

# Project

- This dataset is part of an active competition until March 31, 2022!
- 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. Your audience could be someone guiding those public health efforts.
- This challenge: can you predict whether people got H1N1 and seasonal flu vaccines using data collected in the National 2009 H1N1 Flu Survey? This is a binary classification problem, but there are two potential targets: whether the survey respondent received the seasonal flu vaccine, or whether the respondent received the H1N1 flu vaccine. Please choose just one of these potential targets for your minimum viable project.

## Business Problem

- Stakeholder:
  - Public health organizations or healthcare providers aiming to increase vaccine uptake for H1N1 and seasonal flu to reduce the spread and impact of these illnesses.
- Business Problem
  - Predict whether individuals are likely to get vaccinated for H1N1 and seasonal flu based on demographic, social, and behavioral factors. Insights from the model can guide targeted vaccination campaigns and policy decisions.

## Data understanding

- Dataset overview:
  - Two target variables: H1N1\_vaccine and seasonal\_vaccine (binary: 1 for vaccinated, 0 otherwise).
  - Predictors include demographic (age, gender), social (education, marital status), and behavioral (health conditions, vaccine awareness) features.
- Objective:
  - This is a classification problem, where the task is to predict binary outcomes (vaccinated or not).

```
# importing libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

```
df = pd.read_csv("C:/Users/DELL/Desktop/Projects/FLU
VACCINES/Data/H1N1_Flu_Vaccines.csv")
```

```
df.head()
```

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

	behavioral_avoidance	behavioral_face_mask
behavioral_wash_hands \		
0	0.0	0.0
1	1.0	0.0
2	1.0	0.0
3	1.0	0.0
4	1.0	0.0

	behavioral_large_gatherings	behavioral_outside_home \
0	0.0	1.0
1	0.0	1.0
2	0.0	0.0
3	1.0	0.0
4	1.0	0.0

	behavioral_touch_face	...	rent_or_own	employment_status \
0	1.0	...	Own	Not in Labor Force
1	1.0	...	Rent	Employed
2	0.0	...	Own	Employed
3	0.0	...	Rent	Not in Labor Force
4	1.0	...	Own	Employed

	hhs_geo_region	census_msa	household_adults \
0	oxchjgsf	Non-MSA	0.0
1	bhuqouqj	MSA, Not Principle City	0.0
2	qufhixun	MSA, Not Principle City	2.0
3	lrircsnp	MSA, Principle City	0.0
4	qufhixun	MSA, Not Principle City	1.0

	household_children	employment_industry	employment_occupation	\
0	0.0	NaN	NaN	
1	0.0	pxcmvdjn	xgwztkwe	
2	0.0	rucpziiij	xtkaffoo	
3	0.0	NaN	NaN	
4	0.0	wxleyezf	emcorrxb	

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

[5 rows x 38 columns]

## Descriptive Statistics

df.shape

(26707, 38)

df.info()

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 26707 entries, 0 to 26706

Data columns (total 38 columns):

#	Column	Non-Null Count	Dtype
0	respondent_id	26707 non-null	int64
1	h1n1_concern	26615 non-null	float64
2	h1n1_knowledge	26591 non-null	float64
3	behavioral_antiviral_meds	26636 non-null	float64
4	behavioral_avoidance	26499 non-null	float64
5	behavioral_face_mask	26688 non-null	float64
6	behavioral_wash_hands	26665 non-null	float64
7	behavioral_large_gatherings	26620 non-null	float64
8	behavioral_outside_home	26625 non-null	float64
9	behavioral_touch_face	26579 non-null	float64
10	doctor_recc_h1n1	24547 non-null	float64
11	doctor_recc_seasonal	24547 non-null	float64
12	chronic_med_condition	25736 non-null	float64
13	child_under_6_months	25887 non-null	float64
14	health_worker	25903 non-null	float64
15	health_insurance	14433 non-null	float64
16	opinion_h1n1_vacc_effective	26316 non-null	float64
17	opinion_h1n1_risk	26319 non-null	float64

```

18 opinion_h1n1_sick_from_vacc 26312 non-null float64
19 opinion_seas_vacc_effective 26245 non-null float64
20 opinion_seas_risk 26193 non-null float64
21 opinion_seas_sick_from_vacc 26170 non-null float64
22 age_group 26707 non-null object
23 education 25300 non-null object
24 race 26707 non-null object
25 sex 26707 non-null object
26 income_poverty 22284 non-null object
27 marital_status 25299 non-null object
28 rent_or_own 24665 non-null object
29 employment_status 25244 non-null object
30 hhs_geo_region 26707 non-null object
31 census_msa 26707 non-null object
32 household_adults 26458 non-null float64
33 household_children 26458 non-null float64
34 employment_industry 13377 non-null object
35 employment_occupation 13237 non-null object
36 h1n1_vaccine 26707 non-null int64
37 seasonal_vaccine 26707 non-null int64
dtypes: float64(23), int64(3), object(12)
memory usage: 7.7+ MB

```

```
df.describe()
```

```

      respondent_id  h1n1_concern  h1n1_knowledge
behavioral_antiviral_meds \
count      26707.000000    26615.000000      26591.000000
26636.000000
mean      13353.000000         1.618486         1.262532
0.048844
std       7709.791156         0.910311         0.618149
0.215545
min         0.000000         0.000000         0.000000
0.000000
25%       6676.500000         1.000000         1.000000
0.000000
50%      13353.000000         2.000000         1.000000
0.000000
75%      20029.500000         2.000000         2.000000
0.000000
max      26706.000000         3.000000         2.000000
1.000000

```

```

      behavioral_avoidance  behavioral_face_mask
behavioral_wash_hands \
count          26499.000000      26688.000000
26665.000000
mean              0.725612         0.068982
0.825614

```

std	0.446214	0.253429
0.379448		
min	0.000000	0.000000
0.000000		
25%	0.000000	0.000000
1.000000		
50%	1.000000	0.000000
1.000000		
75%	1.000000	0.000000
1.000000		
max	1.000000	1.000000
1.000000		

	behavioral_large_gatherings	behavioral_outside_home	\
count	26620.00000	26625.000000	
mean	0.35864	0.337315	
std	0.47961	0.472802	
min	0.00000	0.000000	
25%	0.00000	0.000000	
50%	0.00000	0.000000	
75%	1.00000	1.000000	
max	1.00000	1.000000	

	behavioral_touch_face	...	opinion_h1n1_vacc_effective	\
count	26579.000000	...	26316.000000	
mean	0.677264	...	3.850623	
std	0.467531	...	1.007436	
min	0.000000	...	1.000000	
25%	0.000000	...	3.000000	
50%	1.000000	...	4.000000	
75%	1.000000	...	5.000000	
max	1.000000	...	5.000000	

	opinion_h1n1_risk	opinion_h1n1_sick_from_vacc	\
count	26319.000000	26312.000000	
mean	2.342566	2.357670	
std	1.285539	1.362766	
min	1.000000	1.000000	
25%	1.000000	1.000000	
50%	2.000000	2.000000	
75%	4.000000	4.000000	
max	5.000000	5.000000	

	opinion_seas_vacc_effective	opinion_seas_risk	\
count	26245.000000	26193.000000	
mean	4.025986	2.719162	
std	1.086565	1.385055	
min	1.000000	1.000000	
25%	4.000000	2.000000	
50%	4.000000	2.000000	

75%	5.000000	4.000000
max	5.000000	5.000000

	opinion_seas_sick_from_vacc	household_adults
household_children \		
count	26170.000000	26458.000000
26458.000000		
mean	2.118112	0.886499
0.534583		
std	1.332950	0.753422
0.928173		
min	1.000000	0.000000
0.000000		
25%	1.000000	0.000000
0.000000		
50%	2.000000	1.000000
0.000000		
75%	4.000000	1.000000
1.000000		
max	5.000000	3.000000
3.000000		

	h1n1_vaccine	seasonal_vaccine
count	26707.000000	26707.000000
mean	0.212454	0.465608
std	0.409052	0.498825
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	1.000000
max	1.000000	1.000000

[8 rows x 26 columns]

## Exploratory Data Analysis

- Steps:
  - Load and inspect data:
    - check for missing values
    - understand the distribution of target variables and predictors.
  - Visualize relationships
  - Handle missing values
  - Feature engineering:
    - Encode categorical variables
    - Scale numeric features
  - check class imbalance

