Final Project Submission ¶

1.Business Understanding

1.1.*Overview*

> Influenza, commonly known as "the flu", is an infectious disease caused by influenza viruses. Symptoms range from mild to severe and often include fever, runny nose, sore throat, muscle pain, headache, coughing, and fatigue. These symptoms begin from one to four days after exposure to the virus (typically two days) and last for about 2–8 days. Diarrhea and vomiting can occur, particularly in children. Influenza may progress to pneumonia, which can be caused by the virus or by a subsequent bacterial infection. Other complications of infection include acute respiratory distress syndrome, meningitis, encephalitis, and worsening of pre-existing health problems such as asthma and cardiovascular disease.

> There are four types of influenza virus, termed influenza viruses A, B, C, and D. Aquatic birds are the primary source of Influenza A virus (IAV), which is also widespread in various mammals, including humans and pigs. Influenza B virus (IBV) and Influenza C virus (ICV) primarily infect humans, and Influenza D virus (IDV) is found in cattle and pigs. IAV and IBV circulate in humans and cause seasonal epidemics, and ICV causes a mild infection, primarily in children. IDV can infect humans but is not known to cause illness.

> According to the World Health Organization, people such as those aged 65 years and older, young children and people with certain health conditions are at a higher risk of serious flu complications. For the influenza A and B viruses that routinely spread in people, human influenza viruses are responsible. Most experts believe that in humans, influenza viruses are primarily transmitted through respiratory droplets produced from coughing and sneezing. Less often, a person might get flu by touching a surface or object that has flu droplets on it and touching their own mouths, nose or possibly their eyes. The best way to reduce the risk of flu and its serious complications is by getting vaccinated each year.

1.2.Business Objectives

Listed below are ways in which the public can help curb the spread of the flu:

1.Take time to get a flu vaccine.

- CDC recommends a yearly flu vaccine as the first and most important step in protecting against flu viruses.Flu vaccines help to reduce the burden of flu illnesses, hospitalizations and deaths on the health care system each year.

2.Take everyday preventive actions to stop the spread of germs.

- Avoid close contact with people who are sick.
- If you are sick, limit contact with others as much as possible to keep from infecting them.
- Cover coughs and sneezes.
- Cover your nose and mouth with a tissue and throw it away after use when you cough or sneeze.

3.Take flu antiviral drugs if your doctor prescribes them.

- If you are sick with flu, antiviral drugs can be used to treat your illness.
- Antiviral drugs are different from antibiotics. They are prescription medicines (pills, liquid or an inhaled powder) and are not available over-the-counter.

1.3.Determining the project goals

Our main goal for the project is to determine how the following factors affect people's decisions to get the H1N1 and seasonal flu vaccine;

- People's Backgrounds(age,education,race,sex,marital status,employment status)
- Opinions on H1N1 vaccine and seasonal flu vaccine.
- Health behaviours(washing hands,buying face masks,avoiding close contact with others,taking antiviral medication,avoiding touching your face)

1.4.Determining the Project success criteria

We are going to use the following algorithms to come up with our predictive models.

- Using binary relevance(Naive bayes, Logistic regression)
- XG boost
- Random forest
- Multioutput classifier

The success metrics for the mentioned algorithms are:

- Accuracy score of above 65%

2.Data Understanding

In [173]:
```
#importing libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings("ignore")
from sklearn.model_selection import train_test_split,GridSearchCV
from sklearn.pipeline import Pipeline
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,ExtraTreesClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_repo
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import MinMaxScaler
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LogisticRegression
from sklearn.multioutput import MultiOutputClassifier
from sklearn.metrics import roc_curve, roc_auc_score
import xgboost as xgb
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score
```

2.1.Collecting the Data

This data was collected during the national 2009 H1N1 survey.

In [174]:
```
df = pd.read_csv("H1N1_Flu_Vaccines.csv",index_col='respondent_id')
df.head()
```

Out[174]:

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

5 rows × 37 columns

2.2 Description of the data

In [175]:
```
Description = pd.read_csv('Data Description.csv',header=0,squeeze=True,dtype=str,

pd.set_option('max_colwidth', 400)

Description
```

Out[175]:

	respondent_id	Unique and random identifier.
0	h1n1_concern	Level of concern about the H1N1 flu.(0 = Not at all concerned; 1 = Not very concerned; 2 = Somewhat concerned; 3 = Very concerned.)
1	h1n1_knowledge	Level of knowledge about H1N1 flu.(0 = No knowledge; 1 = A little knowledge; 2 = A lot of knowledge.)
2	behavioral_antiviral_meds	Has taken antiviral medications. (binary)
3	behavioral_avoidance	Has avoided close contact with others with flu-like symptoms. (binary)
4	behavioral_face_mask	Has bought a face mask. (binary)
5	behavioral_wash_hands	Has frequently washed hands or used hand sanitizer. (binary)
6	behavioral_large_gatherings	Has reduced time at large gatherings. (binary)
7	behavioral_outside_home	Has reduced contact with people outside of own household. (binary)
8	behavioral_touch_face	Has avoided touching eyes, nose, or mouth. (binary)
9	doctor_recc_h1n1	H1N1 flu vaccine was recommended by doctor. (binary)
10	doctor_recc_seasonal	Seasonal flu vaccine was recommended by doctor. (binary)
11	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)
12	child_under_6_months	Has regular close contact with a child under the age of six months. (binary)
13	health_worker	Is a healthcare worker. (binary)
14	health_insurance	Has health insurance. (binary)
15	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.)
16	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.)
17	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.)
18	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.)
19	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.)
20	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.)
21	age_group	Age group of respondent.

	respondent_id	Unique and random identifier.
22	education	Self-reported education level.
23	race	Race of respondent.
24	sex	Sex of respondent.
25	income_poverty	Household annual income of respondent with respect to 2008 Census poverty thresholds.
26	marital_status	Marital status of respondent.
27	rent_or_own	Housing situation of respondent.
28	employment_status	Employment status of respondent.
29	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.
30	census_msa	Respondent's residence within metropolitan statistical areas (MSA) as defined by the U.S. Census.
31	household_adults	Number of other adults in household, top-coded to 3.
32	household_children	Number of children in household, top-coded to 3.
33	employment_industry	Type of industry respondent is employed in. Values are represented as short random character strings.
34	employment_occupation	Type of occupation of respondent. Values are represented as short random character strings.

In [176]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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
```

In [177]:
```
#finding the number of rows and columns

df.shape
```

Out[177]:
```
(26707, 37)
```

In [178]:
```
# Describing the metrics of the dataset

df.describe()
```

Out[178]:

	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avoidance	behavioral_
count	26615.000000	26591.000000	26636.000000	26499.000000	26
mean	1.618486	1.262532	0.048844	0.725612	
std	0.910311	0.618149	0.215545	0.446214	
min	0.000000	0.000000	0.000000	0.000000	
25%	1.000000	1.000000	0.000000	0.000000	
50%	2.000000	1.000000	0.000000	1.000000	
75%	2.000000	2.000000	0.000000	1.000000	
max	3.000000	2.000000	1.000000	1.000000	

8 rows × 25 columns

In [179]:
```
# checking for duplicated values

df.duplicated().sum()
```

Out[179]: 0

In [180]:
```
df.isna().sum()/len(df) * 100
```

Out[180]:
```
h1n1_concern                    0.344479
h1n1_knowledge                  0.434343
behavioral_antiviral_meds       0.265848
behavioral_avoidance            0.778822
behavioral_face_mask            0.071142
behavioral_wash_hands           0.157262
behavioral_large_gatherings     0.325757
behavioral_outside_home         0.307036
behavioral_touch_face           0.479275
doctor_recc_h1n1                8.087767
doctor_recc_seasonal            8.087767
chronic_med_condition           3.635751
child_under_6_months            3.070356
health_worker                   3.010447
health_insurance               45.957989
opinion_h1n1_vacc_effective     1.464036
opinion_h1n1_risk               1.452803
opinion_h1n1_sick_from_vacc     1.479013
opinion_seas_vacc_effective     1.729884
opinion_seas_risk               1.924589
opinion_seas_sick_from_vacc     2.010709
age_group                       0.000000
education                       5.268282
race                            0.000000
sex                             0.000000
income_poverty                 16.561201
marital_status                  5.272026
rent_or_own                     7.645936
employment_status               5.477965
hhs_geo_region                  0.000000
census_msa                      0.000000
household_adults                0.932340
household_children              0.932340
employment_industry            49.912008
employment_occupation          50.436215
h1n1_vaccine                    0.000000
seasonal_vaccine                0.000000
dtype: float64
```

In [181]:
```
df.groupby('census_msa')['hhs_geo_region'].value_counts()
```

Out[181]:
```
census_msa                 hhs_geo_region
MSA, Not Principle  City   lzgpxyit          2060
                           qufhixun          1568
                           bhuqouqj          1552
                           fpwskwrf          1541
                           kbazzjca           990
                           mlyzmhmf           961
                           lrircsnp           796
                           dqpwygqj           783
                           oxchjgsf           768
                           atmpeygn           626
MSA, Principle City        fpwskwrf          1202
                           lzgpxyit           991
                           kbazzjca           969
                           mlyzmhmf           956
                           qufhixun           815
                           oxchjgsf           771
                           lrircsnp           738
                           atmpeygn           622
                           bhuqouqj           514
                           dqpwygqj           286
Non-MSA                    oxchjgsf          1320
                           lzgpxyit          1246
                           kbazzjca           899
                           atmpeygn           785
                           bhuqouqj           780
                           qufhixun           719
                           lrircsnp           544
                           fpwskwrf           522
                           mlyzmhmf           326
                           dqpwygqj            57
Name: hhs_geo_region, dtype: int64
```

3.Data Preparation

3.1.Selecting the Data

Guided by the goals for the project we are going to use the following data for our data analysis and modeling,our data set contains only categorical data.

- People's Backgrounds
  - age_group
  - education
  - race
  - sex
  - employment_status
- Opinions on H1N1 vaccine and seasonal flu vaccine.
  - opinion_h1n1_vacc_effective
  - opinion_h1n1_risk

    - opinion_seas_vacc_effective
    - opinion_h1n1_sick_from_vacc
    - opinion_seas_risk
    - opinion_seas_sick_from_vacc
- Health behaviours
    - behavioral_avoidance
    - behavioral_antiviral_meds
    - behavioral_face_mask
    - behavioral_wash_hands
    - behavioral_large_gatherings
    - behavioral_outside_home
    - behavioral_touch_face
    - doctor_recc_h1n1
    - doctor_recc_seasonal
    - chronic_med_condition
    - child_under_6_months
    - health_worker
- Geographical Location

3.2.Creating a new dataframe

In [182]:
```
new_df = df[["age_group","education","race", "sex","employment_status","opinion_h
new_df
```

Out[182]:

	age_group	education	race	sex	employment_status	opinion_h1n1_vacc_effe
respondent_id						
0	55 - 64 Years	< 12 Years	White	Female	Not in Labor Force	
1	35 - 44 Years	12 Years	White	Male	Employed	
2	18 - 34 Years	College Graduate	White	Male	Employed	
3	65+ Years	12 Years	White	Female	Not in Labor Force	
4	45 - 54 Years	Some College	White	Female	Employed	
...	...	...	...	...	...	
26702	65+ Years	Some College	White	Female	Not in Labor Force	
26703	18 - 34 Years	College Graduate	White	Male	Employed	
26704	55 - 64 Years	Some College	White	Female	NaN	
26705	18 - 34 Years	Some College	Hispanic	Female	Employed	
26706	65+ Years	Some College	White	Male	Not in Labor Force	

26707 rows × 26 columns

3.3.Cleaning the Data

3.3.1 Missing Values

Missing data in the H1N1 seasonal flu vaccine data set can reduce the power / fit of a model or can lead to a biased model because we have not analysed the behavior and relationship with other variables correctly. It can lead to wrong prediction or classification.

In [183]:
```
# checking the percenntage of misiing values

new_df.isna().sum()/len(new_df)* 100
```

Out[183]:
```
age_group                      0.000000
education                      5.268282
race                           0.000000
sex                            0.000000
employment_status              5.477965
opinion_h1n1_vacc_effective    1.464036
opinion_h1n1_risk              1.452803
opinion_seas_vacc_effective    1.729884
opinion_h1n1_sick_from_vacc    1.479013
opinion_seas_risk              1.924589
opinion_seas_sick_from_vacc    2.010709
behavioral_antiviral_meds      0.265848
behavioral_face_mask           0.071142
behavioral_wash_hands          0.157262
behavioral_large_gatherings    0.325757
behavioral_outside_home        0.307036
behavioral_touch_face          0.479275
doctor_recc_h1n1               8.087767
doctor_recc_seasonal           8.087767
chronic_med_condition          3.635751
child_under_6_months           3.070356
health_worker                  3.010447
census_msa                     0.000000
hhs_geo_region                 0.000000
h1n1_vaccine                   0.000000
seasonal_vaccine               0.000000
dtype: float64
```

In [184]:
```
# converting  objects to categorical
list_str_obj_cols = df.columns[df.dtypes == "object"].tolist()
for str_obj_col in list_str_obj_cols:
    df[str_obj_col] = df[str_obj_col].astype("category")
```

In [ ]:
```

```

In [185]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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  category
 22  education                    25300 non-null  category
 23  race                         26707 non-null  category
 24  sex                          26707 non-null  category
 25  income_poverty               22284 non-null  category
 26  marital_status               25299 non-null  category
 27  rent_or_own                  24665 non-null  category
 28  employment_status            25244 non-null  category
 29  hhs_geo_region               26707 non-null  category
 30  census_msa                   26707 non-null  category
 31  household_adults             26458 non-null  float64 
 32  household_children           26458 non-null  float64 
 33  employment_industry          13377 non-null  category
 34  employment_occupation        13237 non-null  category
 35  h1n1_vaccine                 26707 non-null  int64   
 36  seasonal_vaccine             26707 non-null  int64   
dtypes: category(12), float64(23), int64(2)
memory usage: 5.6 MB
```

In [186]:
```
# replacing missing values using mode

new_df = new_df.fillna(new_df.mode().iloc[0])

new_df.isnull().sum()
```

Out[186]:
```
age_group                      0
education                      0
race                           0
sex                            0
employment_status              0
opinion_h1n1_vacc_effective    0
opinion_h1n1_risk              0
opinion_seas_vacc_effective    0
opinion_h1n1_sick_from_vacc    0
opinion_seas_risk              0
opinion_seas_sick_from_vacc    0
behavioral_antiviral_meds      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
doctor_recc_seasonal           0
chronic_med_condition          0
child_under_6_months           0
health_worker                  0
census_msa                     0
hhs_geo_region                 0
h1n1_vaccine                   0
seasonal_vaccine               0
dtype: int64
```

