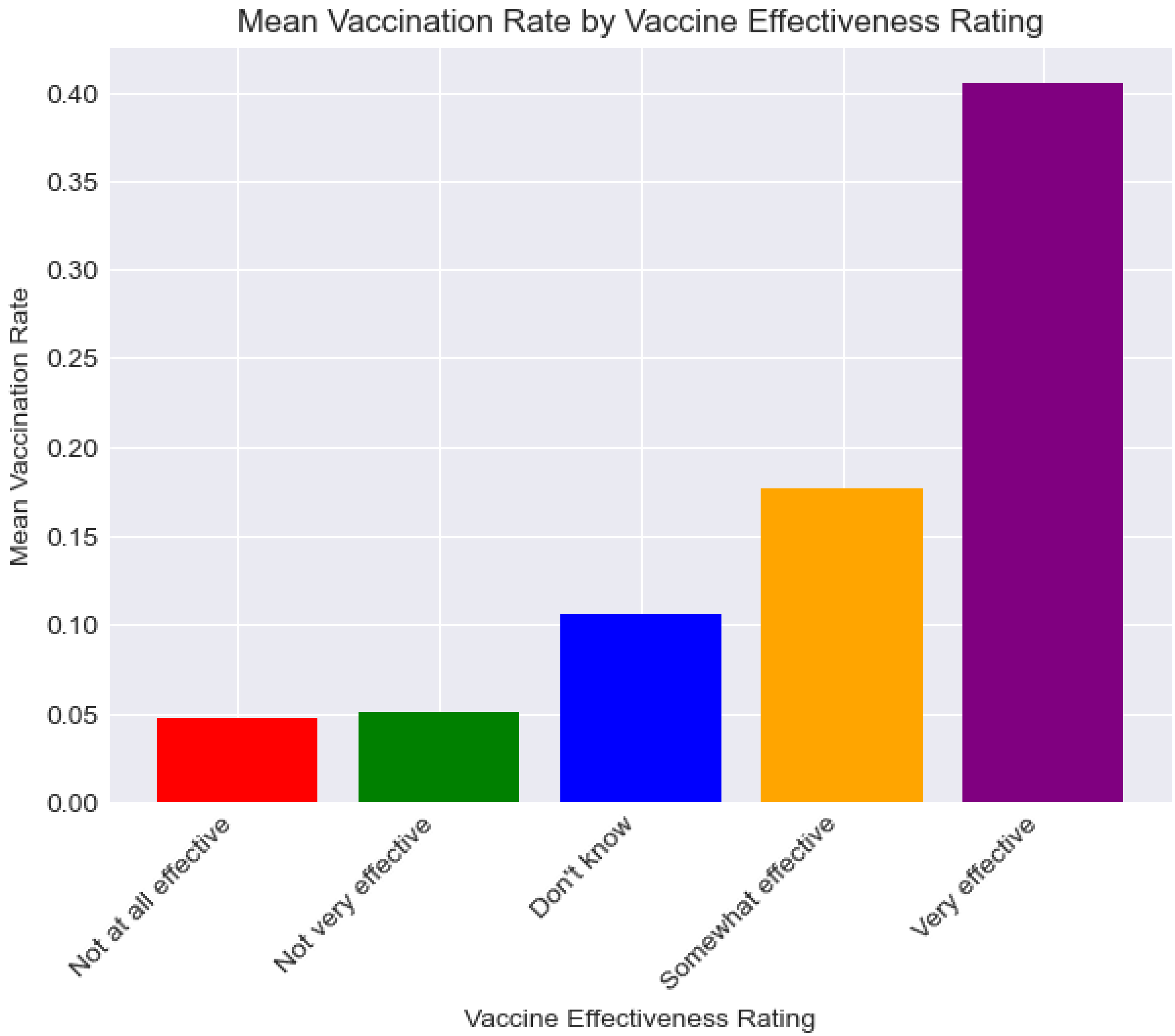
1. Opinion on H1N1 vaccine effectiveness.
2. Doctor’s recommendation.
3. H1N1 concern.
4. Gender.
5. H1N1 Knowledge.
6. Perceived side-effects from H1N1 vaccine.
7. Chronic medical condition.
8. Number of adults in an household.