```
df.isnull().sum()
```

```
respondent_id          0
h1n1_concern           92
h1n1_knowledge        116
behavioral_antiviral_meds  71
behavioral_avoidance   208
behavioral_face_mask    19
behavioral_wash_hands   42
behavioral_large_gatherings  87
behavioral_outside_home  82
behavioral_touch_face  128
doctor_recc_h1n1      2160
doctor_recc_seasonal  2160
chronic_med_condition  971
child_under_6_months  820
health_worker          804
health_insurance     12274
opinion_h1n1_vacc_effective  391
opinion_h1n1_risk      388
opinion_h1n1_sick_from_vacc  395
opinion_seas_vacc_effective  462
opinion_seas_risk      514
opinion_seas_sick_from_vacc  537
age_group              0
education             1407
race                  0
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
```

```
# Create a figure with two subplots side by side
```

```
fig, axes = plt.subplots(1, 2, figsize=(16, 8))
```

```
# First plot: h1n1_vaccine
```

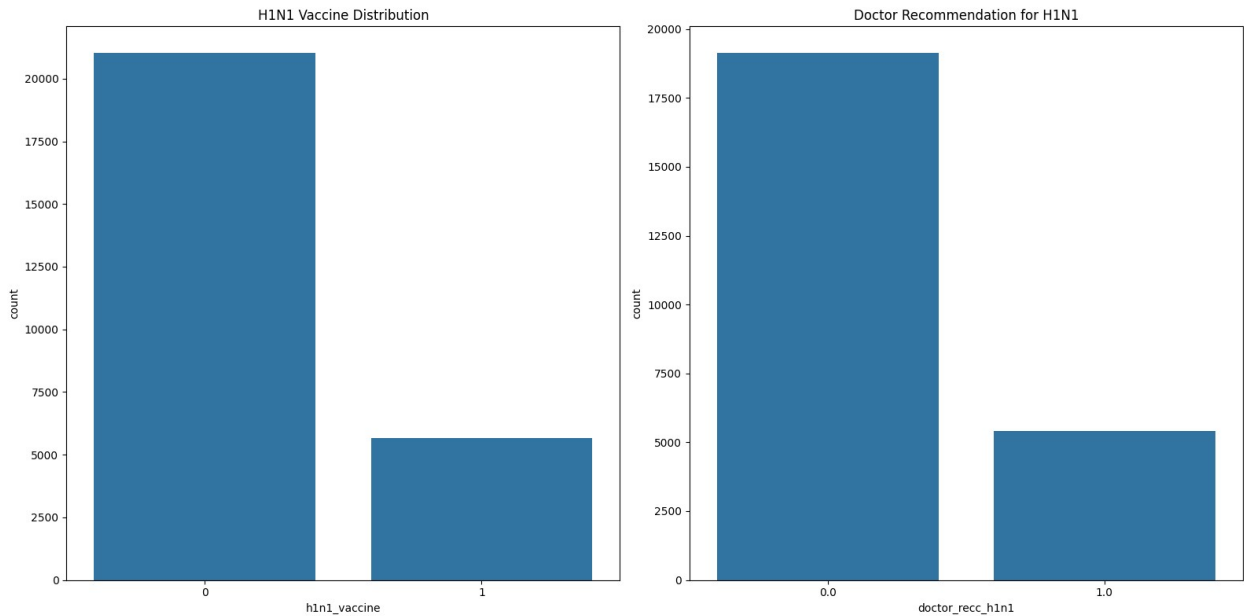
```
sns.countplot(x="h1n1_vaccine", data=df, ax=axes[0])
```

```
axes[0].set_title("H1N1 Vaccine Distribution")
```

```
# Second plot: doctor_recc_h1n1
```

```
sns.countplot(x="doctor_recc_h1n1", data=df, ax=axes[1])
axes[1].set_title("Doctor Recommendation for H1N1")
```

```
# Display the plots
plt.tight_layout()
plt.show()
```



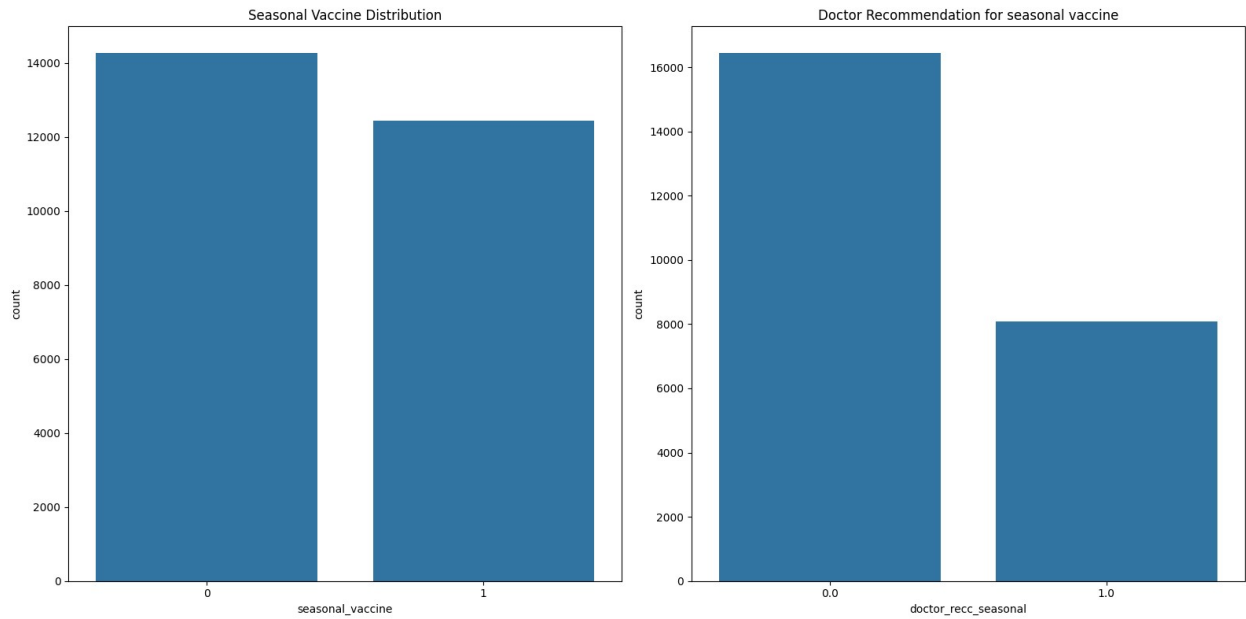
```
# Create a figure with two subplots side by side
fig, axes = plt.subplots(1, 2, figsize=(16, 8))
```