3.3.2.Renaming geographical region

In [187]:
```
new_df["hhs_geo_region"].value_counts()
```

Out[187]:
```
lzgpxyit    4297
fpwskwrf    3265
qufhixun    3102
oxchjgsf    2859
kbazzjca    2858
bhuqouqj    2846
mlyzmhmf    2243
lrircsnp    2078
atmpeygn    2033
dqpwygqj    1126
Name: hhs_geo_region, dtype: int64
```

In [188]:
```
hhs_geo_region = {"hhs_geo_region":     {"lzgpxyit": "region_1", "fpwskwrf": "reg
                                         "oxchjgsf":"region_4","kbazzjca":"regior
                                         "bhuqouqj":"region_6","mlyzmhmf":"regior
                                         "lrircsnp":"region_8","atmpeygn":"regior


new_df = new_df.replace(hhs_geo_region)
new_df
```

Out[188]:

respondent_id	age_group	education	race	sex	employment_status	opinion_h1n1_vacc_effe
0	55 - 64 Years	< 12 Years	White	Female	Not in Labor Force	
1	35 - 44 Years	12 Years	White	Male	Employed	
2	18 - 34 Years	College Graduate	White	Male	Employed	
3	65+ Years	12 Years	White	Female	Not in Labor Force	
4	45 - 54 Years	Some College	White	Female	Employed	
...	...	...	...	...	...	
26702	65+ Years	Some College	White	Female	Not in Labor Force	
26703	18 - 34 Years	College Graduate	White	Male	Employed	
26704	55 - 64 Years	Some College	White	Female	Employed	
26705	18 - 34 Years	Some College	Hispanic	Female	Employed	
26706	65+ Years	Some College	White	Male	Not in Labor Force	

26707 rows × 26 columns

3.2.2.Renaming

Renaming Opinion columns

In [189]:
```
new_df.opinion_h1n1_vacc_effective=new_df.opinion_h1n1_vacc_effective.replace({1
                                                                    4 :"Somewhat effecti
 # opinion on effectiveness of seasonal flu vaccines
new_df.opinion_seas_vacc_effective=new_df.opinion_seas_vacc_effective.replace({1
                                                                    4 :"Somewhat effecti
```

In [190]:
```
new_df.opinion_seas_sick_from_vacc= new_df.opinion_seas_sick_from_vacc.replace({1

new_df.opinion_h1n1_risk=new_df.opinion_h1n1_risk.replace({1 :"Very Low", 2 : "So
                                                            4 : "Somewhat high
new_df.opinion_h1n1_sick_from_vacc= new_df.opinion_h1n1_sick_from_vacc.replace({1

new_df.opinion_h1n1_risk=new_df.opinion_h1n1_risk.replace({1 :"Very Low", 2 : "So
                                                            4 : "Somewhat high
#opinion on gettibg sick from seasonal  flu without vaccines
new_df.opinion_seas_risk=new_df.opinion_seas_risk.replace({1 :"Very Low", 2 : "So
                                                            4 : "Somewhat high
```

In [191]:
```
new_df['age_group'] =new_df['age_group'].str.rstrip(' Years')
new_df['age_group']= new_df['age_group'].astype(str)
new_df['age_cat']=new_df['age_group'].replace({'18 - 34':'youth','35 - 44':'young
                                                 '55 - 64':'older adults','65+':'e
```

In [192]:
```
# stripping and converting floats to integers
float_col = new_df.select_dtypes(include=['float64'])
for col in float_col.columns.values:
     new_df[col] =new_df[col].astype('int64')
```

In [193]:
```
new_df.head()
```

Out[193]:

	age_group	education	race	sex	employment_status	opinion_h1n1_vacc_effecti
respondent_id						
0	55 - 64	< 12 Years	White	Female	Not in Labor Force	Don't knc
1	35 - 44	12 Years	White	Male	Employed	Very effecti
2	18 - 34	College Graduate	White	Male	Employed	Don't knc
3	65+	12 Years	White	Female	Not in Labor Force	Don't knc
4	45 - 54	Some College	White	Female	Employed	Don't knc

5 rows × 27 columns

3.3.Exploratory Data Analysis

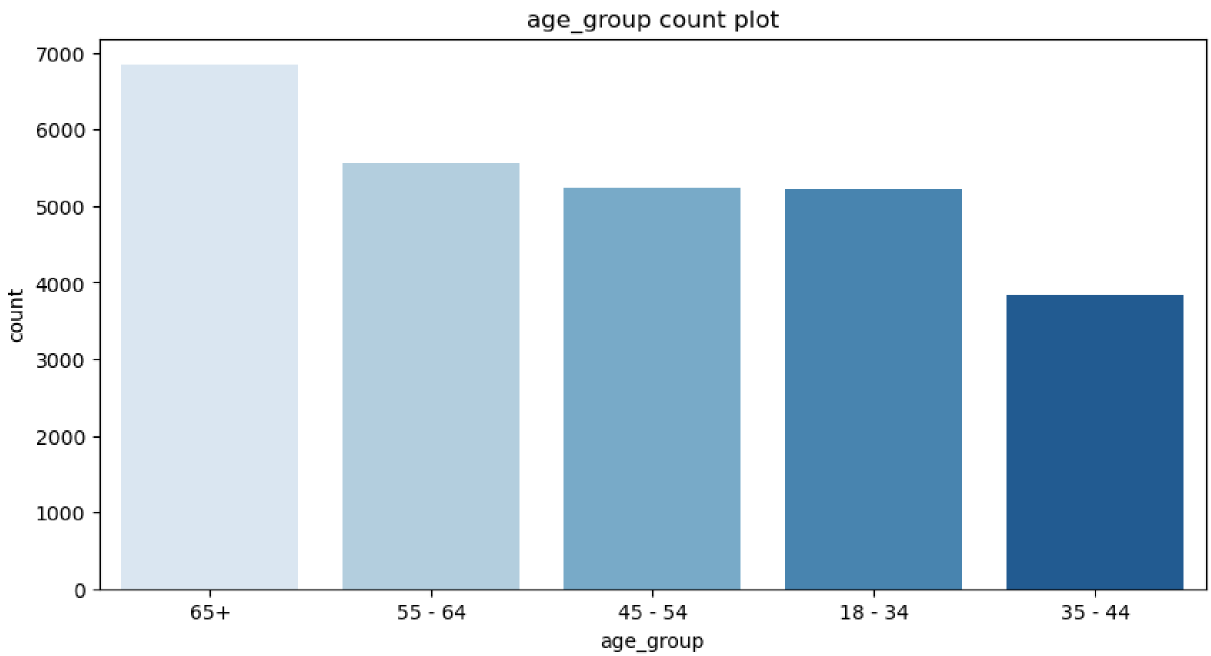
3.3.1.Univariate Analysis

3.3.1.1.People's Background

3.3.1.1.1.Age

In [194]:
```
def count_plot1(data,column):

    plt.figure(figsize=(10,5))
    sns.countplot(x=column,data=data,order=data[column].value_counts().index,pale
    plt.title(f'{column} count plot')
    plt.ylabel('count')
    plt.show
```

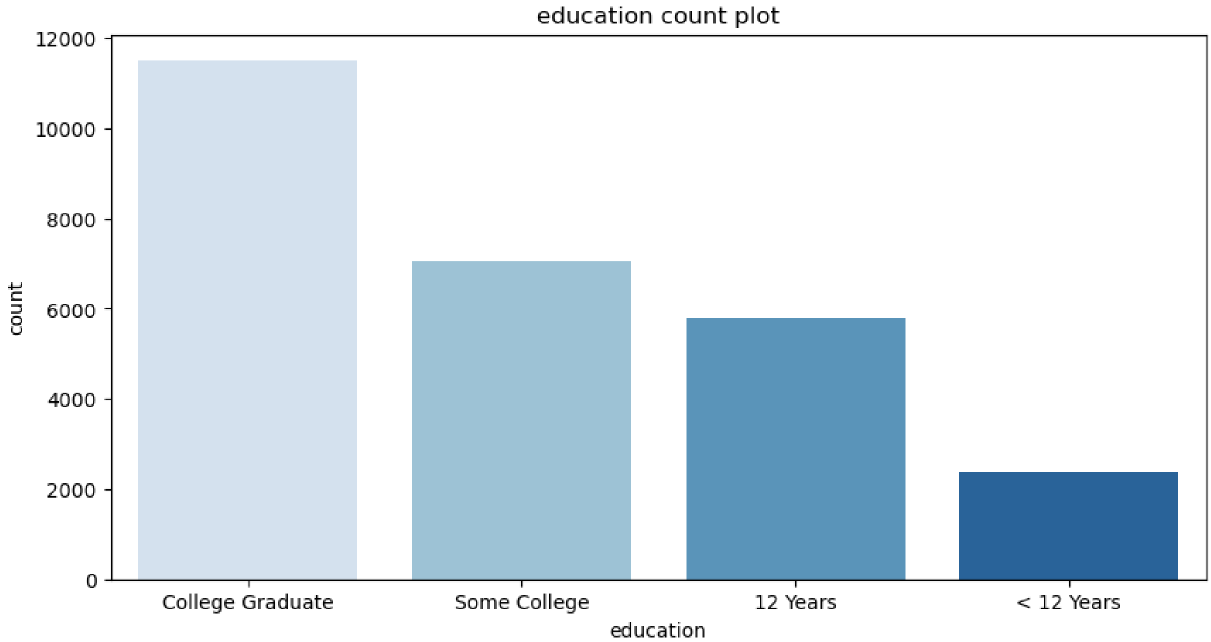
In [195]:
```
count_plot1(new_df,'age_group')
```



The highest age group is 65 years and above and the lowest age group is 35-44 years

3.3.1.1.2.Education

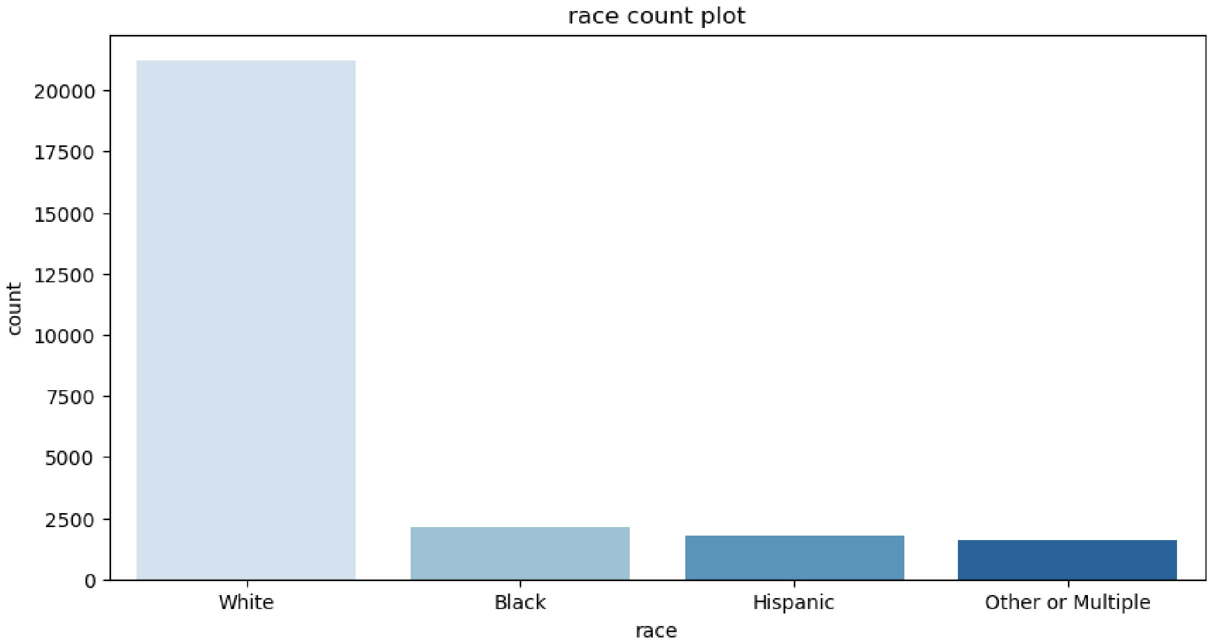
In [196]:
```
count_plot1(new_df,'education')
```



College graduates had the highest count while below 12 years had the lowest count