In [112]:
```
# Define a function to generate the plots for the important features

def create_vaccination_rate_plot(feature, target, data, x_label, y_label, plot_title,
                                 x_tick_labels=None, plot_width=7, plot_height=5):
    mean_vaccination_rate = data.groupby(feature)[target].mean().reset_index()

    # Define a list of colors to assign to each category
    colors = ['red', 'green', 'blue', 'orange', 'purple', 'black']

    fig, ax = plt.subplots(figsize=(plot_width, plot_height))
    ax.bar(mean_vaccination_rate[feature], mean_vaccination_rate[target],
           color=colors[:len(mean_vaccination_rate[feature])])

    ax.set_title(plot_title)
    ax.set_xlabel(x_label)
    ax.set_ylabel(y_label)
    if x_tick_labels:
        ax.set_xticks(mean_vaccination_rate[feature])
        ax.set_xticklabels(x_tick_labels, rotation=45, ha='right')

    plt.show()
```

Plot of the top 5 most important features in prediciting vactination status of H1N1

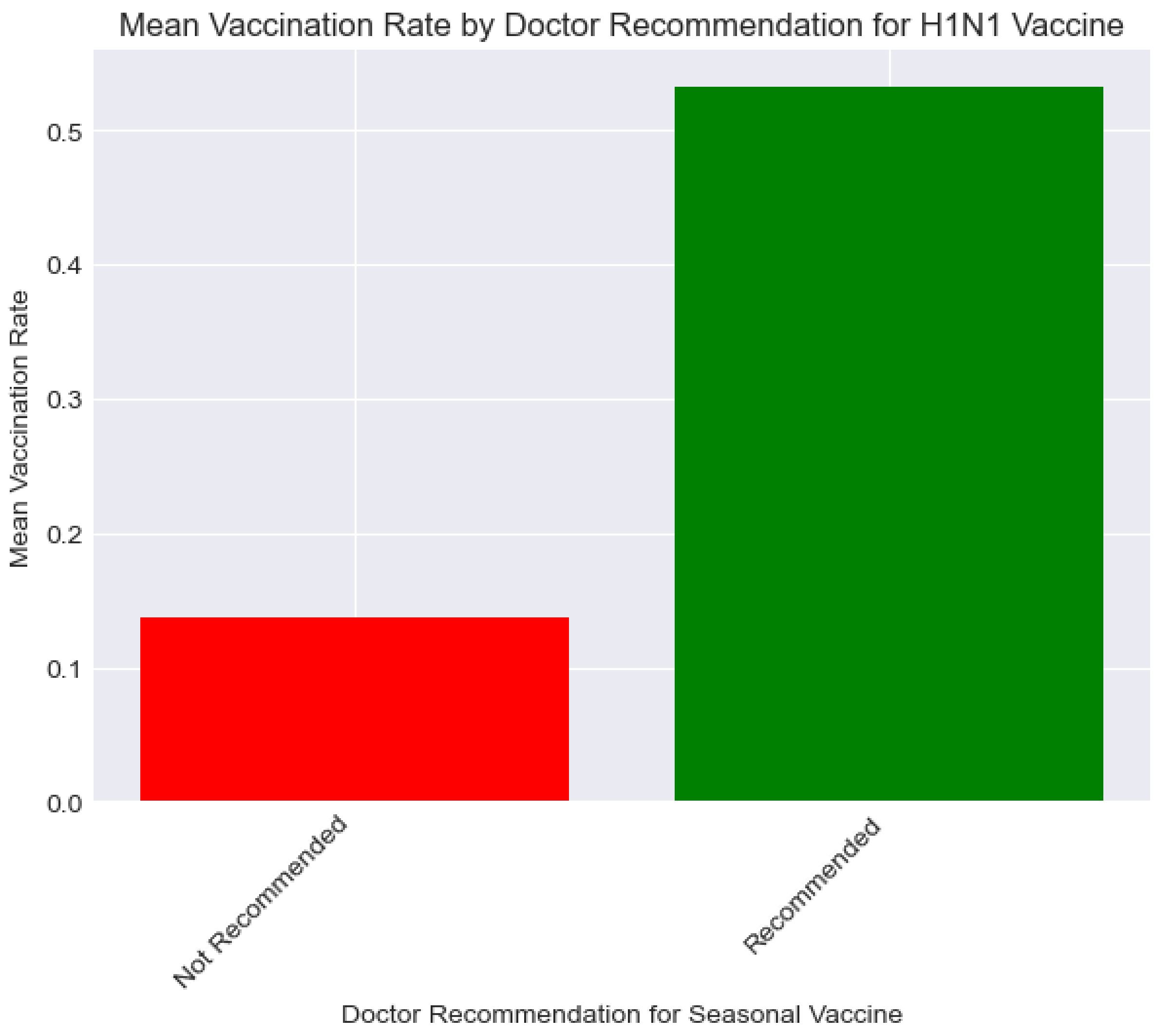
1. Respondent's opinion about H1N1 flu vaccine effectiveness.