```
# First plot: seasonal_vaccine
sns.countplot(x="seasonal_vaccine", data=df, ax=axes[0])
axes[0].set_title("Seasonal Vaccine Distribution")
```

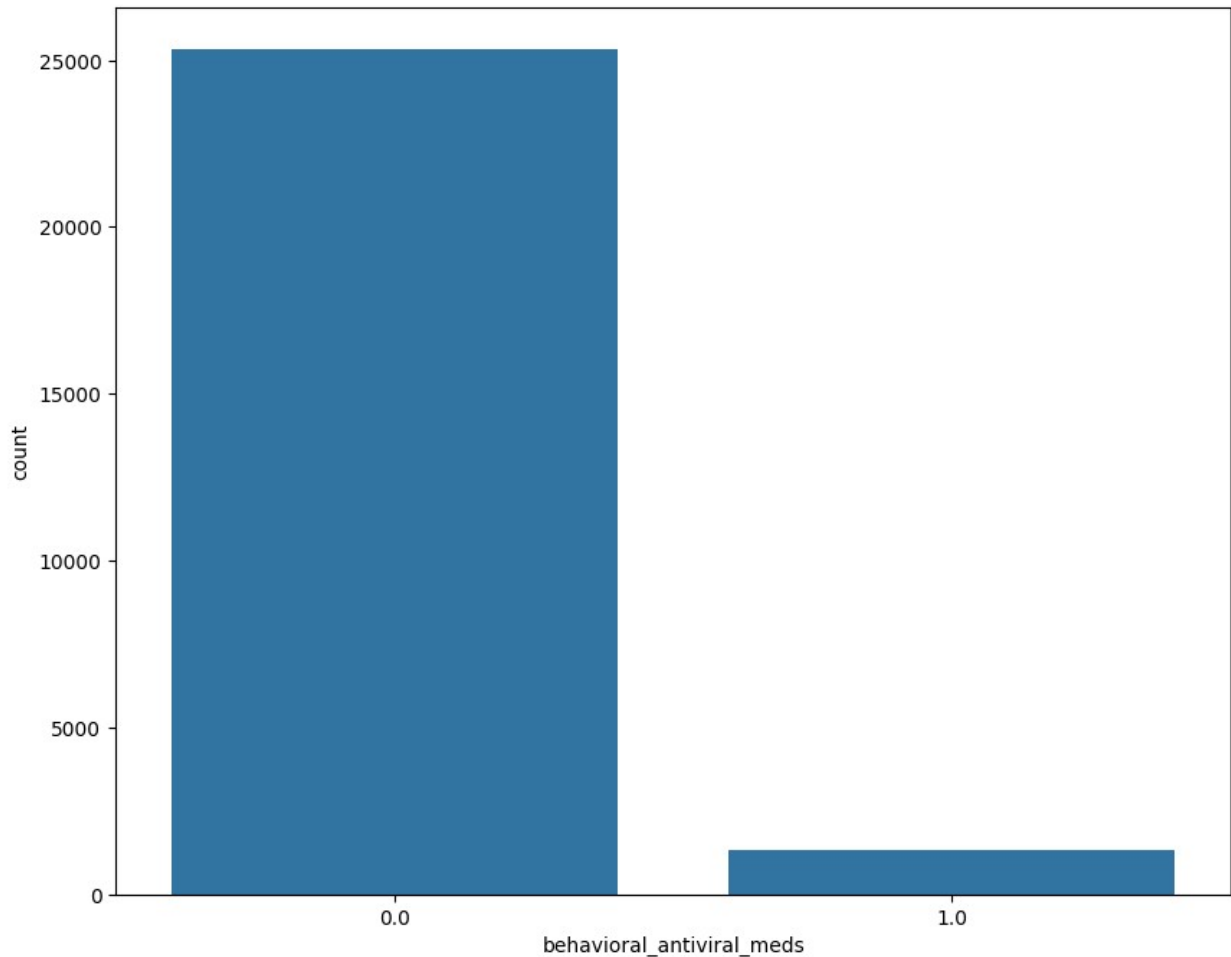
```
# Second plot: doctor_recc_seasonal
sns.countplot(x="doctor_recc_seasonal", data=df, ax=axes[1])
axes[1].set_title("Doctor Recommendation for seasonal vaccine")
```

```
# Display the plots
plt.tight_layout()
plt.show()
```





```
plt.figure(figsize=(10,8))
sns.countplot(x="behavioral_antiviral_meds",data=df)
plt.show()
```



## Dropping data with more than 30% missing data

```
# Calculate the percentage of null values per column
null_percentage = (df.isnull().sum() / len(df)) * 100

# Identify columns with more than 50% null values
columns_to_drop = null_percentage[null_percentage > 30].index

# Drop those columns from the DataFrame
df = df.drop(columns=columns_to_drop)

(df.isnull().sum() / len(df) * 100).sort_values(ascending=False)
```

income_poverty	16.561201
doctor_recc_h1n1	8.087767
doctor_recc_seasonal	8.087767
rent_or_own	7.645936

employment_status	5.477965
marital_status	5.272026
education	5.268282
chronic_med_condition	3.635751
child_under_6_months	3.070356
health_worker	3.010447
opinion_seas_sick_from_vacc	2.010709
opinion_seas_risk	1.924589
opinion_seas_vacc_effective	1.729884
opinion_h1n1_sick_from_vacc	1.479013
opinion_h1n1_vacc_effective	1.464036
opinion_h1n1_risk	1.452803
household_adults	0.932340
household_children	0.932340
behavioral_avoidance	0.778822
behavioral_touch_face	0.479275
h1n1_knowledge	0.434343
h1n1_concern	0.344479
behavioral_large_gatherings	0.325757
behavioral_outside_home	0.307036
behavioral_antiviral_meds	0.265848
behavioral_wash_hands	0.157262
behavioral_face_mask	0.071142
respondent_id	0.000000
race	0.000000
age_group	0.000000
sex	0.000000
census_msa	0.000000
hhs_geo_region	0.000000
h1n1_vaccine	0.000000
seasonal_vaccine	0.000000
dtype: float64	

## Mode Imputation for categorical variables

```

from sklearn.impute import SimpleImputer

# Separate categorical and numerical columns
categorical_cols = df.select_dtypes(include=['object']).columns

# Imputer for categorical columns (mode)
mode_imputer = SimpleImputer(strategy='most_frequent')
df[categorical_cols] =
mode_imputer.fit_transform(df[categorical_cols])

```

# Median imputer for numerical data

```
from sklearn.impute import SimpleImputer

# Separate categorical and numerical columns
numerical_cols = df.select_dtypes(include=['int64',
'float64']).columns

# Imputer for numerical columns (median)
median_imputer = SimpleImputer(strategy='median')
df[numerical_cols] = median_imputer.fit_transform(df[numerical_cols])

# Check if there are any remaining missing values
remaining_missing = df.isnull().sum()
remaining_missing[remaining_missing > 0]

Series([], dtype: int64)

df.isna().sum()

respondent_id      0
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
doctor_recc_seasonal  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
opinion_seas_vacc_effective  0
opinion_seas_risk    0
opinion_seas_sick_from_vacc  0
age_group          0
education          0
race               0
sex               0
income_poverty     0
marital_status     0
rent_or_own        0
employment_status  0
hhs_geo_region     0
```

```
census_msa          0
household_adults    0
household_children  0
h1n1_vaccine        0
seasonal_vaccine    0
dtype: int64
```

## EDA after cleaning data

```
df.shape
```

```
(26707, 35)
```

```
df.describe()
```

```

      respondent_id  h1n1_concern  h1n1_knowledge
behavioral_antiviral_meds \
count      26707.000000    26707.000000      26707.000000
26707.000000
mean       13353.000000         1.619800         1.261392
0.048714
std         7709.791156         0.909016         0.617047
0.215273
min           0.000000         0.000000         0.000000
0.000000
25%          6676.500000         1.000000         1.000000
0.000000
50%         13353.000000         2.000000         1.000000
0.000000
75%         20029.500000         2.000000         2.000000
0.000000
max          26706.000000         3.000000         2.000000
1.000000

```