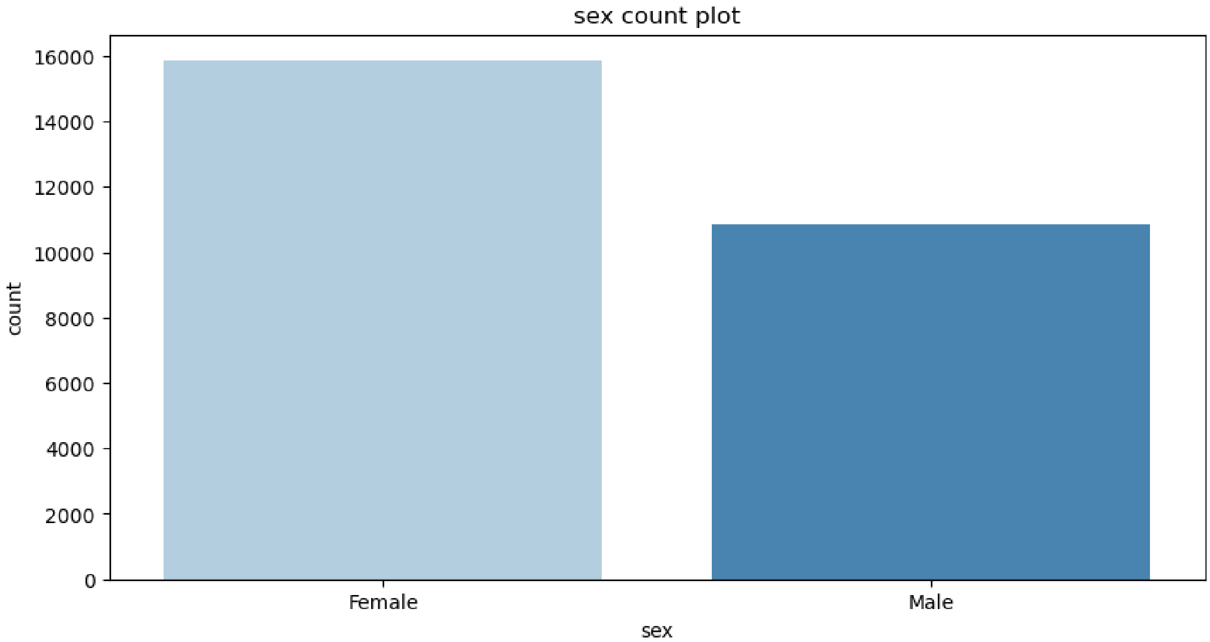
3.3.1.1.3.Race

In [197]:
```
count_plot1(new_df,'race')
```



3.3.1.1.3.Sex

In [198]:
```
count_plot1(new_df,'sex')
```

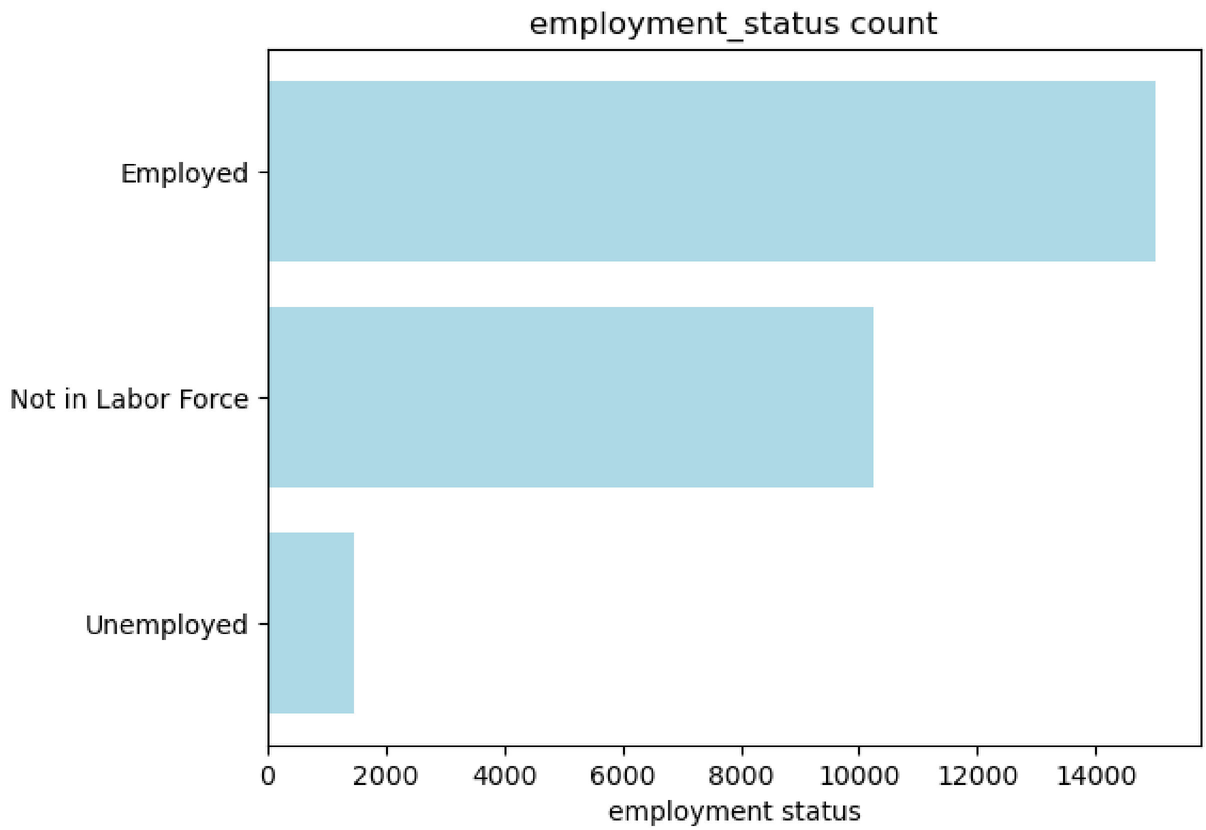


A larger part of the population are female

3.3.1.1.4.Employment_status

In [199]:
```
def bar_plot(data,column):
    X_count= data[column].value_counts().head(20).sort_values()
    plt.barh(X_count.index,X_count,color='lightblue')
    plt.title(f'{column} count')
    plt.xlabel('employment status')
    plt.show
```

In [200]:
```
bar_plot(new_df,'employment_status')
```

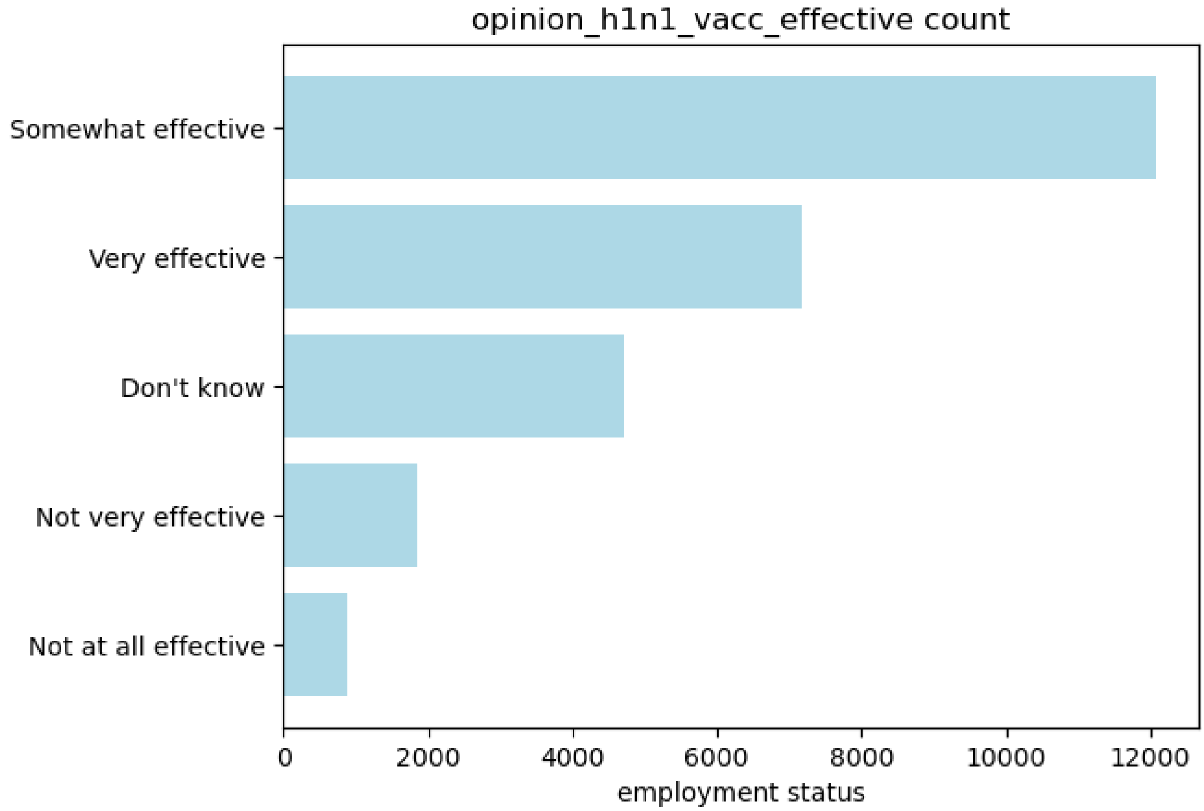


There is a high rate of employment compared to unemployment

3.3.1.2.Opinions on H1N1 vaccine and seasonal flu vaccine

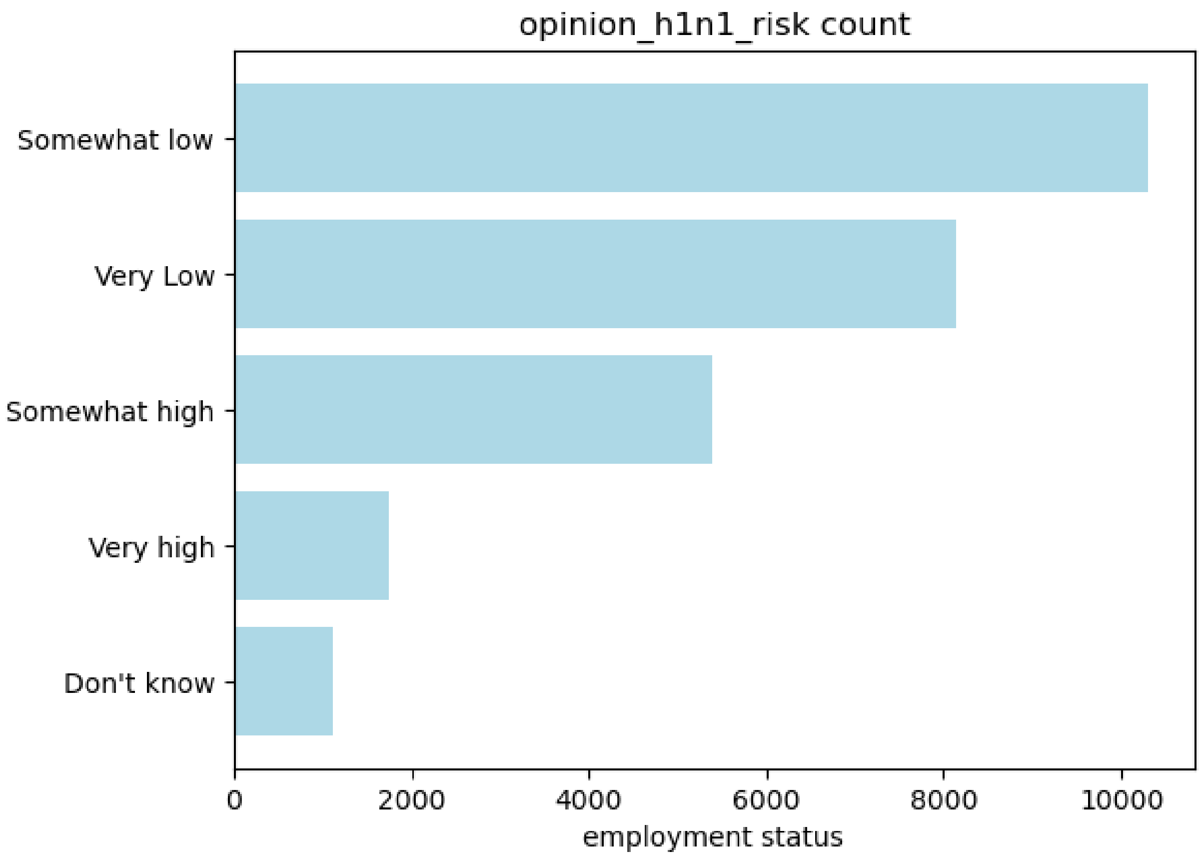
3.3.1.2.1.H1N1 vaccine

In [201]:
```
bar_plot(new_df,'opinion_h1n1_vacc_effective')
```



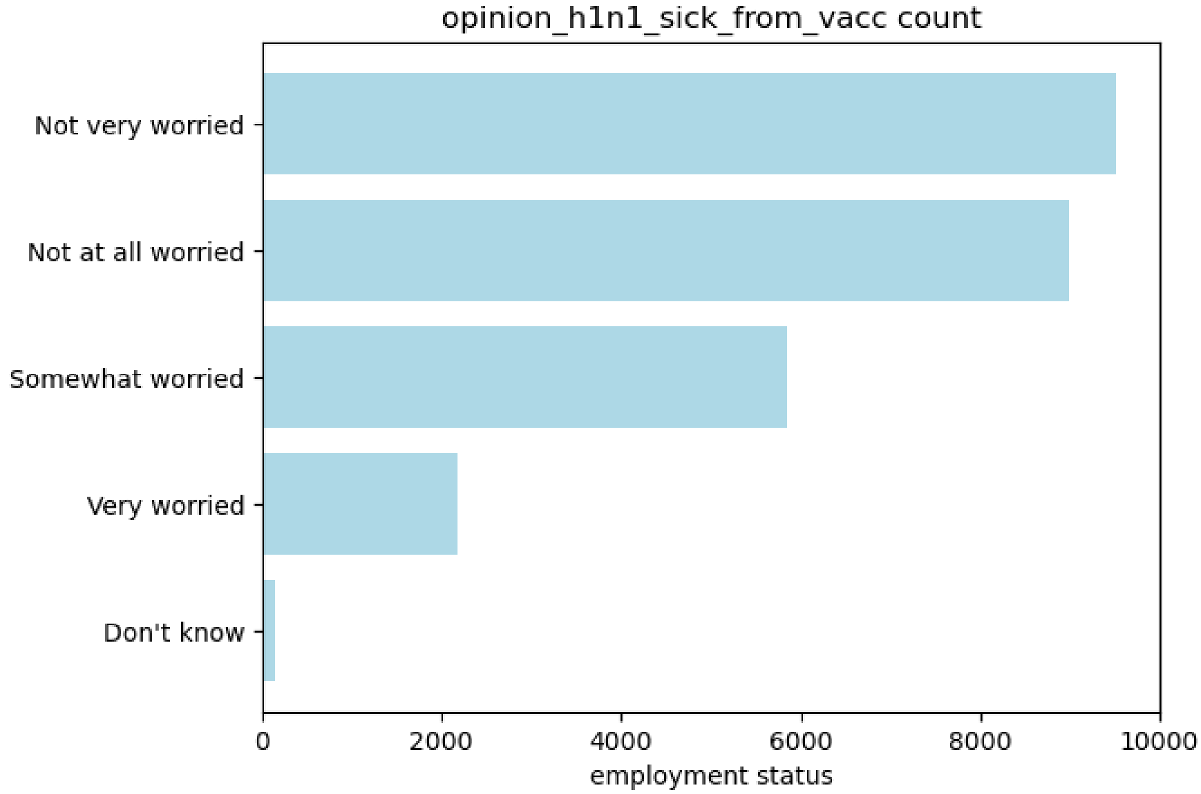
The most popular opinion is that the vaccine is somewhat effective.

In [202]:
```
bar_plot(new_df,'opinion_h1n1_risk')
```



Most people believe they will not get the flu even if they dont get the h1n1 flu vaccine.