In [113]:
```
fig = create_vaccination_rate_plot('opinion_h1n1_vacc_effective', 'h1n1_vaccine', merged_df,
                                   'Vaccine Effectiveness Rating',
                                   'Mean Vaccination Rate',
                                   'Mean Vaccination Rate by Vaccine Effectiveness Rating',
                                    x_tick_labels=['Not at all effective', 'Not very effective', "Don't know",
                                                   'Somewhat effective', 'Very effective'],
                                    plot_width=7, plot_height=5)

plt.show()
```



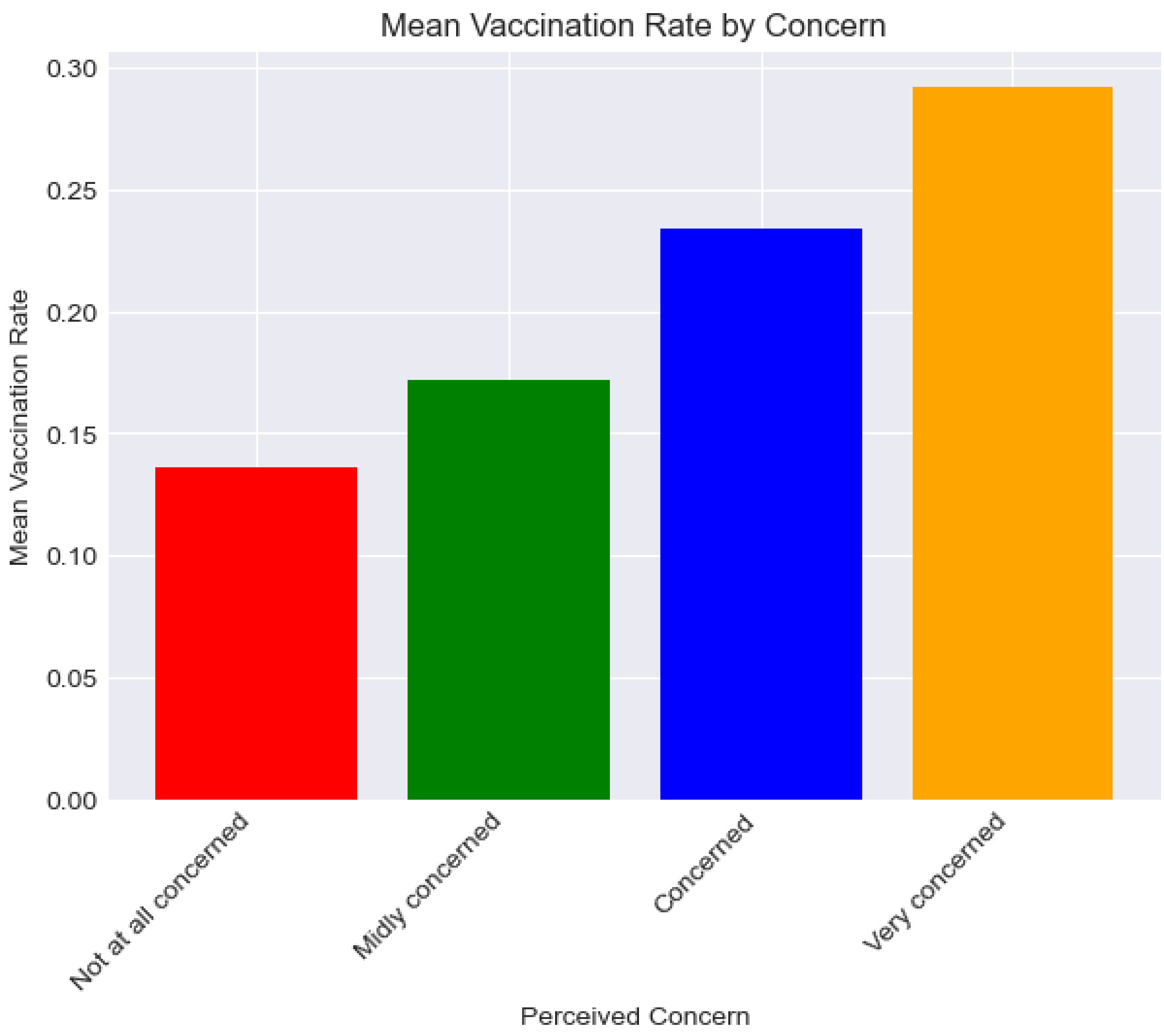
2. Doctor’s recommendation.