```

      behavioral_avoidance  behavioral_face_mask
behavioral_wash_hands \
count           26707.000000      26707.000000
26707.000000
mean                0.727749         0.068933
0.825888
std                0.445127         0.253345
0.379213
min                0.000000         0.000000
0.000000
25%                0.000000         0.000000
1.000000
50%                1.000000         0.000000
1.000000

```

75%	1.000000	0.000000
1.000000		
max	1.000000	1.000000
1.000000		

	behavioral_large_gatherings	behavioral_outside_home \
count	26707.000000	26707.000000
mean	0.357472	0.336279
std	0.479264	0.472444
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	1.000000	1.000000
max	1.000000	1.000000

	behavioral_touch_face	...	opinion_h1n1_vacc_effective \
count	26707.000000	...	26707.000000
mean	0.678811	...	3.852810
std	0.466942	...	1.000195
min	0.000000	...	1.000000
25%	0.000000	...	3.000000
50%	1.000000	...	4.000000
75%	1.000000	...	5.000000
max	1.000000	...	5.000000

	opinion_h1n1_risk	opinion_h1n1_sick_from_vacc \
count	26707.000000	26707.000000
mean	2.337589	2.352380
std	1.276825	1.353339
min	1.000000	1.000000
25%	1.000000	1.000000
50%	2.000000	2.000000
75%	4.000000	4.000000
max	5.000000	5.000000

	opinion_seas_vacc_effective	opinion_seas_risk \
count	26707.000000	26707.000000
mean	4.025536	2.705321
std	1.077131	1.375216
min	1.000000	1.000000
25%	4.000000	2.000000
50%	4.000000	2.000000
75%	5.000000	4.000000
max	5.000000	5.000000

	opinion_seas_sick_from_vacc	household_adults
household_children \		
count	26707.000000	26707.000000
26707.000000		
mean	2.115737	0.887558

0.529599		
std	1.319585	0.749980
0.925264		
min	1.000000	0.000000
0.000000		
25%	1.000000	0.000000
0.000000		
50%	2.000000	1.000000
0.000000		
75%	2.000000	1.000000
1.000000		
max	5.000000	3.000000
3.000000		

	h1n1_vaccine	seasonal_vaccine
count	26707.000000	26707.000000
mean	0.212454	0.465608
std	0.409052	0.498825
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	1.000000
max	1.000000	1.000000

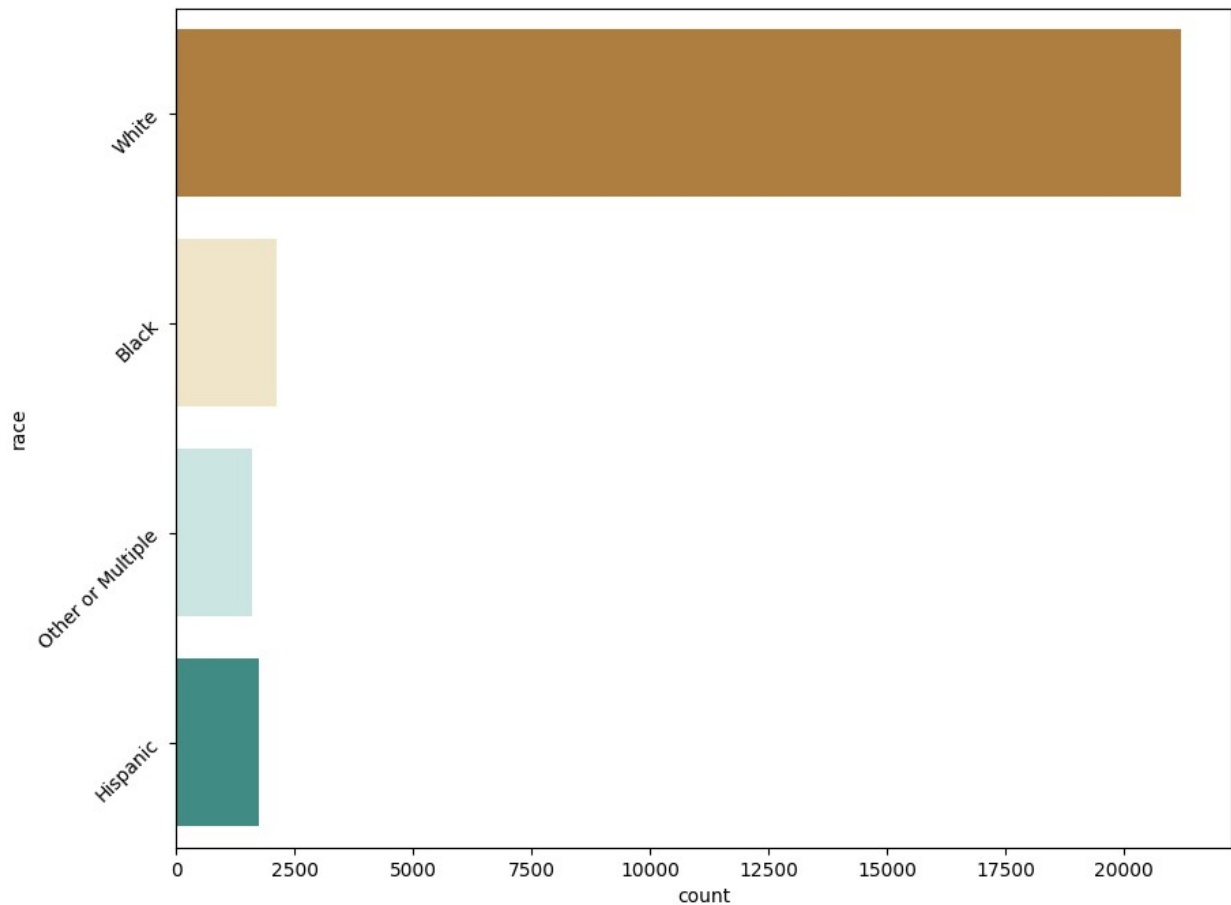
[8 rows x 25 columns]

```
plt.figure(figsize=(10,8))
sns.countplot(y="race",data=df,palette="BrBG")
plt.yticks(rotation=45)
plt.show()
```

C:\Users\DELL\AppData\Local\Temp\ipykernel\_22004\584491901.py:2:  
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

```
sns.countplot(y="race",data=df,palette="BrBG")
```



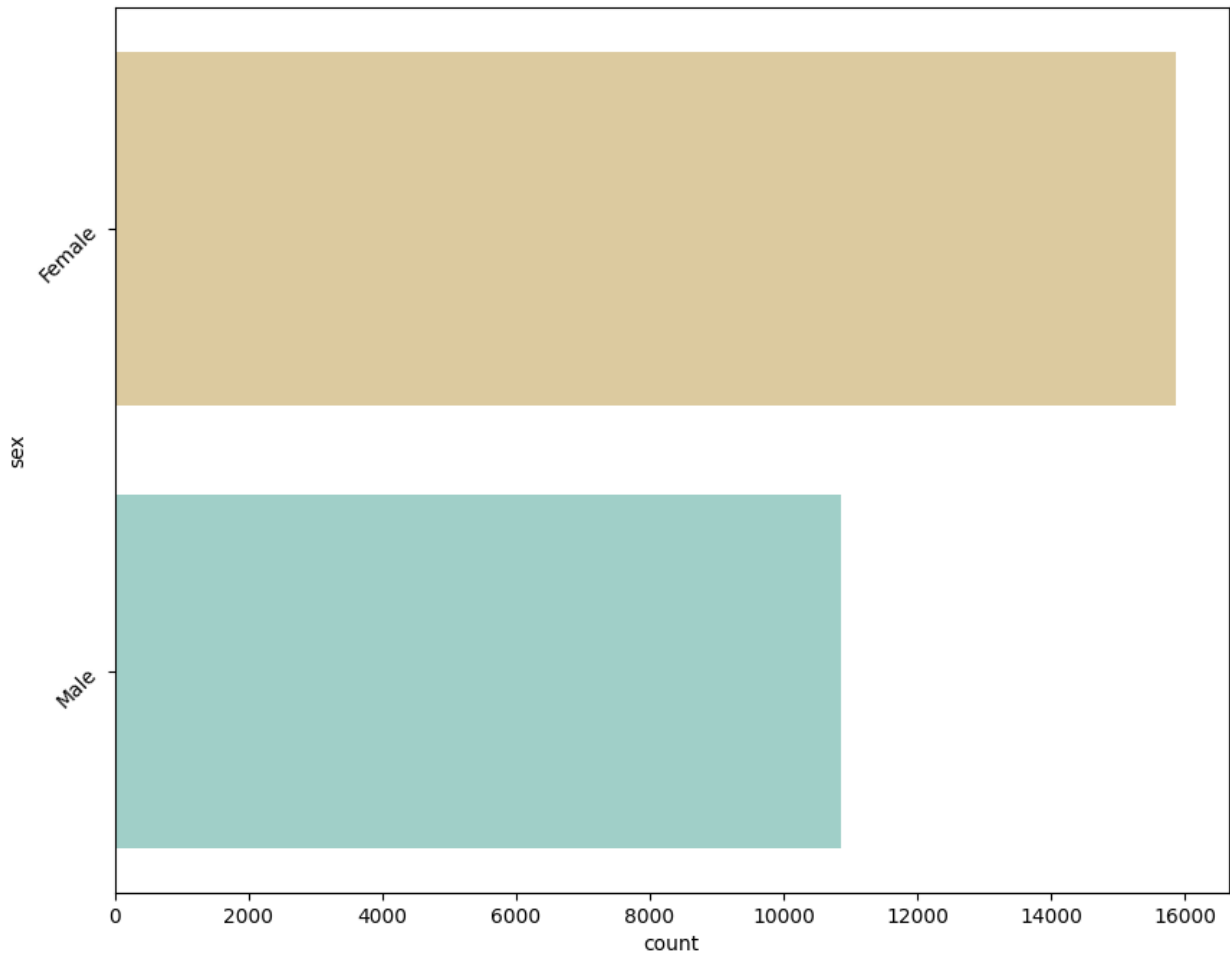
```
plt.figure(figsize=(10,8))
sns.countplot(y="sex",data=df,palette="BrBG")
plt.yticks(rotation=45)
plt.show()
```

C:\Users\DELL\AppData\Local\Temp\ipykernel\_22004\2993517352.py:2:  
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