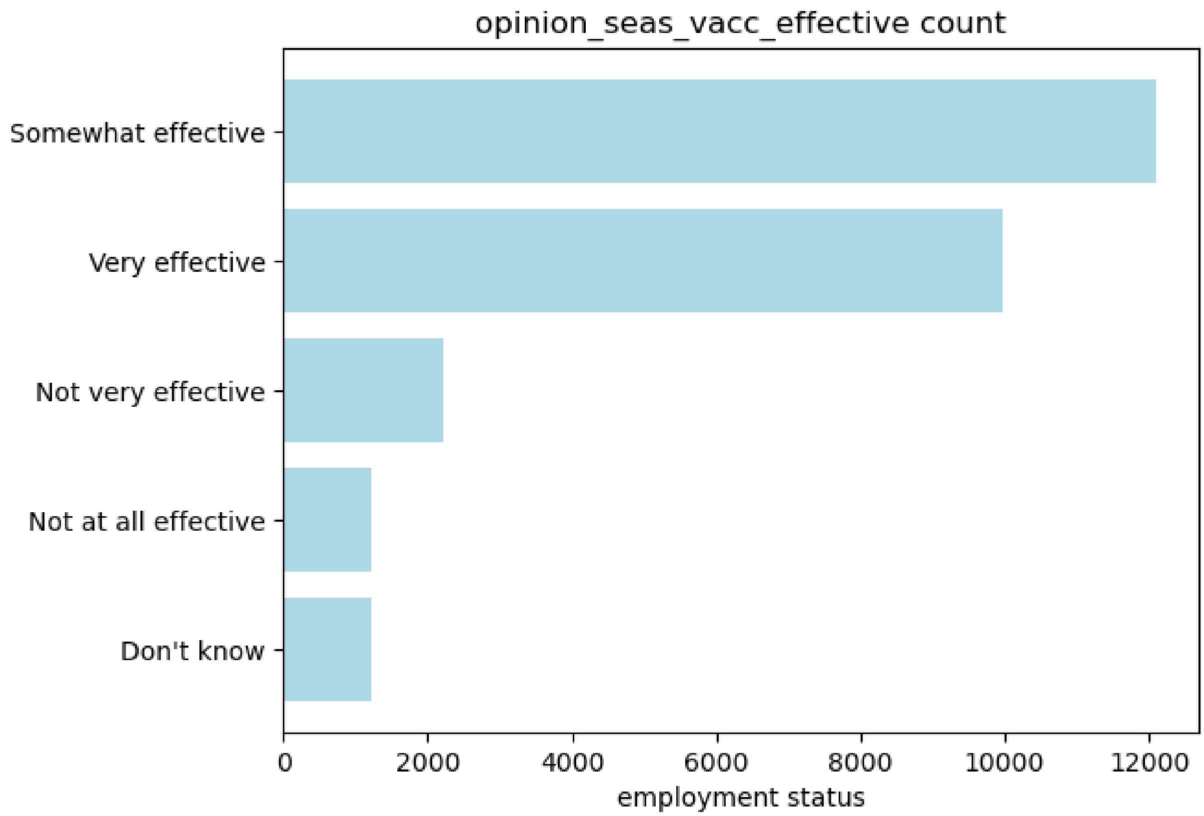
In [203]:
```
bar_plot(new_df,'opinion_h1n1_sick_from_vacc')
```



Most people are not very worried about getting sick after getting the h1n1 flu vaccine.

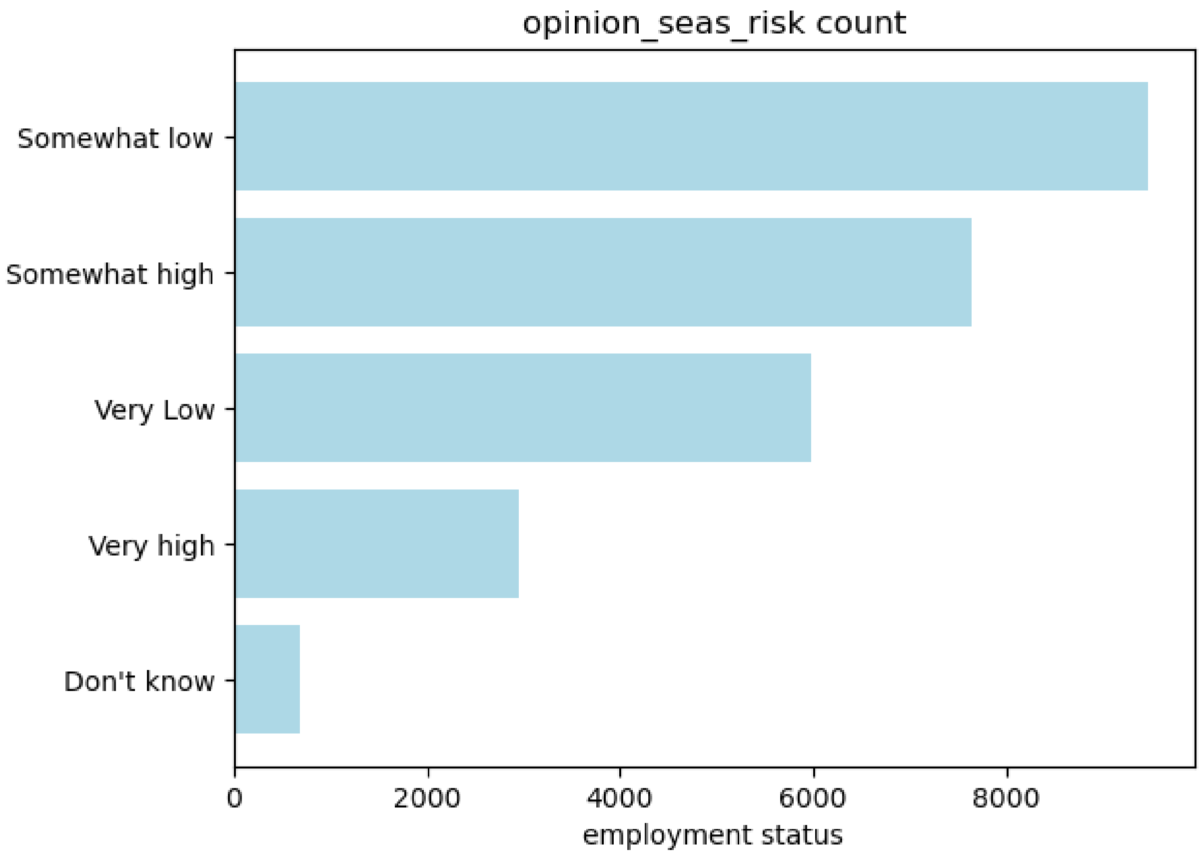
3.3.1.2.2.Seasonal flu vaccine

In [204]:
```
bar_plot(new_df,'opinion_seas_vacc_effective')
```



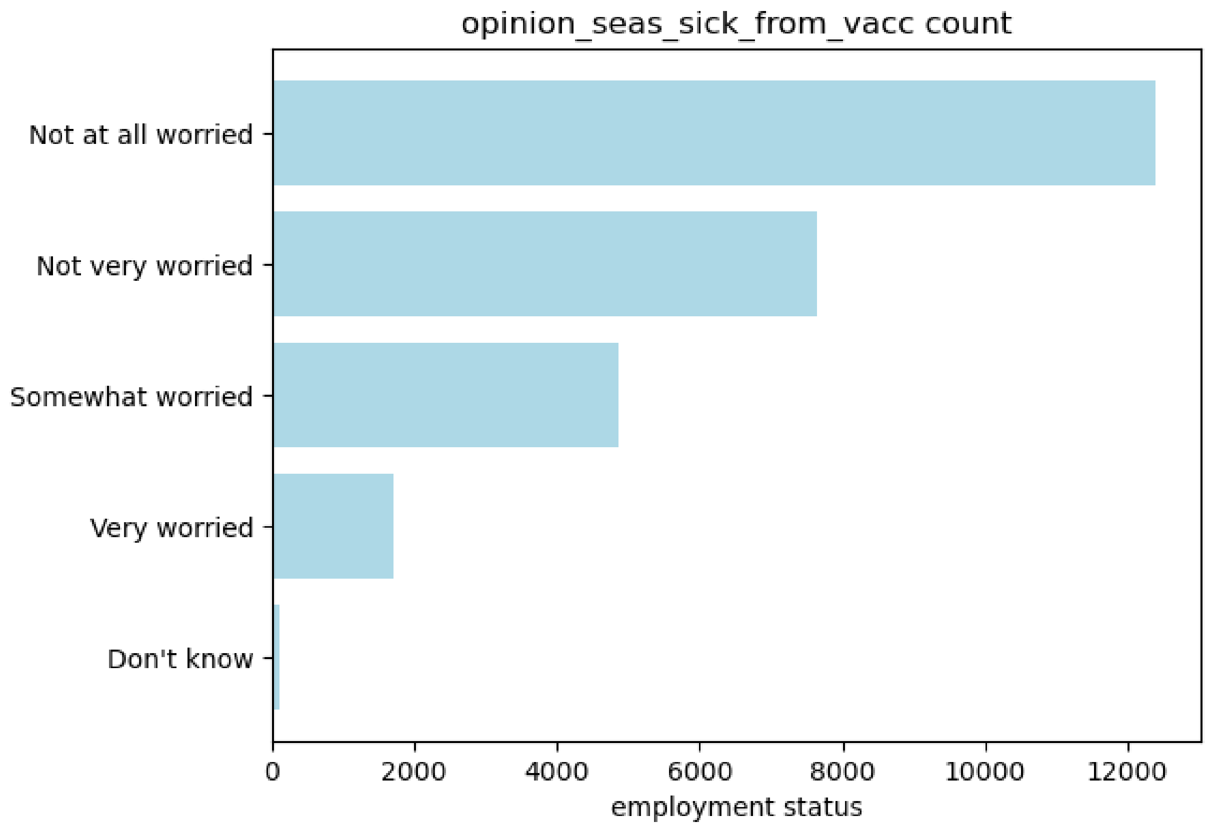
The most popular opinion is that the seasonal flu is somewhat effective

In [205]:
```
bar_plot(new_df,'opinion_seas_risk')
```



Most people believe they will not get the seasonal flu even if they dont get the seasonal flu vaccine.

In [206]:
```
bar_plot(new_df,'opinion_seas_sick_from_vacc')
```



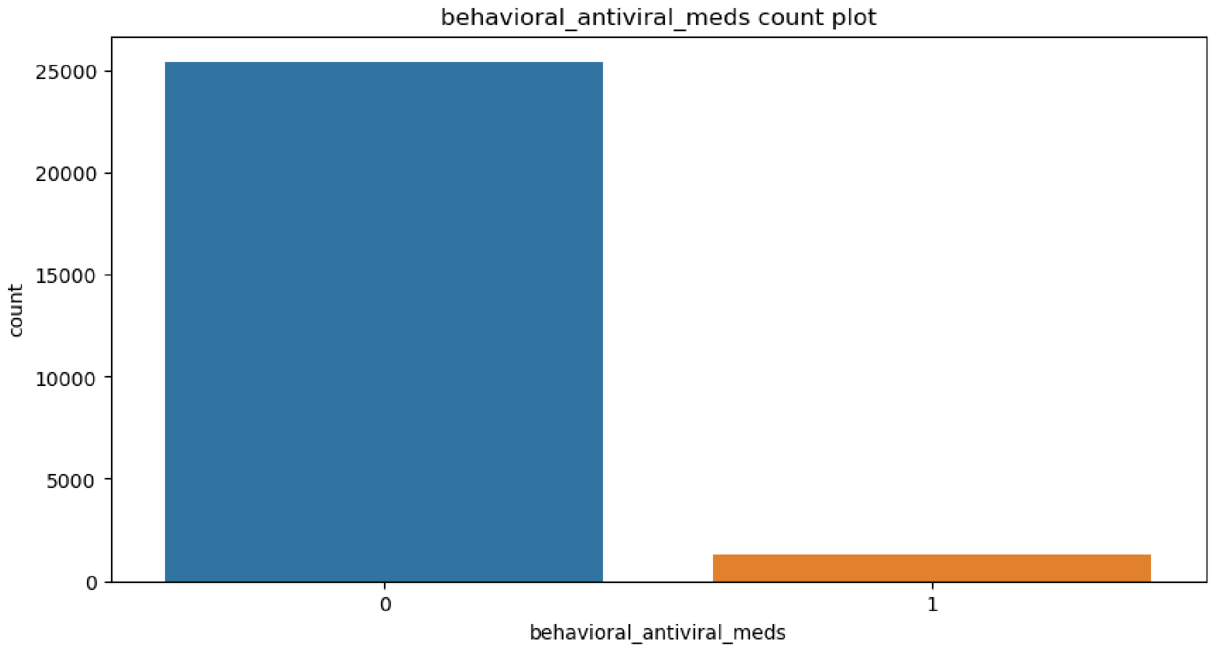
Most people are not worried at all about being sick from the vaccine.