In [114]:
```
fig = create_vaccination_rate_plot('doctor_recc_h1n1', 'h1n1_vaccine', merged_df,
                                   'Doctor Recommendation for H1N1 Vaccine',
                                   'Mean Vaccination Rate',
                                   'Mean Vaccination Rate by Doctor Recommendation for H1N1 Vaccine',
                                    x_tick_labels=['Not Recommended', 'Recommended'],
                                    plot_width=7, plot_height=5)

plt.show()
```



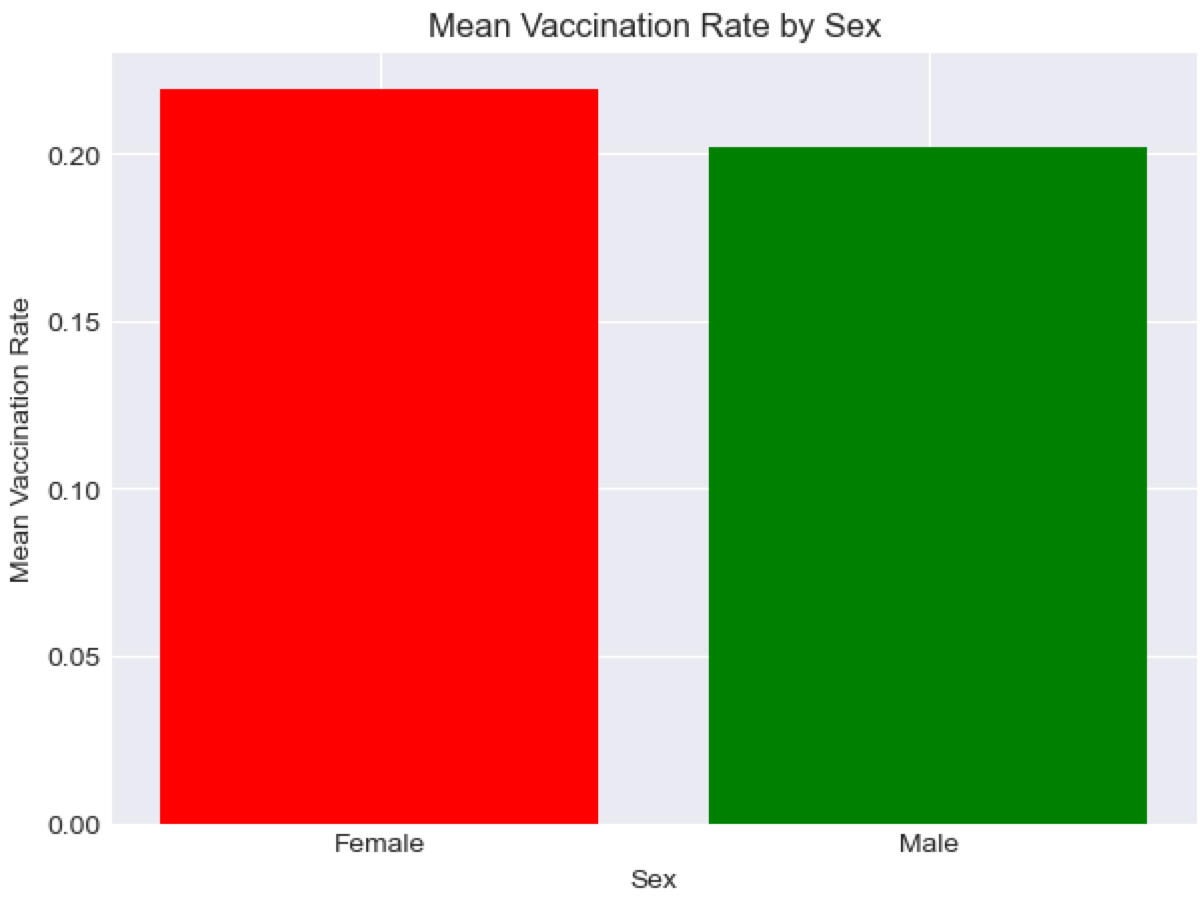
3. H1N1 concern

In [115]:
```
fig = create_vaccination_rate_plot('h1n1_concern', 'h1n1_vaccine', merged_df,
                                   'Perceived Concern',
                                   'Mean Vaccination Rate',
                                   'Mean Vaccination Rate by Concern',
                                    x_tick_labels=['Not at all concerned', 'Midly concerned',"Concerned",
                                                   'Very concerned'],
                                    plot_width=7, plot_height=5)

plt.show()
```


Mean Vaccination Rate by Concern
Mean Vaccination Rate
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Not at all concerned
Midly concerned
Concerned
Very concerned
Perceived Concern