```
sns.countplot(y="sex",data=df,palette="BrBG")
```





```
df["income_poverty"].value_counts()
```

```
income_poverty
<= $75,000, Above Poverty    17200
> $75,000                    6810
Below Poverty                2697
Name: count, dtype: int64
```

```
df["marital_status"].value_counts()
```

```
marital_status
Married        14963
Not Married    11744
Name: count, dtype: int64
```

```
df["rent_or_own"].value_counts()
```

```
rent_or_own
Own        20778
Rent       5929
Name: count, dtype: int64
```

```

df["employment_status"].value_counts()

employment_status
Employed          15023
Not in Labor Force 10231
Unemployed         1453
Name: count, dtype: int64

df["census_msa"].value_counts()

census_msa
MSA, Not Principle City    11645
MSA, Principle City        7864
Non-MSA                    7198
Name: count, dtype: int64

# Create a figure with two subplots side by side
fig, axes = plt.subplots(1, 4, figsize=(20, 8))

# First plot: h1n1_concern
sns.countplot(x="h1n1_concern", data=df, ax=axes[0])
axes[0].set_title("Level of concern about the H1N1 flu.")

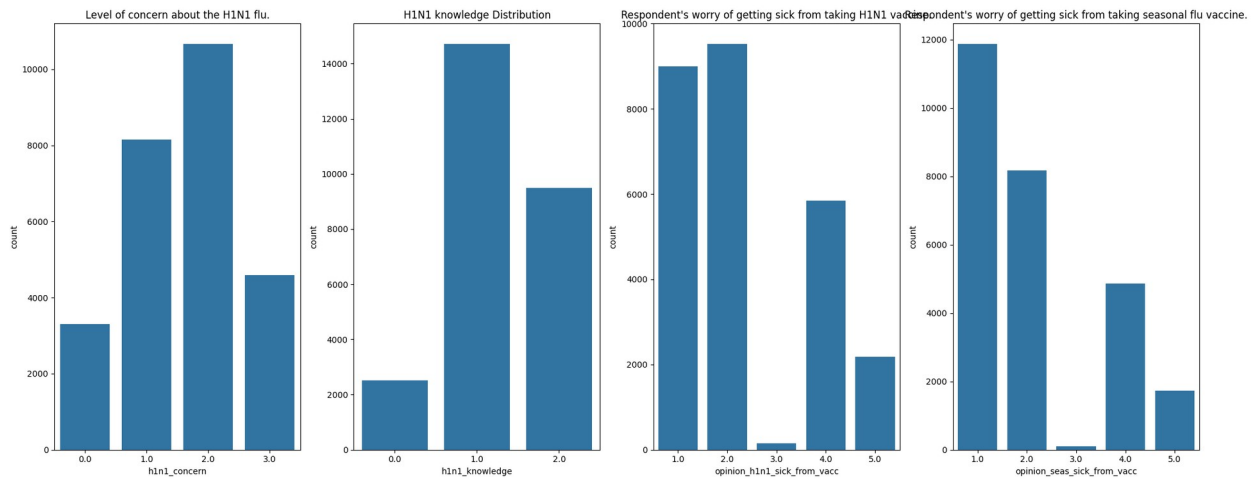
# Second plot: h1n1_vaccine
sns.countplot(x="h1n1_knowledge", data=df, ax=axes[1])
axes[1].set_title("H1N1 knowledge Distribution")

# Third plot: doctor_recc_h1n1
sns.countplot(x="opinion_h1n1_sick_from_vacc", data=df, ax=axes[2])
axes[2].set_title("Respondent's worry of getting sick from taking H1N1 vaccine.")

# Third plot: doctor_recc_h1n1
sns.countplot(x="opinion_seas_sick_from_vacc", data=df, ax=axes[3])
axes[3].set_title("Respondent's worry of getting sick from taking seasonal flu vaccine.")

# Display the plots
plt.tight_layout()
plt.show()

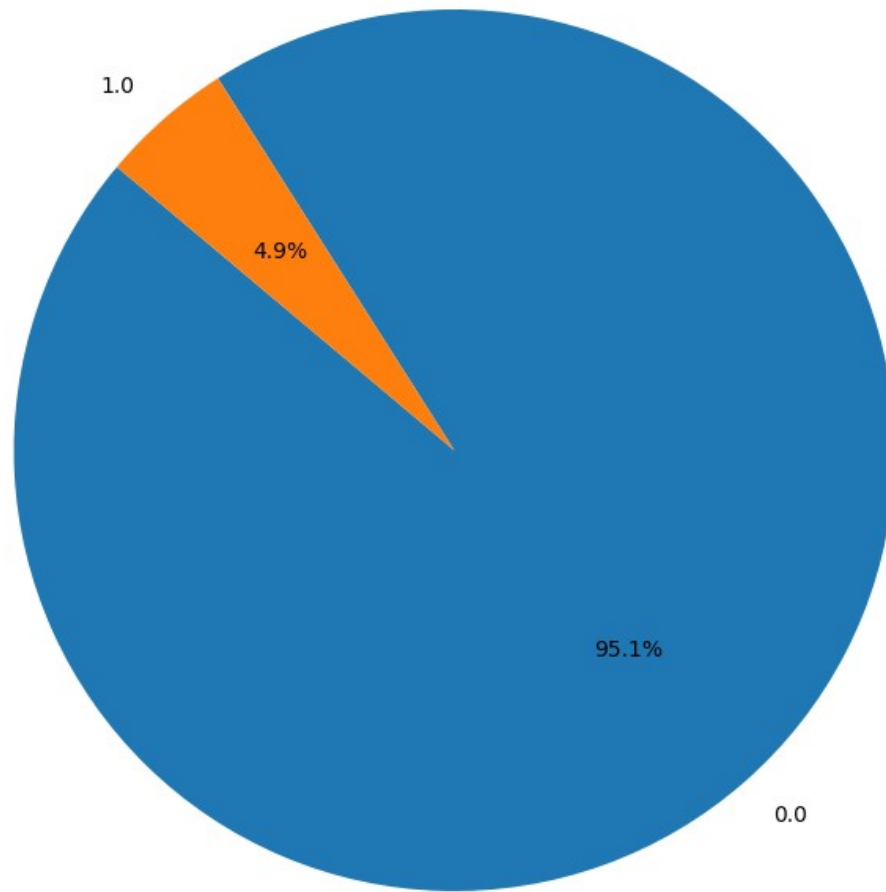
```



```
value_counts = df["behavioral_antiviral_meds"].value_counts()