3.3.1.3.Health behaviours

3.3.1.3.1.behavioral_antiviral_meds

In [207]:
```
def count_plot(data,column):

    plt.figure(figsize=(10,5))
    sns.countplot(x=column,data=data)
    plt.title(f'{column} count plot')
    plt.ylabel('count')
    plt.show
```

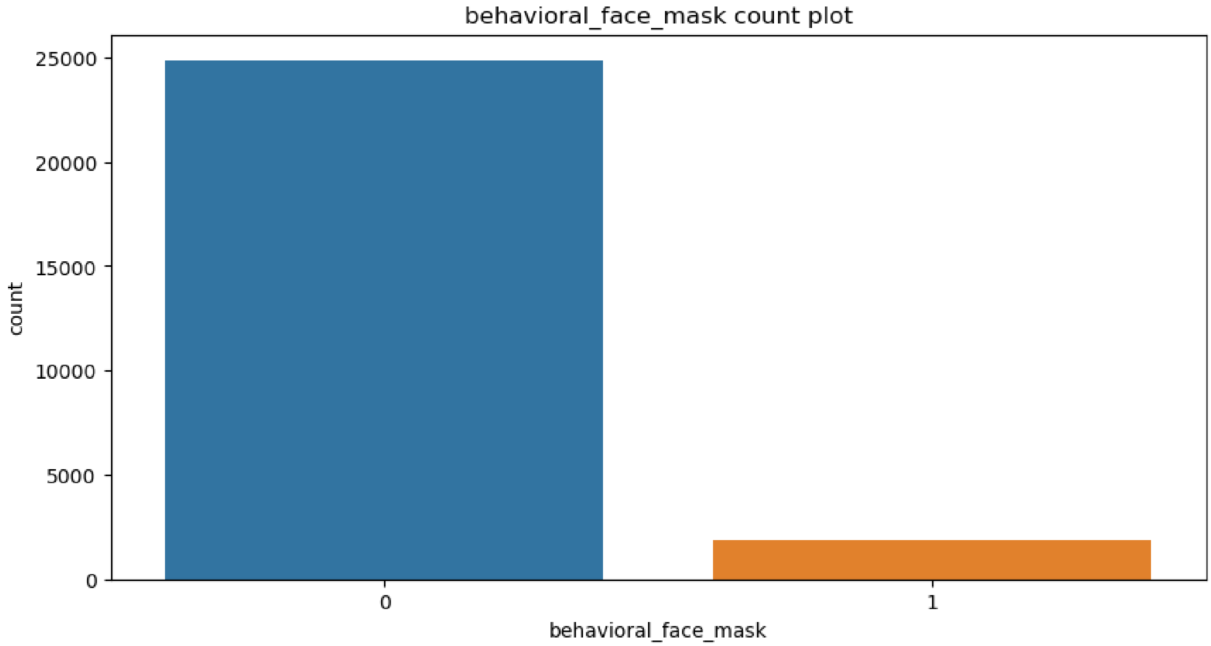
In [208]:
```
count_plot(new_df,'behavioral_antiviral_meds')
```



A larger percentage of the population have not taken antiviral medication

3.3.1.3.2.behavioral_face_mask

In [209]:
```
count_plot(new_df,'behavioral_face_mask')
```

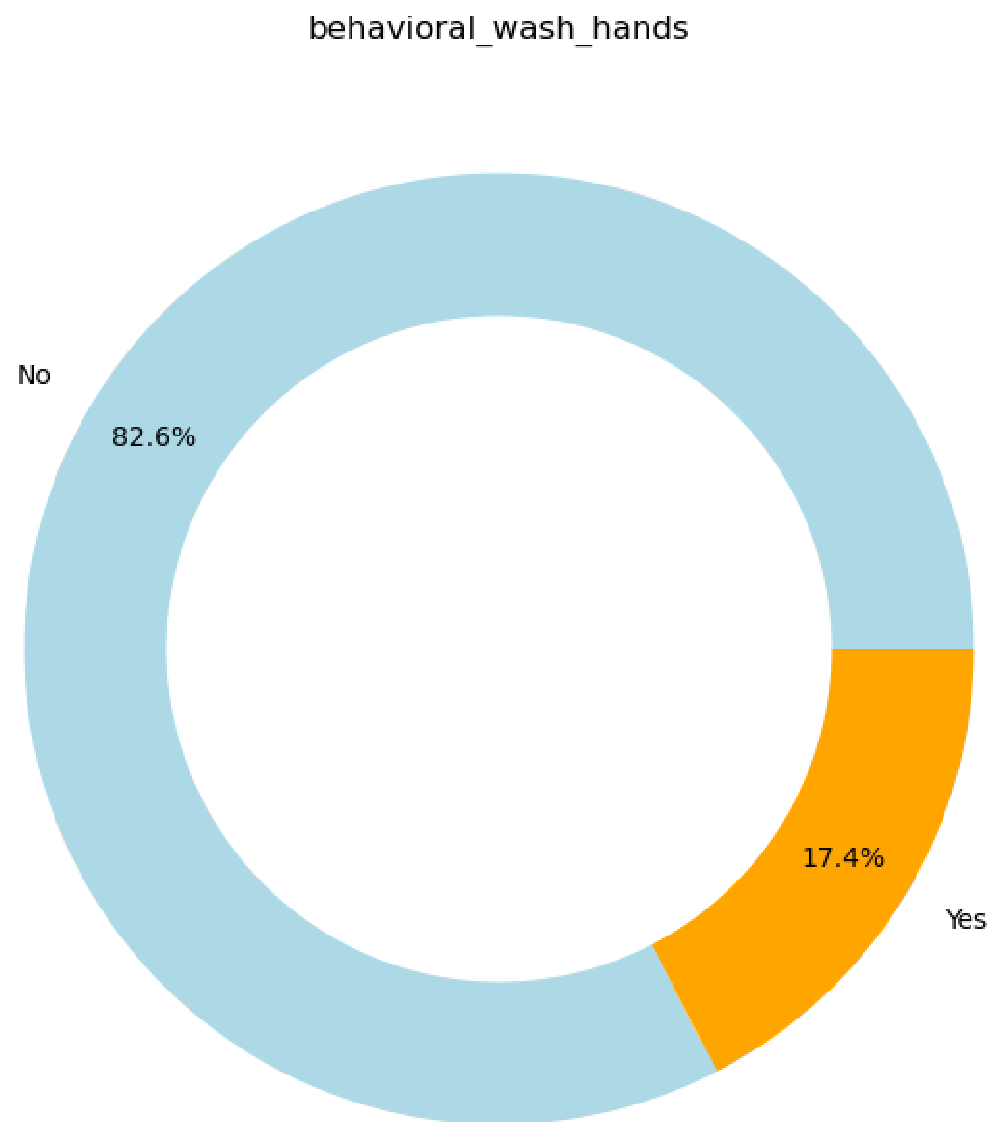


A larger percentage of the population do not buy face masks.

3.3.1.3.3.behavioral_wash_hands

In [210]:
```
# defining a function to get doughnuts
def get_doughnut(data,column):
    count=data[column].value_counts()
    plt.figure(figsize=(10,8))
    c='lightblue','orange'
    mylabels='No','Yes'
    plt.pie(count,labels=mylabels,colors=c,autopct='%1.1f%%', pctdistance=0.85)
    # draw circle
    centre_circle = plt.Circle((0, 0), 0.70, fc='white')
    fig = plt.gcf()
    # Adding Circle in Pie chart
    fig.gca().add_artist(centre_circle)
    plt.title(f'{column}')
```

In [211]:
```
get_doughnut(new_df,'behavioral_wash_hands')
```

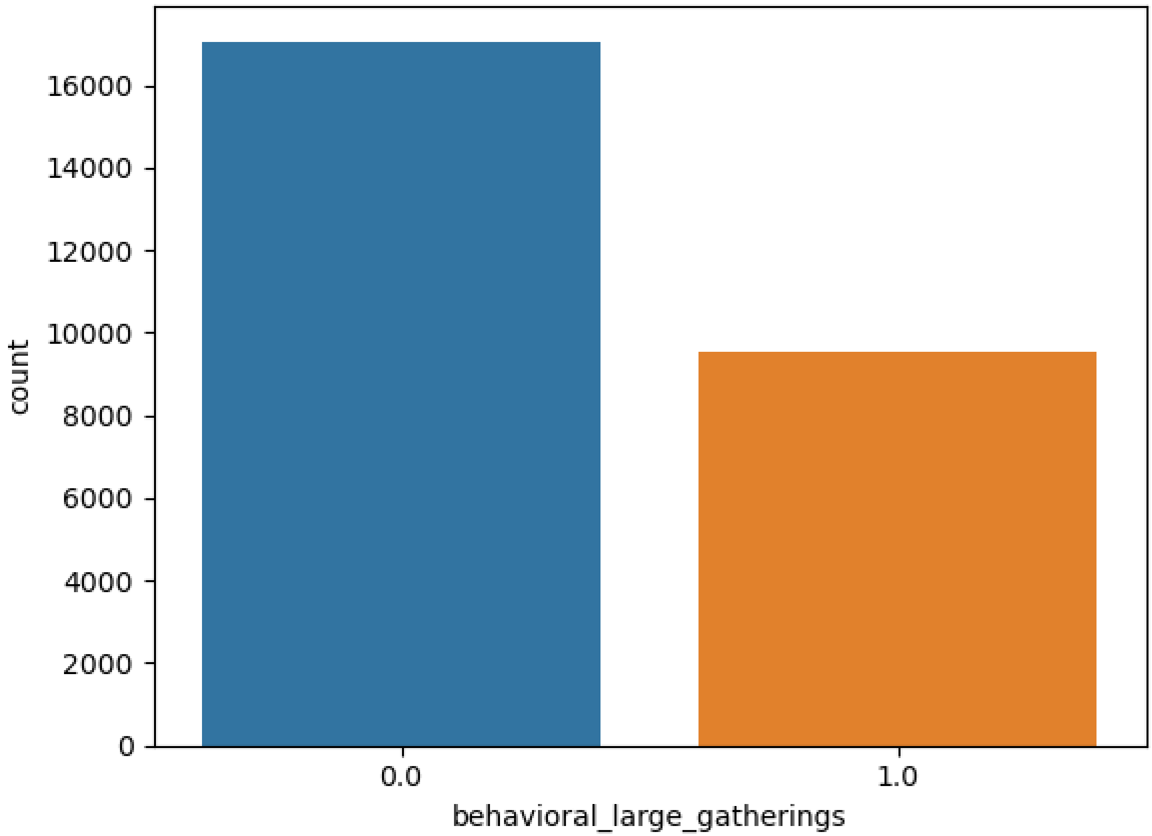


Most don't frequently wash their hands or use hand sanitiser.

3.3.1.3.4.behavioral_large_gatherings

In [212]:
```
sns.countplot(x ='behavioral_large_gatherings', data = df)
```

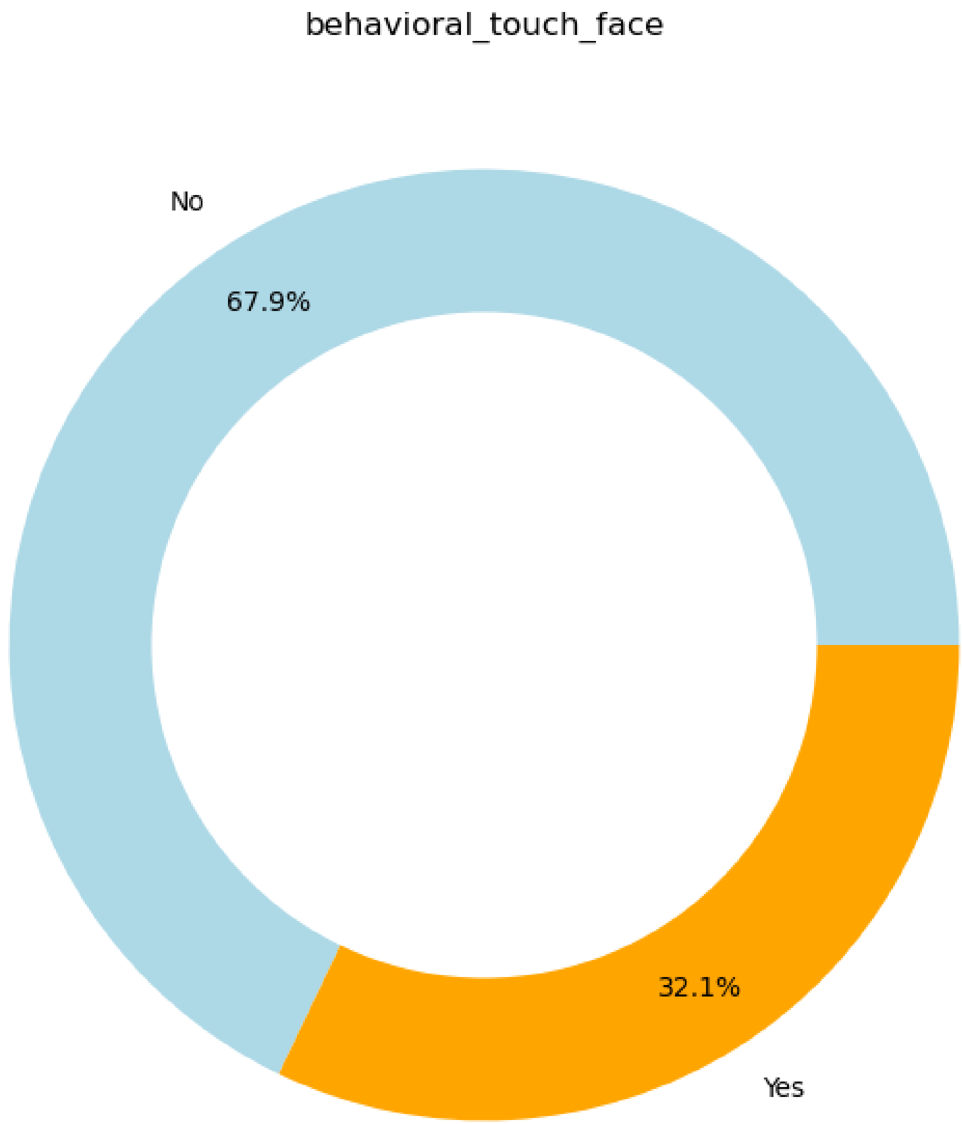
Out[212]:
```
<AxesSubplot:xlabel='behavioral_large_gatherings', ylabel='count'>
```



Most of the people have not reduced their time at large gatherings.

3.3.1.3.5.behavioral_touch_face

In [213]:
```
get_doughnut(new_df,'behavioral_touch_face')
```

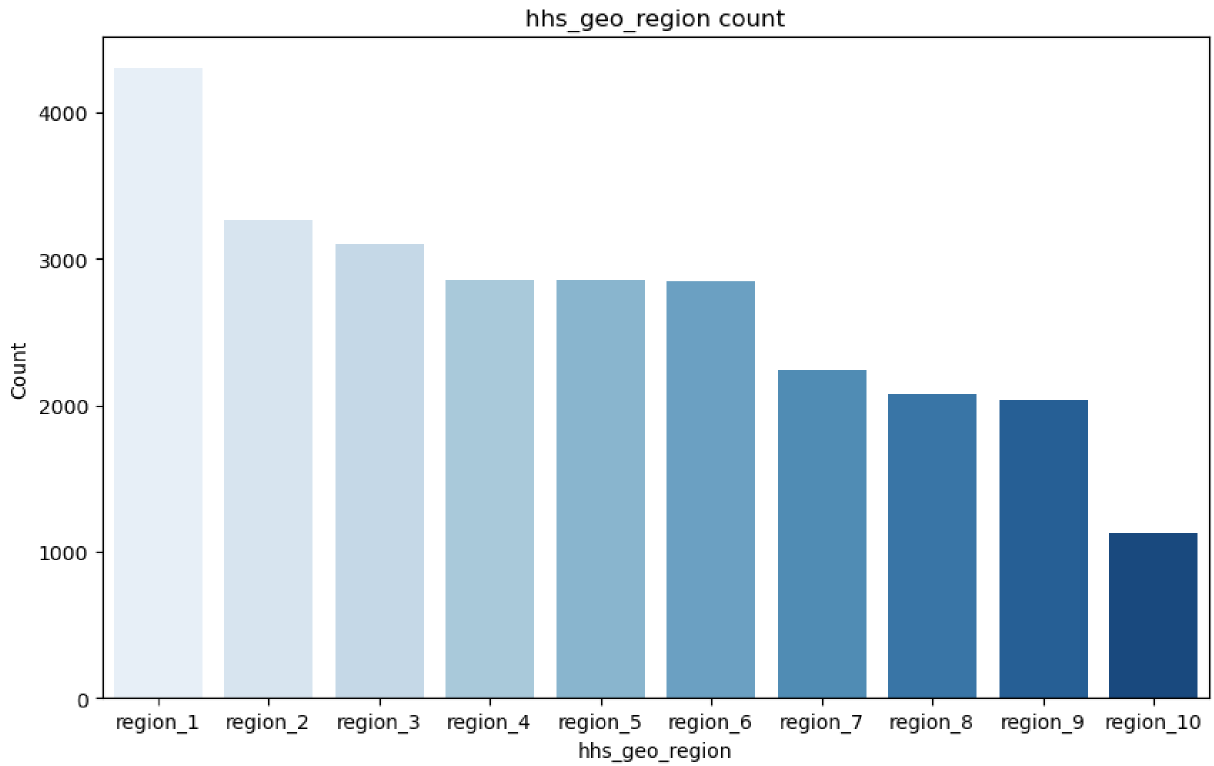


Most people have noot avoided touching their face.