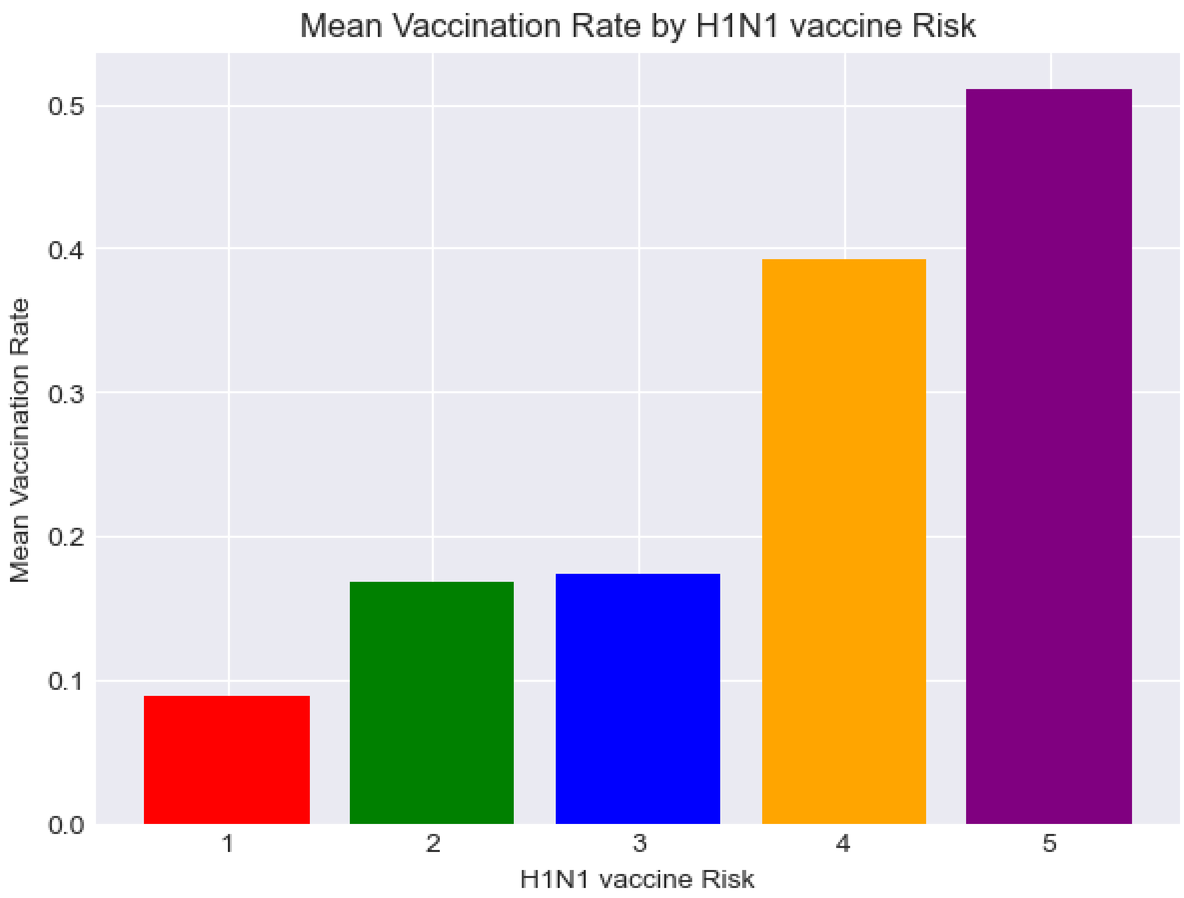
4. Gender

In [116]:
```
fig = create_vaccination_rate_plot('sex', 'h1n1_vaccine', merged_df,
                                   'Sex',
                                   'Mean Vaccination Rate',
                                   'Mean Vaccination Rate by Sex',
                                    x_tick_labels=[],
                                    plot_width=7, plot_height=5)

plt.show()
```



5. Perceived side effects from H1N1 vaccine

In [117]:
```
fig = create_vaccination_rate_plot('opinion_h1n1_risk', 'h1n1_vaccine', merged_df,
                                    'H1N1 vaccine Risk',
                                    'Mean Vaccination Rate',
                                    'Mean Vaccination Rate by H1N1 vaccine Risk',
                                     x_tick_labels=[],
                                     plot_width=7, plot_height=5)

plt.show()
```



Recommendations

1. Dispel vaccine myths and promote preventative measures against the flu.
2. Identify high risk groups partcularly those with lower levels of education and indviduals expressing low concern for H1N1, to implement targeted messaging to them.
3. Utilize predictive model for efficent resource allocation on the vaccination campaign.
4. Implement policies that emphasize on face masks, minimizing gatherings and hand washing.
5. Collaboration with health experts to encouraage medical checkups and doctor's recommendation. tion

Next Steps

1. Monitoring and Assessment: Keep a close eye on the results of the interventions and communication tactics used. Compare the vaccination uptake rates before and after the interventions to assess the efficacy of various strategies.

2. Update the predictive model often with fresh information to enhance future interventions and targeting tactics.