plt.figure(figsize=(10,8))
plt.pie(value_counts, labels=value_counts.index, autopct='%1.1f%%',
startangle=140)
plt.title('Antiviral Medication Distribution')
plt.axis('equal')
plt.show()
```

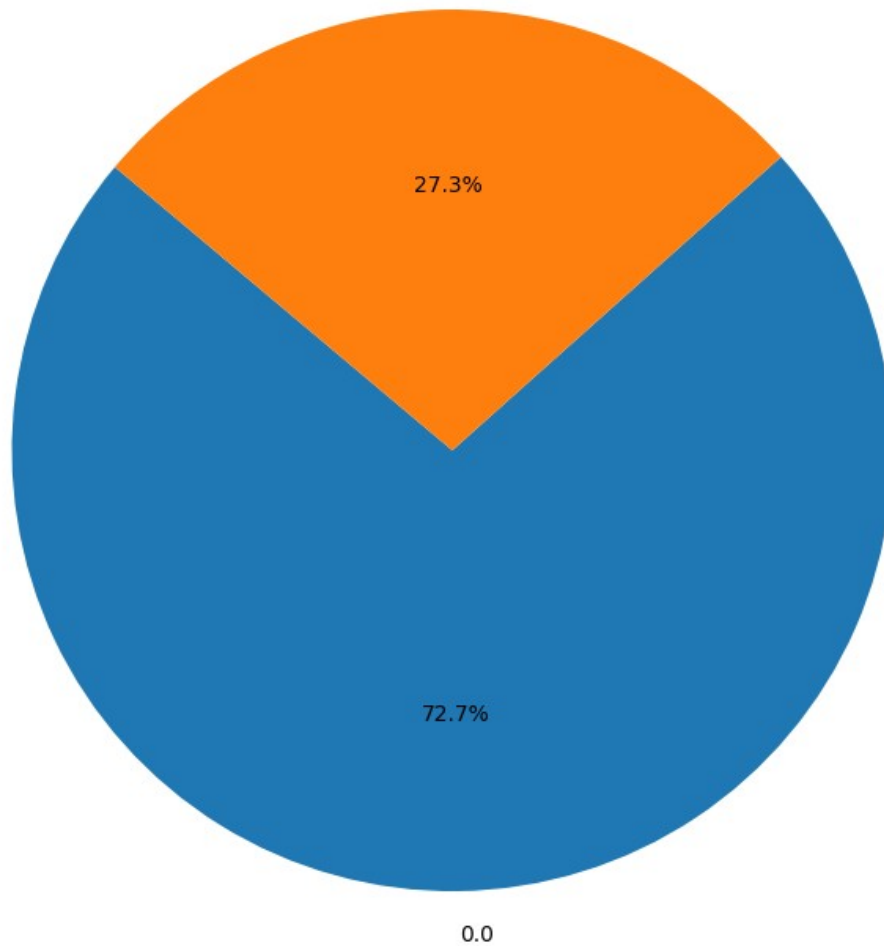
Antiviral Medication Distribution



```
value_counts = df["chronic_med_condition"].value_counts()

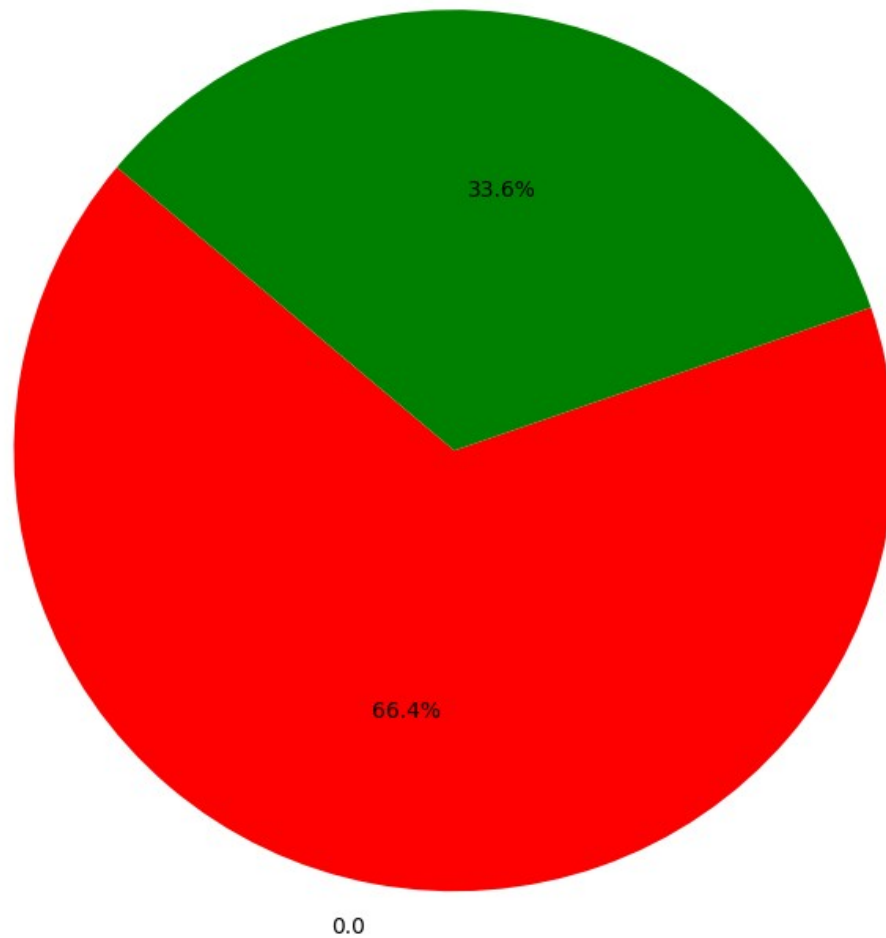
plt.figure(figsize=(10,8))
plt.pie(value_counts, labels=value_counts.index, autopct='%1.1f%%',
startangle=140)
plt.title('chronic medical condition Distribution')
plt.axis('equal')
plt.show()
```

chronic medical condition Distribution



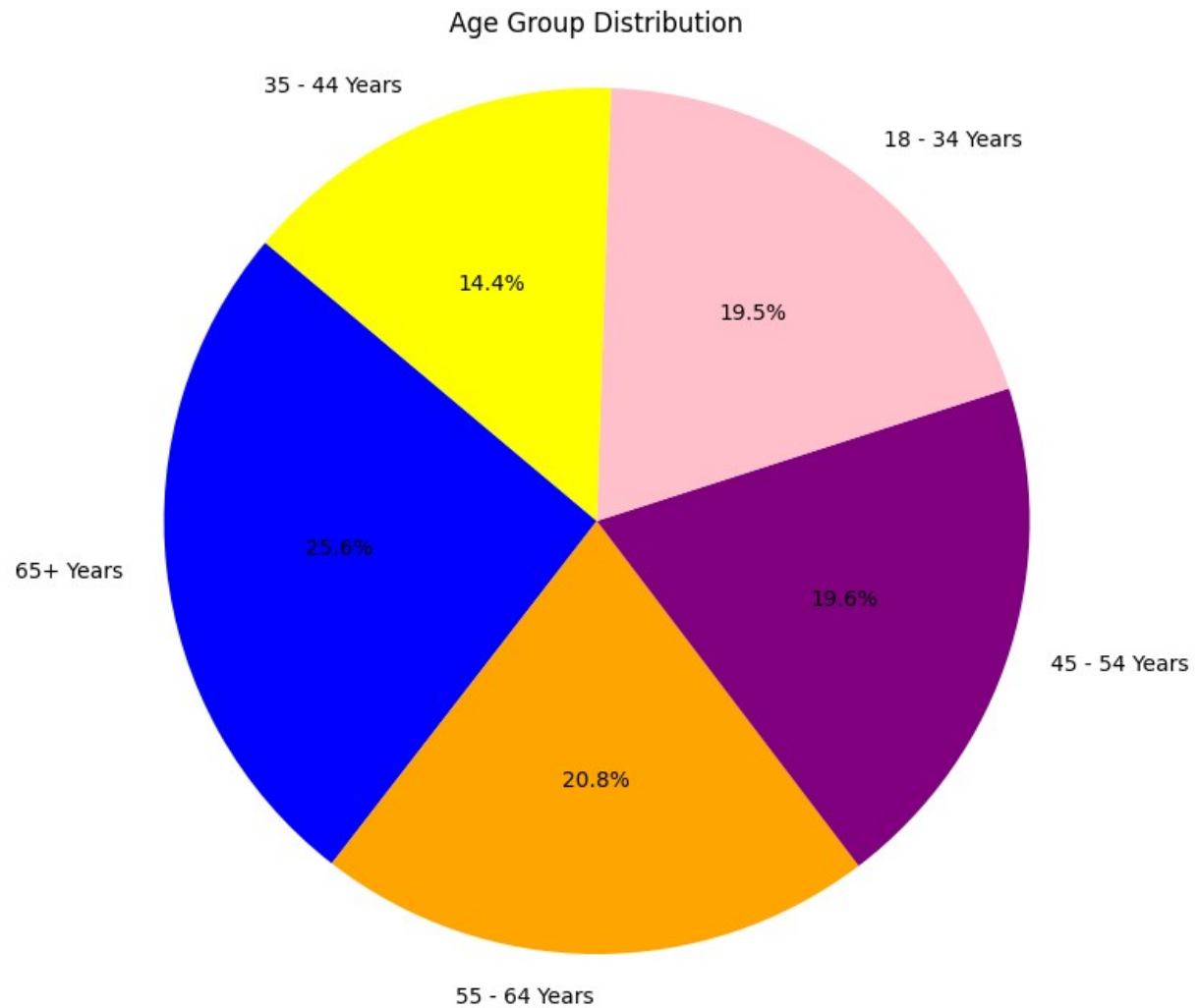
```
contact_avoidance_counts =  
df["behavioral_outside_home"].value_counts()  
  