3.3.1.4. Geographical Location

3.3.1.4.hhs_geo_region

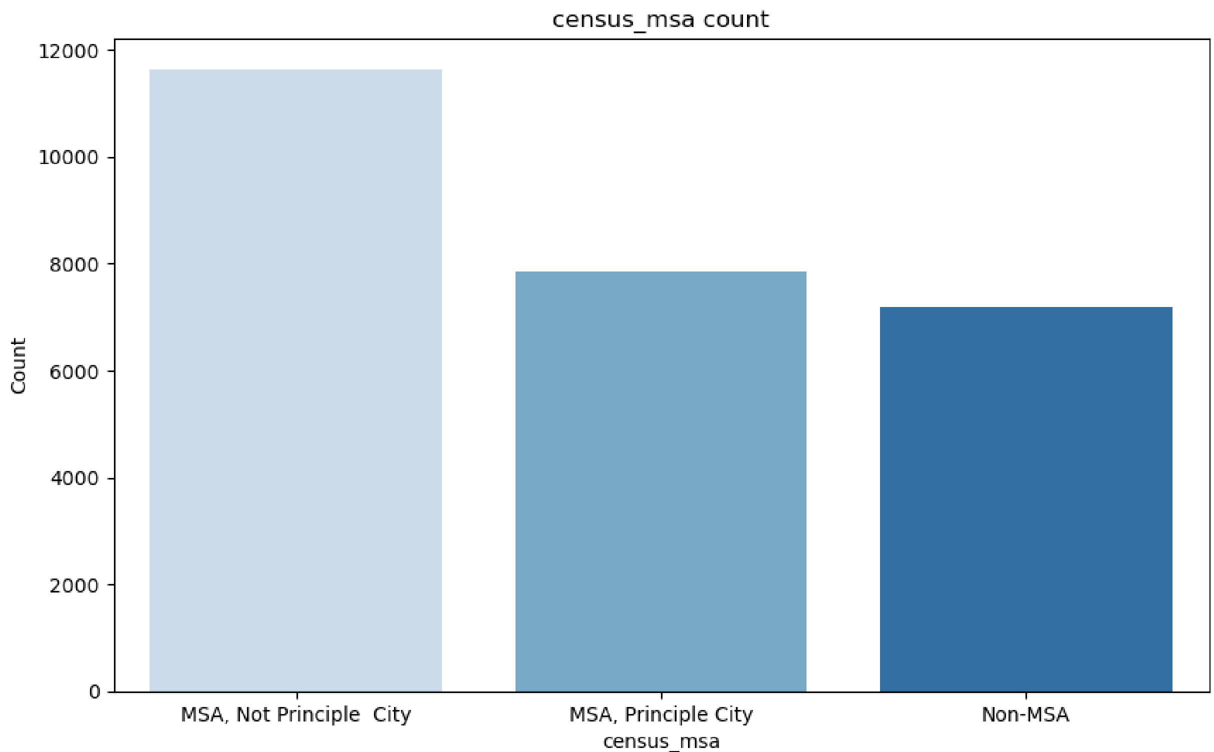
In [214]:
```
# A bar graph showing the hhs_geo_region

plt.figure(figsize=(10,6))
sns.countplot(x='hhs_geo_region', data= new_df,order=new_df["hhs_geo_region"].val
plt.title('hhs_geo_region count')
plt.xlabel('hhs_geo_region')
plt.ylabel('Count')
plt.show()
```



Region 1 is the most populated region.

3.3.1.4.census_msa

In [215]:
```
# A bar graph showing the census_msa

plt.figure(figsize=(10,6))
sns.countplot(x='census_msa', data= new_df,order=new_df["census_msa"].value_count
plt.title('census_msa count')
plt.xlabel('census_msa')
plt.ylabel('Count')
plt.show();
```

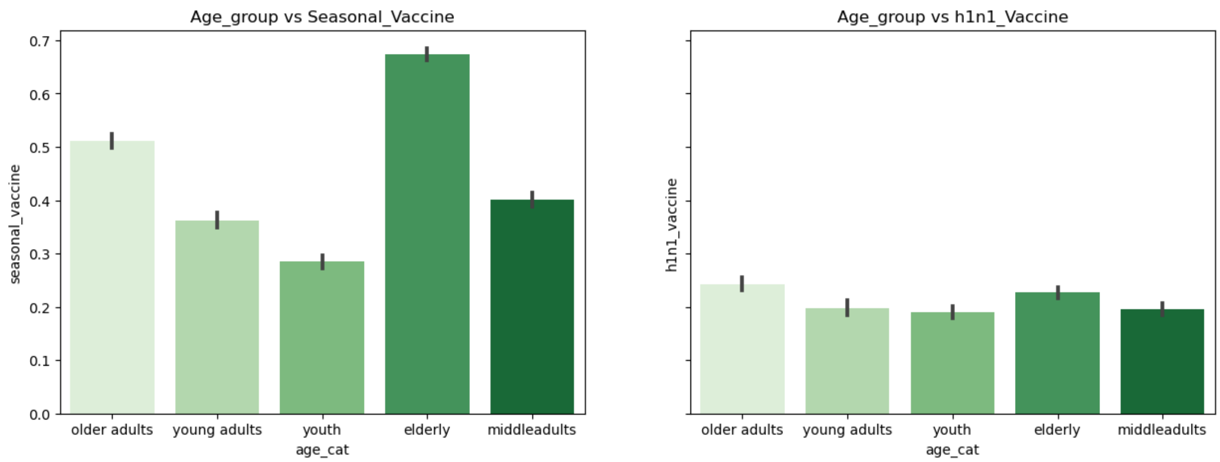


The metropolitan that is not a principle city had the highest population according to the census.

3.3.1.Bivariate Analysis

3.3.1.1. Age

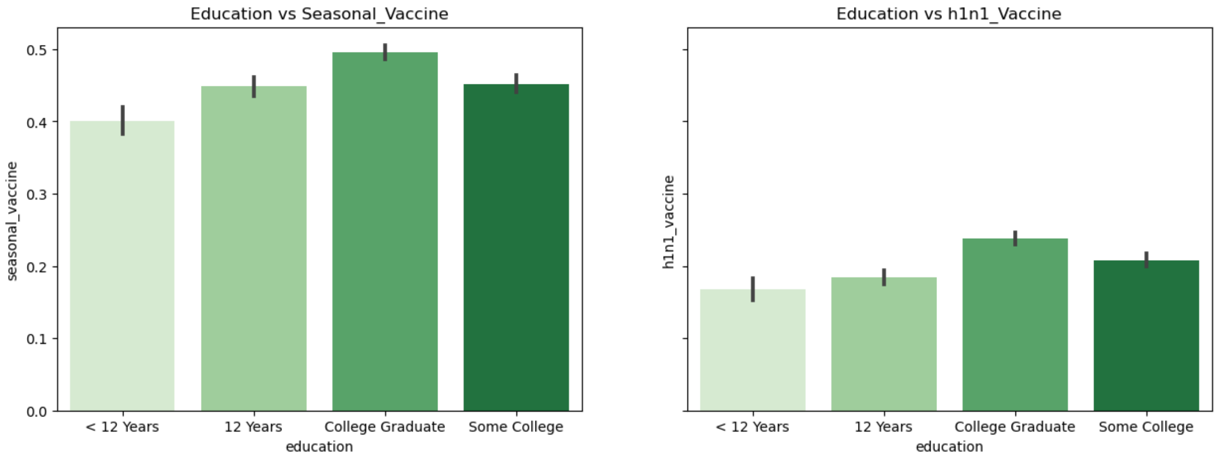
In [216]:
```
# Age vs H1N1 Vaccine
fig, axes = plt.subplots(1, 2, figsize=(15, 5), sharey=True)
sns.barplot(ax=axes[0],x='age_cat', y='seasonal_vaccine', data=new_df, palette =
axes[0].set_title('Age_group vs Seasonal_Vaccine')
sns.barplot(ax=axes[1],x='age_cat', y='h1n1_vaccine', data=new_df, palette = 'Gre
axes[1].set_title('Age_group vs h1n1_Vaccine');
```



The elderly and older adults seem to have taken the h1n1 and seasonal flu vaccine more than other age groups

3.3.1.2. Education

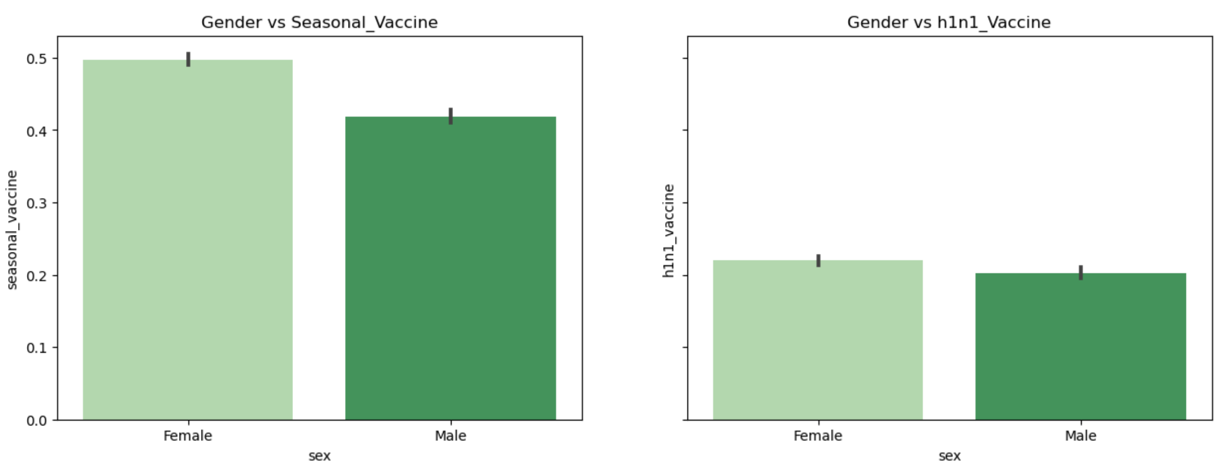
In [217]:
```
# Plot showing the education status of those who took H1N1 and Seasonal Flu vacci

fig, axes = plt.subplots(1, 2, figsize=(15, 5), sharey=True)
sns.barplot(ax=axes[0],x='education', y='seasonal_vaccine', data=new_df, palette
axes[0].set_title('Education vs Seasonal_Vaccine')
sns.barplot(ax=axes[1],x='education', y='h1n1_vaccine', data=new_df, palette = 'G
axes[1].set_title('Education vs h1n1_Vaccine');
```



3.3.1.3 Gender

In [218]:
```
fig, axes = plt.subplots(1, 2, figsize=(15, 5), sharey=True)
sns.barplot(ax=axes[0],x='sex', y='seasonal_vaccine', data=new_df, palette = 'Gre
axes[0].set_title('Gender vs Seasonal_Vaccine')
sns.barplot(ax=axes[1],x='sex', y='h1n1_vaccine', data=new_df, palette = 'Greens'
axes[1].set_title('Gender vs h1n1_Vaccine')
```

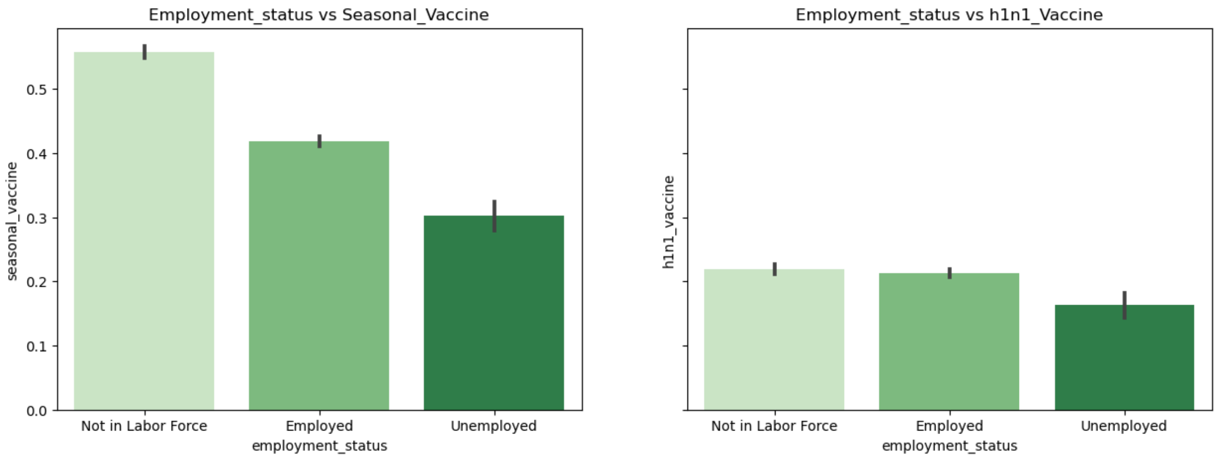
Out[218]:
```
Text(0.5, 1.0, 'Gender vs h1n1_Vaccine')
```



females tend to get more vaccines compared to the males

3.3.1.4 Employment status

In [219]:
```
fig, axes = plt.subplots(1, 2, figsize=(15, 5), sharey=True)
sns.barplot(ax=axes[0],x='employment_status', y='seasonal_vaccine', data=new_df,
axes[0].set_title('Employment_status vs Seasonal_Vaccine')
sns.barplot(ax=axes[1],x='employment_status', y='h1n1_vaccine', data=new_df, pale
axes[1].set_title('Employment_status vs h1n1_Vaccine');
```

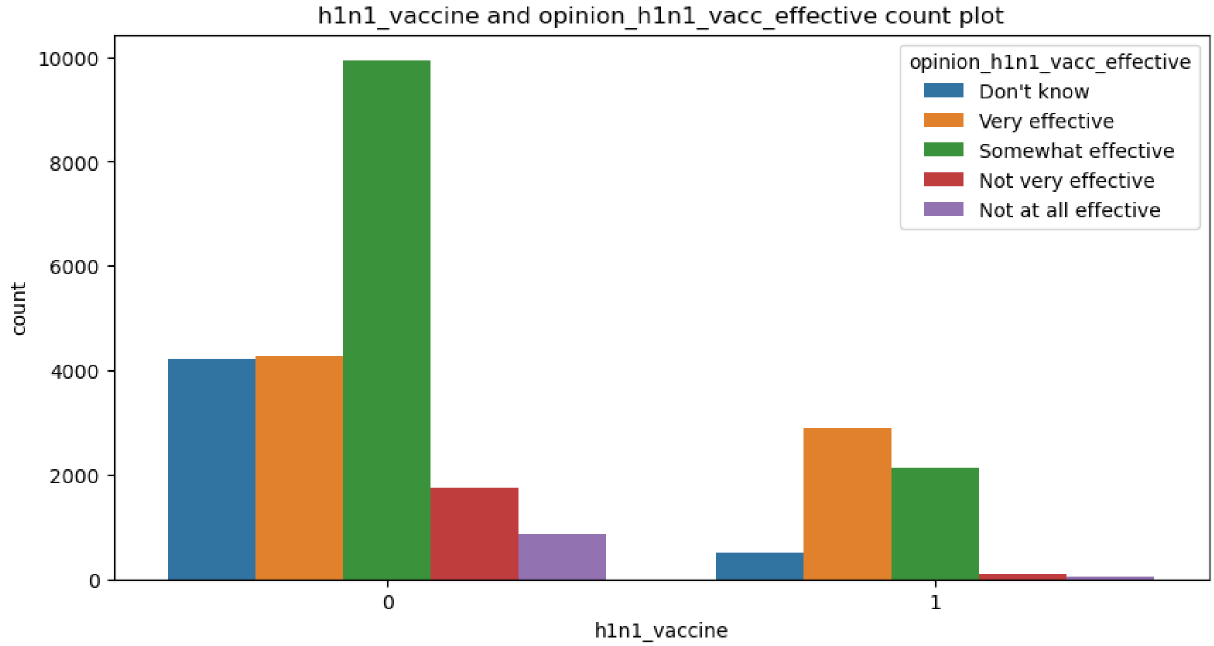


Those not in the labour force have had a huge turnout of taking the vaccines compared to those who are employed.

3.3.1.5 Opinions

In [220]:
```
def count_plot(data,column1,column2):

    plt.figure(figsize=(10,5))
    sns.countplot(x=column1,data=data,hue=column2)
    plt.title(f'{column1.name} and {column2.name} count plot')
    plt.ylabel('count')
    plt.show
```

In [221]:
```
count_plot(new_df, new_df['h1n1_vaccine'],new_df['opinion_h1n1_vacc_effective'])
```



3.3.1.6 Correlation

In [222]:
```
# checking the correlations of the vaccines with the target of seasonal_vaccine

corr = new_df.corr()
corr = corr.stack().reset_index()
corr = corr.rename(columns = {'level_0':'Target', 'level_1':'Features', 0:'Correl
corr = corr.loc[corr['Target'] == 'seasonal_vaccine']
corr.sort_values(by = 'Correlation_Values', ascending = False)
```

Out[222]:

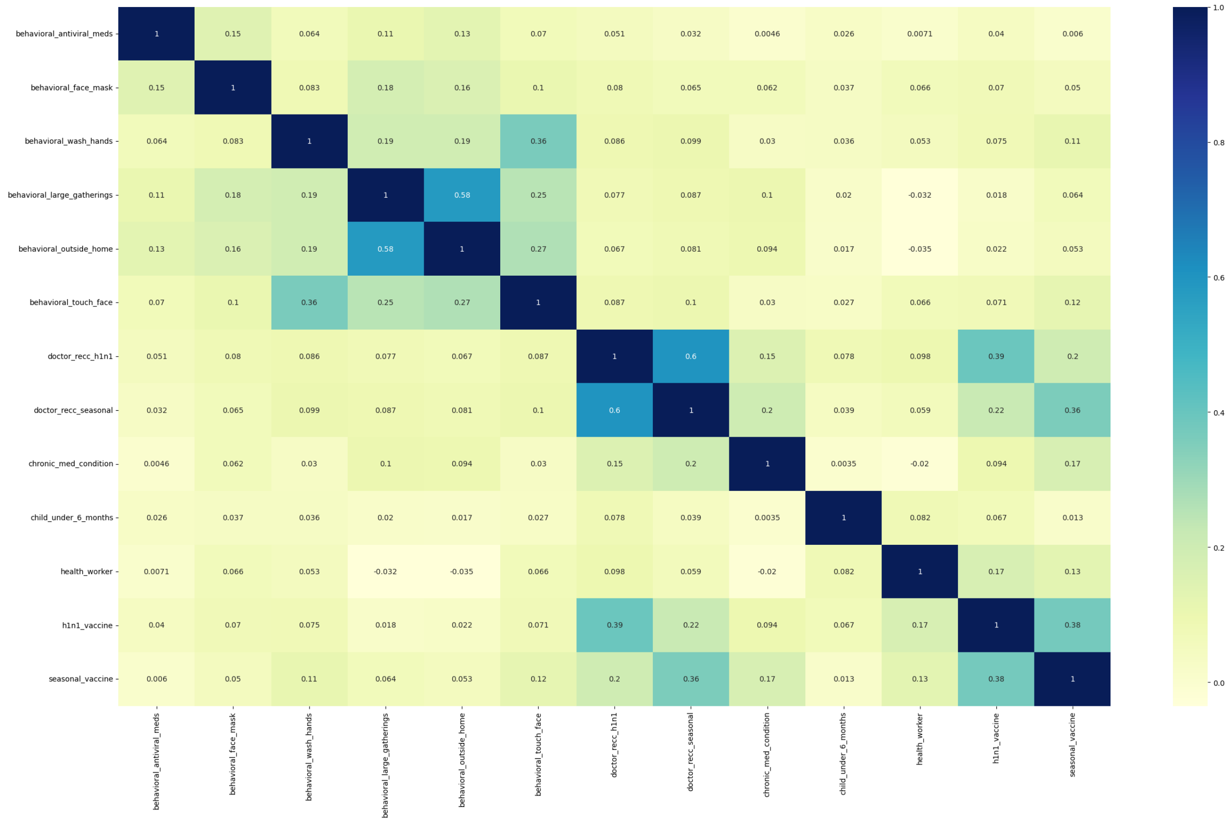
	Target	Features	Correlation_Values
168	seasonal_vaccine	seasonal_vaccine	1.000000
167	seasonal_vaccine	h1n1_vaccine	0.377143
163	seasonal_vaccine	doctor_recc_seasonal	0.360696
162	seasonal_vaccine	doctor_recc_h1n1	0.198560
164	seasonal_vaccine	chronic_med_condition	0.169465
166	seasonal_vaccine	health_worker	0.126977
161	seasonal_vaccine	behavioral_touch_face	0.119925
158	seasonal_vaccine	behavioral_wash_hands	0.112254
159	seasonal_vaccine	behavioral_large_gatherings	0.063722
160	seasonal_vaccine	behavioral_outside_home	0.053287
157	seasonal_vaccine	behavioral_face_mask	0.050020
165	seasonal_vaccine	child_under_6_months	0.013424
156	seasonal_vaccine	behavioral_antiviral_meds	0.006013

In [223]:
```
# checking the correlations of the vaccines with the target of h1n1_vaccine

corr = new_df.corr()
corr = corr.stack().reset_index()
corr = corr.rename(columns = {'level_0':'Target', 'level_1':'Features', 0:'Correl
corr = corr.loc[corr['Target'] == 'h1n1_vaccine']
corr.sort_values(by = 'Correlation_Values', ascending = False)
```

Out[223]:

	Target	Features	Correlation_Values
154	h1n1_vaccine	h1n1_vaccine	1.000000
149	h1n1_vaccine	doctor_recc_h1n1	0.394086
155	h1n1_vaccine	seasonal_vaccine	0.377143
150	h1n1_vaccine	doctor_recc_seasonal	0.218976
153	h1n1_vaccine	health_worker	0.168056
151	h1n1_vaccine	chronic_med_condition	0.094360
145	h1n1_vaccine	behavioral_wash_hands	0.074570
148	h1n1_vaccine	behavioral_touch_face	0.070855
144	h1n1_vaccine	behavioral_face_mask	0.070413
152	h1n1_vaccine	child_under_6_months	0.066712
143	h1n1_vaccine	behavioral_antiviral_meds	0.040226
147	h1n1_vaccine	behavioral_outside_home	0.022080
146	h1n1_vaccine	behavioral_large_gatherings	0.018089

In [224]:
```
# plotting correlation heatmap
# plotting correlation heatmap
plt.figure(figsize=(30,17))
#sns.set_context("paper", font_scale= 3)
dataplot = sns.heatmap(new_df.corr(), cmap="YlGnBu", annot=True)

# displaying heatmap
```



In [225]:
```
new_df.drop('age_group',axis=1)
```

Out[225]:

respondent_id	education	race	sex	employment_status	opinion_h1n1_vacc_effective	opinic
0	< 12 Years	White	Female	Not in Labor Force	Don't know	
1	12 Years	White	Male	Employed	Very effective	S
2	College Graduate	White	Male	Employed	Don't know	
3	12 Years	White	Female	Not in Labor Force	Don't know	
4	Some College	White	Female	Employed	Don't know	
...	...	...	...	...	...	
26702	Some College	White	Female	Not in Labor Force	Don't know	
26703	College Graduate	White	Male	Employed	Somewhat effective	S
26704	Some College	White	Female	Employed	Somewhat effective	S
26705	Some College	Hispanic	Female	Employed	Don't know	
26706	Some College	White	Male	Not in Labor Force	Very effective	

26707 rows × 26 columns

3.3.2.Data Preprocessing

3.3.2.1. Renaming Opinion columns to numerical

In [226]:
```
new_df.opinion_h1n1_vacc_effective=new_df.opinion_h1n1_vacc_effective.replace({"N
                                                                        "Somewhat effective'
 # opinion on effectiveness of seasonal flu vaccines
new_df.opinion_seas_vacc_effective=new_df.opinion_seas_vacc_effective.replace({"N
                                                                        "Somewhat effective'
```

In [227]:
```
new_df.opinion_seas_sick_from_vacc= new_df.opinion_seas_sick_from_vacc.replace({
                                                                                  '
new_df.opinion_h1n1_risk=new_df.opinion_h1n1_risk.replace({"Very Low":1,"Somewhat
                                                                "Somewhat high":4,
new_df.opinion_h1n1_sick_from_vacc= new_df.opinion_h1n1_sick_from_vacc.replace({'
                                                                "Somewhat high":4,
new_df.opinion_h1n1_risk=new_df.opinion_h1n1_risk.replace({"Very Low":1,"Somewhat
                                                                "Somewhat high":4,
#opinion on gettibg sick from seasonal  flu without vaccines
new_df.opinion_seas_risk=new_df.opinion_seas_risk.replace({"Very Low":1,"Somewhat
                                                                "Somewhat high":4,
```

3.3.2.2 Selection of the data

With our features ready, we can begin by running some preliminary models. We'll adopt a few different techniques since we have a unique problem here with multiple targets.

In [228]:
```
features=new_df.drop(columns=['h1n1_vaccine','seasonal_vaccine'],axis=1)
labels = new_df.iloc[:,[24,25]]
```

3.3.2.3 One hot encoding our predictor variables

In [229]:
```
X=pd.get_dummies(features)
y=labels
```

3.3.2.4 Scaling our data using min max scaler

In [230]:
```

scaler = MinMaxScaler()
features = scaler.fit_transform(X)
```

3.3.2.5 Feature Selection Using Kbest

In [231]:
```
# selecting the best features to use on our model
bestfeatures = SelectKBest(score_func=chi2, k=30)
```

We looked at the model and decided to select we the best 30 categories.

3.3.2.5.1 Fitting Kbest

In [232]:
```
fit = bestfeatures.fit(X,y)
```

In [233]:
```
X.head()
```

Out[233]:

respondent_id	opinion_h1n1_vacc_effective	opinion_h1n1_risk	opinion_seas_vacc_effective	opinion
0	3	1	2	
1	5	4	4	
2	3	1	4	
3	3	3	5	
4	3	3	3	