plt.figure(figsize=(10,8))  
color=["red","green"]  
plt.pie(contact_avoidance_counts,  
labels=contact_avoidance_counts.index, autopct='%1.1f%%',  
startangle=140,colors=color)  
plt.title('Contact Avoidance Distribution')  
plt.axis('equal')  
plt.show()
```

Contact Avoidance Distribution  
1.0



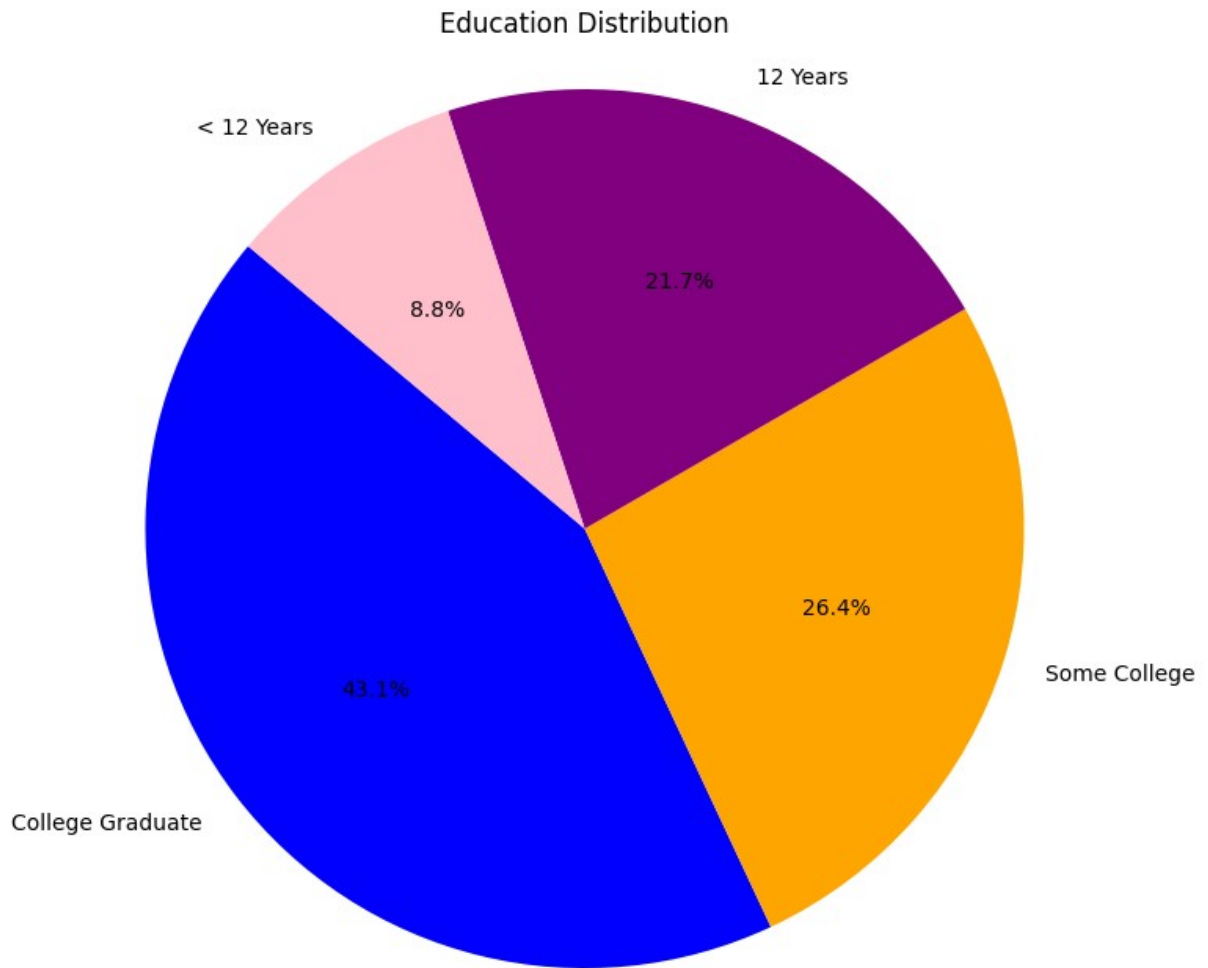
```
age_group_counts = df["age_group"].value_counts()

plt.figure(figsize=(10,8))
color=["blue","orange", 'purple', 'pink', 'yellow']
plt.pie(age_group_counts, labels=age_group_counts.index,
autopct='%1.1f%%', startangle=140,colors=color)
plt.title('Age Group Distribution')
plt.axis('equal')
plt.show()
```



```
education = df["education"].value_counts()

plt.figure(figsize=(10,8))
color=["blue","orange", 'purple', 'pink', 'yellow']
plt.pie(education, labels=education.index, autopct='%1.1f%%',
startangle=140,colors=color)
plt.title('Education Distribution')
plt.axis('equal')
plt.show()
```



```
numerical_cols
```

```
Index(['respondent_id', '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',  
      'doctor_recc_seasonal',  
      'chronic_med_condition', 'child_under_6_months',  
      'health_worker',  
      'opinion_h1n1_vacc_effective', 'opinion_h1n1_risk',  
      'opinion_h1n1_sick_from_vacc', 'opinion_seas_vacc_effective',  
      'opinion_seas_risk', 'opinion_seas_sick_from_vacc',  
      'household_adults',  
      'household_children', 'h1n1_vaccine', 'seasonal_vaccine'],  
      dtype='object')
```

```
categorical_cols
```



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

## Data preprocessing

- Feature Engineering

```
from sklearn.preprocessing import LabelEncoder, MinMaxScaler
encoder = LabelEncoder()
df_categorical = df.select_dtypes(include=['object'])
df_categorical_preprocessed =
pd.DataFrame(df_categorical.apply(encoder.fit_transform))
df_categorical_preprocessed
```

	age_group	education	race	sex	income_poverty	marital_status
0	3	1	3	0	2	1
1	1	0	3	1	2	1
2	0	2	3	1	0	1
3	4	0	3	0	2	1
4	2	3	3	0	0	0
...	...	...	...	...	...	...
26702	4	3	3	0	0	1
26703	0	2	3	1	0	1
26704	3	3	3	0	0	1
26705	0	3	1	0	0	0
26706	4	3	3	1	0	0

	rent_or_own	employment_status	hhs_geo_region	census_msa
0	0	1	8	2
1	1	0	1	0
2	0	0	9	0
3	1	1	5	1
4	0	0	9	0
...	...	...	...	...
26702	0	1	9	2

26703	1	0	6	1
26704	0	0	6	0
26705	1	0	5	2
26706	0	1	7	1

[26707 rows x 10 columns]