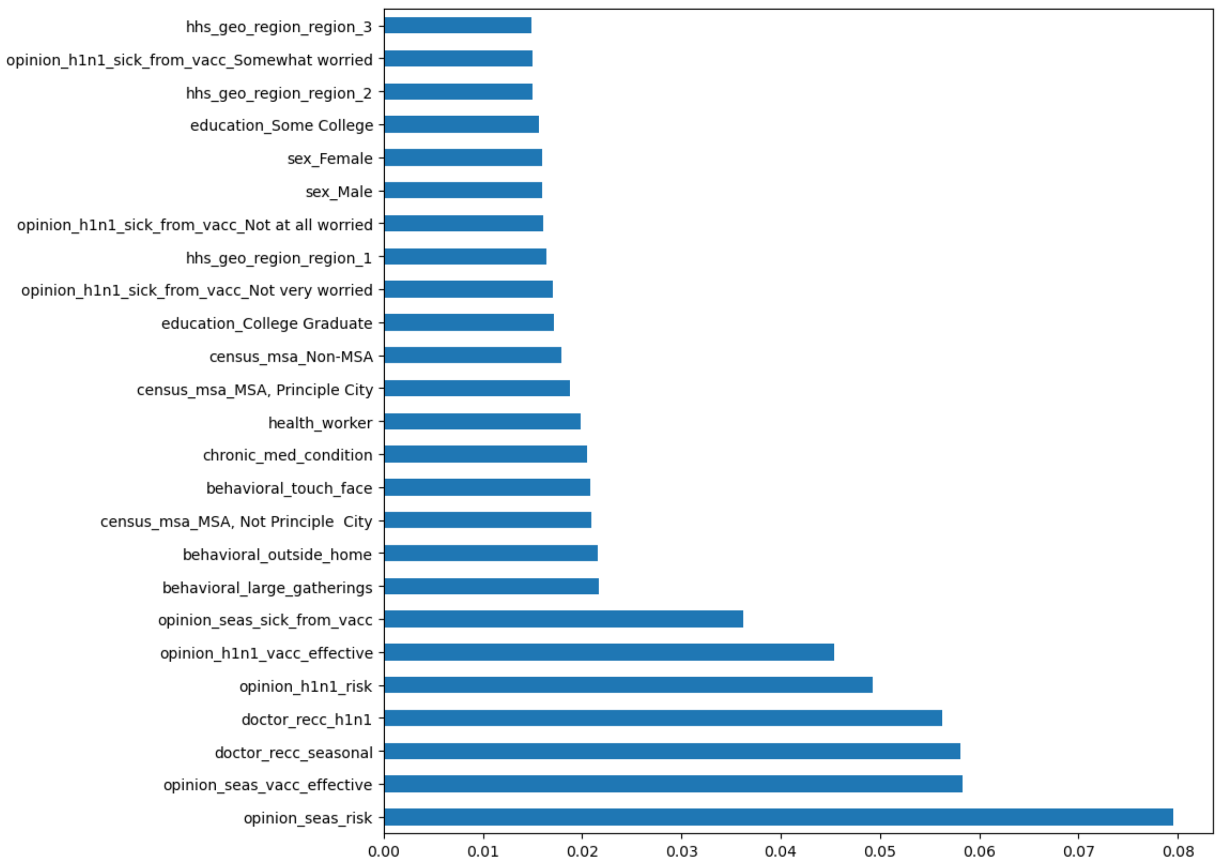
5 rows × 57 columns

In [234]:
```
fit = bestfeatures.fit(X,y)
```

3.3.2.5.2 Feature importance

In [235]:
```
model = ExtraTreesClassifier()
model.fit(X,y)
print(model.feature_importances_)
plt.figure(figsize=(10,10))
feat_importances = pd.Series(model.feature_importances_, index=X.columns)
feat_importances.nlargest(25).plot(kind='barh')
plt.show();
```

```
[0.04540134 0.04930359 0.05835309 0.07951883 0.03618166 0.0081343
 0.01028663 0.01436901 0.02166742 0.02158737 0.02077613 0.05631842
 0.05807814 0.02052974 0.01116125 0.01987089 0.00697422 0.00473132
 0.00510267 0.00529321 0.01314729 0.01374238 0.00896037 0.01711069
 0.01566739 0.0075446  0.00670119 0.00685754 0.01247741 0.01594808
 0.01595685 0.01295242 0.01286427 0.00569785 0.00088762 0.01603951
 0.01708766 0.01499386 0.00837039 0.0209704  0.01877915 0.01796012
 0.01635227 0.00722152 0.01500207 0.01490472 0.01371079 0.0134949
 0.01479206 0.01170663 0.01179732 0.01172795 0.0123568  0.00521502
 0.00545237 0.00495234 0.00695698]
```



This particular process of feature importance has enabled us to understand how our data is distributed.

4.Modelling

4.1.Splitting our data into training and testing

The data at hand represents information about respondents in a survey that were asked questions about their backgrounds, opinions, and health behaviors. With the help of this data we want to predict whether an individual has received the H1N1 vaccine and seasonal flu vaccine.

We will train the model with the training features (X_train) and training labels (y_train) and give it some new data it hasn't seen before (X_test) to evaluate how well it classifies the new data.

As you can see below there's 26707 observations in the training set and 26708 in the test set. This is somewhat uncommon, since the training/test split is usually 80%/20% for train and test respectively, or 70/30. However it won't affect our workflow.

In [236]:
```
x_train, x_test, y_train, y_test = train_test_split(X,y,test_size=0.3, random_sta
```

In [237]:
```
y_train
```

Out[237]:

	h1n1_vaccine	seasonal_vaccine
respondent_id		
5303	0	1
2703	0	0
6586	0	0
22563	1	1
2338	1	1
...	...	...
21575	0	1
5390	0	0
860	0	0
15795	0	0
23654	0	0

18694 rows × 2 columns

4.2 KNearest Neighbours Classification

In [238]:
```
# Build a pipeline with StandardScaler and KNeighborsClassifier
scaled_pipeline_1 = Pipeline([('MMS',MinMaxScaler()),('KNC',KNeighborsClassifier(
```

In [239]:
```
# Fit the training data to pipeline
scaled_pipeline_1.fit(x_train,y_train)

# Print the accuracy on test set
KN=scaled_pipeline_1.score(x_test,y_test)
KN
```

Out[239]:
```
0.5659553226007737
```

4.3 Random Forest Classification

In [240]:
```
# Build a pipeline with StandardScaler and RandomForestClassifier
scaled_pipeline_2 = Pipeline([('mms',MinMaxScaler()),('RF',RandomForestClassifier
```

In [241]:
```
# Define the grid
grid = [{'RF__max_depth': [4, 5, 6],
         'RF__min_samples_split': [2, 5, 10],
         'RF__min_samples_leaf': [1, 3, 5]}]
```

In [242]:
```
# Define a grid search
gridsearch = GridSearchCV(estimator=scaled_pipeline_2,
                          param_grid=grid,
                          scoring="accuracy",
                          cv=5)
```

In [243]:
```
# Fit the training data
gridsearch.fit(x_train,y_train)

# Print the accuracy on test set
GS=gridsearch.score(x_test,y_test)
GS
```

Out[243]:
```
0.640084862099089
```

In [244]:
```
y_train.value_counts().sort_index()
```

Out[244]:
```
h1n1_vaccine  seasonal_vaccine
0             0                   9263
              1                   5451
1             0                    667
              1                   3313
dtype: int64
```

4.4 XGBOOST Classification

In [245]:
```
x_train.head()
```

Out[245]:

	opinion_h1n1_vacc_effective	opinion_h1n1_risk	opinion_seas_vacc_effective	opinion
respondent_id				
5303	4	1	5	
2703	4	2	2	
6586	4	2	5	
22563	5	2	5	
2338	5	4	5	

5 rows × 57 columns

In [246]:
```
import re
```

In [247]:
```
regex = re.compile(r"\[|\]|<", re.IGNORECASE)
```

In [248]:
```
import re

regex = re.compile(r"\[|\]|<", re.IGNORECASE)

x_train.columns = [regex.sub("_", col) if any(x in str(col) for x in set(('[', ']
```

In [249]:
```
model=XGBClassifier()
model.fit(x_train,y_train)
```

Out[249]:
```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
              importance_type=None, interaction_constraints='',
              learning_rate=0.300000012, max_bin=256, max_cat_to_onehot=4,
              max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=1,
              missing=nan, monotone_constraints='()', n_estimators=100,
              n_jobs=0, num_parallel_tree=1, predictor='auto', random_state=0,
              reg_alpha=0, reg_lambda=1, ...)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

First, we're going to try Binary Relevance, which takes each label and splits into separate single class classification problems.

In other words, we use all our same predictors for the h1n1_vaccine target, and then run the same model for the seasonal vaccine target.

In [250]:
```
y_pred = model.predict(x_test)
XG=accuracy_score(y_test,y_pred)
XG
```

Out[250]: 0.6619243728940472

4.5 BinaryRelevance Classification

In [251]:
```
from skmultilearn.problem_transform import BinaryRelevance
```

In [252]:
```
# Initializing

model_BR_LR = BinaryRelevance(LogisticRegression())

# Training

model_BR_LR.fit(x_train,y_train)

# Predicting

y_pred_BR_LR = model_BR_LR.predict(x_test)

# Testing

BR_LR = accuracy_score(y_test,y_pred_BR_LR)
BR_LR
```

Out[252]: 0.6722825408710845

4.6 Naive Bayes Classification

In [253]:
```
# Gaussian Naive Bayes
from sklearn.naive_bayes import GaussianNB
# Initializing

model_BR_GNB = BinaryRelevance(GaussianNB())

# Training

model_BR_GNB.fit(x_train,y_train)

# Predicting

y_pred_BR_GNB = model_BR_GNB.predict(x_test)

# Testing

BR_GNB = accuracy_score(y_test,y_pred_BR_GNB)
BR_GNB
```

Out[253]:
```
0.5875452389866467
```

4.7 MultiOutput Classification

In [254]:
```
#multioutput classifier
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LogisticRegression
from sklearn.multioutput import MultiOutputClassifier

from sklearn.metrics import roc_curve, roc_auc_score
estimators = MultiOutputClassifier(
    estimator = LogisticRegression(penalty='l2', C=1))
full_pipeline = Pipeline([
    ('standard_scaler', StandardScaler()),
    ('estimators', estimators),
])
```

In [255]:
```
#Training the model
full_pipeline.fit(x_train, y_train)

#Predict on evaluation set
preds = full_pipeline.predict_proba(x_test)
preds
```

Out[255]:
```
[array([[0.92088831, 0.07911169],
        [0.92493103, 0.07506897],
        [0.94046944, 0.05953056],
        ...,
        [0.99564758, 0.00435242],
        [0.9632662 , 0.0367338 ],
        [0.87037792, 0.12962208]]),
 array([[0.77483645, 0.22516355],
        [0.76877921, 0.23122079],
        [0.13699371, 0.86300629],
        ...,
        [0.98011293, 0.01988707],
        [0.88125717, 0.11874283],
        [0.1081813 , 0.8918187 ]])]
```

In [256]:
```
y_preds = pd.DataFrame(
    {
        'h1n1_vaccine': preds[0][:,1],
        'seasonal_vaccine':preds[1][:,1],
    },
    index=y_test.index
)
print('y_preds.shape:', y_preds.shape)
y_preds.head()
```

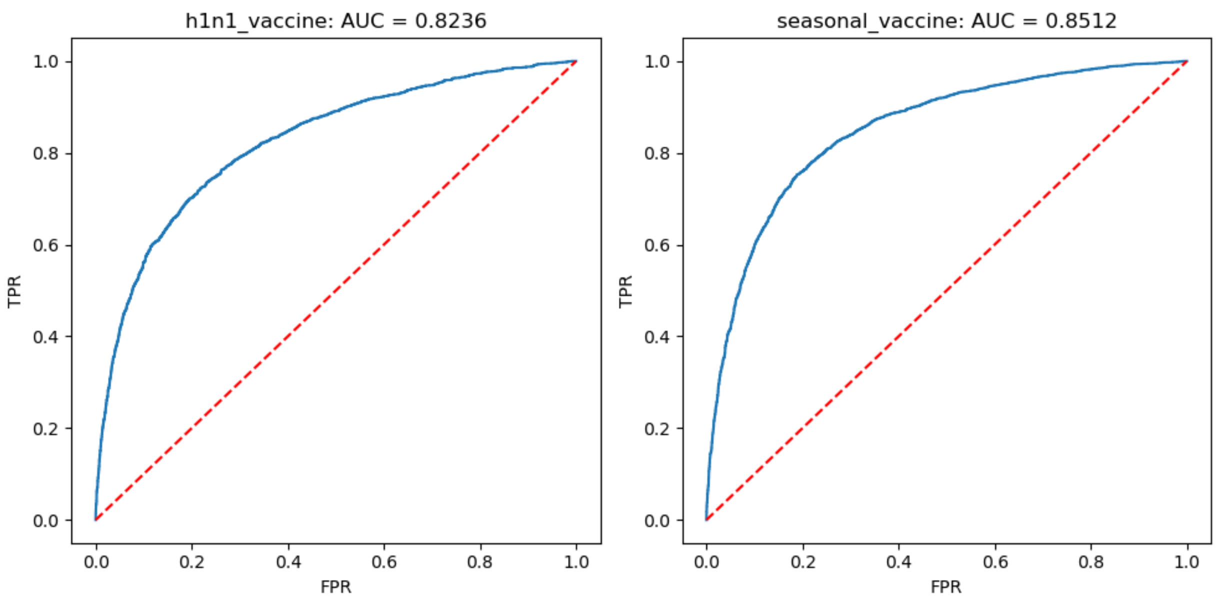
```
y_preds.shape: (8013, 2)
```

Out[256]:

	h1n1_vaccine	seasonal_vaccine
respondent_id		
15772	0.079112	0.225164
9407	0.075069	0.231221
16515	0.059531	0.863006
23353	0.147012	0.209509
10008	0.126487	0.237774

In [257]:
```
def plot_roc(y_true, y_score, label_name, ax):
    fpr, tpr, thresholds = roc_curve(y_true, y_score)
    ax.plot(fpr, tpr)
    ax.plot([0,1], [0,1], color='red', linestyle='--')
    ax.set_ylabel('TPR')
    ax.set_xlabel('FPR')
    ax.set_title(
        f"{label_name}: AUC = {roc_auc_score(y_true, y_score):.4f}")
```

In [258]:
```
fig, ax = plt.subplots(1, 2, figsize=(10,5))
plot_roc(
    y_test['h1n1_vaccine'],
    y_preds['h1n1_vaccine'],
    'h1n1_vaccine',
    ax=ax[0])

plot_roc(
    y_test['seasonal_vaccine'],
    y_preds['seasonal_vaccine'],
    'seasonal_vaccine',
    ax=ax[1])

fig.tight_layout()
```



In [259]:
```
roc_auc_score(y_test, y_preds)
```

Out[259]:
```
0.8373788308839246
```

An AUC score of 0.5 is no better than random, and an AUC score of 1.0 is a perfect model. Both models look like they generally perform similarly. Our scores of around 0.83 are not great, but they're not bad either!

The competition metric is the average between these two AUC values.

5. Evaluation

We used different models to come up with a succesfull predictions,our succes metrics was based on the accuracy score of above 65% or an A_U_C score of above 70%.Listed below are the various models that we used and their accuracy score

- KNeighborsClassifier with an accuracy score of 56.59%
- Random forest classifier with an accuracy score of 64.00%
- XG boost with an accuracy score of 66%
- BinaryRelevance(LogisticRegression) classifier with an accuracy score of 67%
- BinaryRelevance guassian naive bayes with an accuracy score of 58..75%
- Multioutput classifier with an average auc of 83.73%

Hence we decided that the best model ,was the multioutput classifier with an average AUC of 83.73 %

6. Deployment

Retrain model on full dataset

Now that we have an idea of our performance, we'll want to retrain our model on the full dataset before generating our predictions on the test set.

In [260]:
```
full_pipeline.fit(features, labels)
```

Out[260]:
```
Pipeline(steps=[('standard_scaler', StandardScaler()),
                ('estimators',
                 MultiOutputClassifier(estimator=LogisticRegression(C=1)))])
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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7. Reccomendations

Since vaccination is the main preventive strategy for influenza, optimizing formations and identifying factors that interfere with the administration of the vaccine is vital. Identifying factors that produce a priming effect and enhance response is important in understanding how to improve efficiency of influenza vaccine. Prospective safety monitoring followed by rigorous signal refinement is critical to inform decision making by regulatory and public health agencies.