```
df_numerical = pd.DataFrame(df.select_dtypes(exclude=['object']))
df_numerical
```

	respondent_id	h1n1_concern	h1n1_knowledge
behavioral_antiviral_meds \			
0	0.0	1.0	0.0
0.0			
1	1.0	3.0	2.0
0.0			
2	2.0	1.0	1.0
0.0			
3	3.0	1.0	1.0
0.0			
4	4.0	2.0	1.0
0.0			
...	...	...	...
...			
26702	26702.0	2.0	0.0
0.0			
26703	26703.0	1.0	2.0
0.0			
26704	26704.0	2.0	2.0
0.0			
26705	26705.0	1.0	1.0
0.0			
26706	26706.0	0.0	0.0
0.0			

	behavioral_avoidance	behavioral_face_mask
behavioral_wash_hands \		
0	0.0	0.0
0.0		
1	1.0	0.0
1.0		
2	1.0	0.0
0.0		
3	1.0	0.0
1.0		
4	1.0	0.0
1.0		
...	...	...
..		
26702	1.0	0.0

0.0		
26703	1.0	0.0
1.0		
26704	1.0	1.0
1.0		
26705	0.0	0.0
0.0		
26706	1.0	0.0
0.0		

	behavioral_large_gatherings	behavioral_outside_home	\
0	0.0	1.0	
1	0.0	1.0	
2	0.0	0.0	
3	1.0	0.0	
4	1.0	0.0	
...	...	...	
26702	0.0	1.0	
26703	0.0	0.0	
26704	1.0	0.0	
26705	0.0	0.0	
26706	0.0	0.0	

	behavioral_touch_face	...	opinion_h1n1_vacc_effective	\
0	1.0	...	3.0	
1	1.0	...	5.0	
2	0.0	...	3.0	
3	0.0	...	3.0	
4	1.0	...	3.0	
...	...	...	...	
26702	0.0	...	3.0	
26703	0.0	...	4.0	
26704	1.0	...	4.0	
26705	1.0	...	3.0	
26706	0.0	...	5.0	

	opinion_h1n1_risk	opinion_h1n1_sick_from_vacc	\
0	1.0	2.0	
1	4.0	4.0	
2	1.0	1.0	
3	3.0	5.0	
4	3.0	2.0	
...	...	...	
26702	1.0	1.0	
26703	2.0	2.0	
26704	4.0	2.0	
26705	1.0	2.0	
26706	1.0	1.0	

	opinion_seas_vacc_effective	opinion_seas_risk	\
--	-----------------------------	-------------------	---

0	2.0	1.0
1	4.0	2.0
2	4.0	1.0
3	5.0	4.0
4	3.0	1.0
...	...	...
26702	5.0	2.0
26703	5.0	1.0
26704	5.0	4.0
26705	2.0	1.0
26706	5.0	1.0

	opinion_seas_sick_from_vacc	household_adults
household_children \		

0	2.0	0.0
0.0		
1	4.0	0.0
0.0		
2	2.0	2.0
0.0		
3	1.0	0.0
0.0		
4	4.0	1.0
0.0		
...	...	...
..		
26702	2.0	0.0
0.0		
26703	1.0	1.0
0.0		
26704	2.0	0.0
0.0		
26705	2.0	1.0
0.0		
26706	1.0	1.0
0.0		

	h1n1_vaccine	seasonal_vaccine
0	0.0	0.0
1	0.0	1.0
2	0.0	0.0
3	0.0	1.0
4	0.0	0.0
...	...	...
26702	0.0	0.0
26703	0.0	0.0
26704	0.0	1.0
26705	0.0	0.0
26706	0.0	0.0

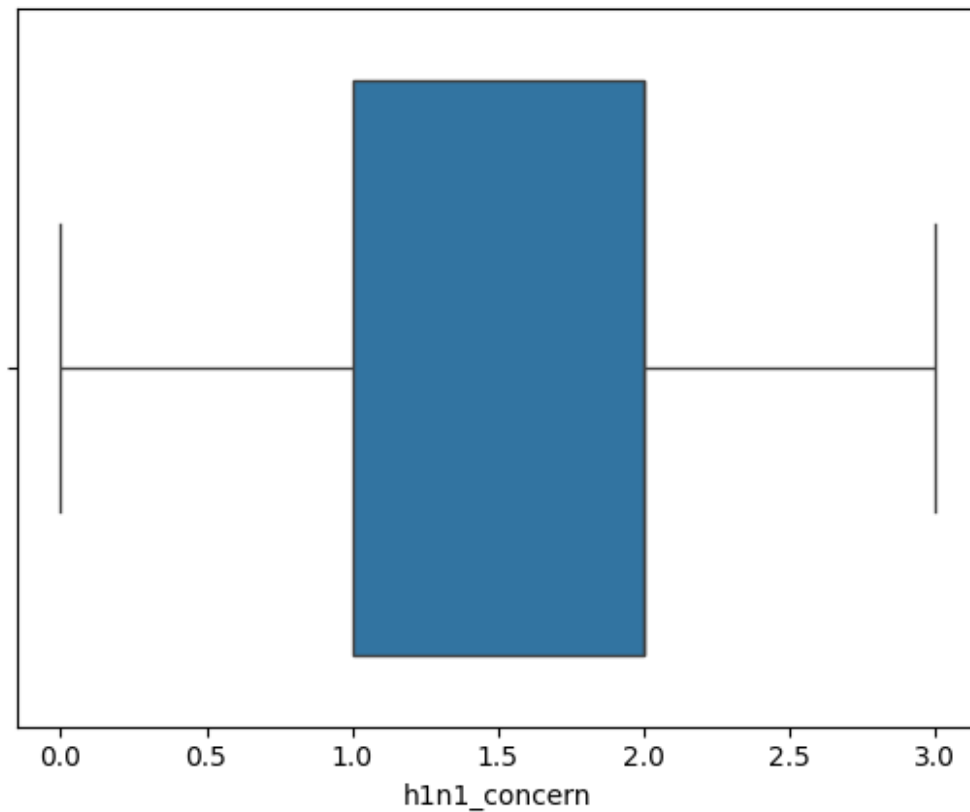
```
[26707 rows x 25 columns]

df_new = pd.concat(
    [pd.DataFrame(df_categorical_preprocessed),
    pd.DataFrame(df_numerical)], axis=1
)
```

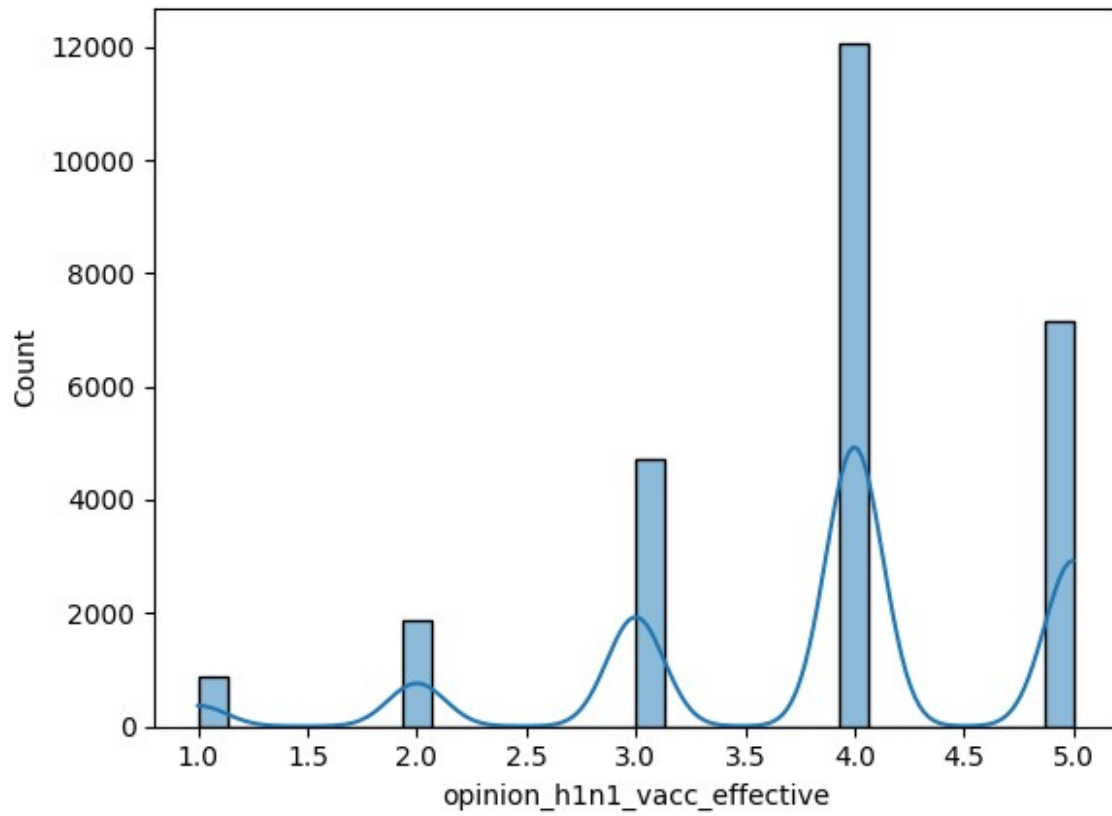
## Statistical Analysis

### Univariate analysis

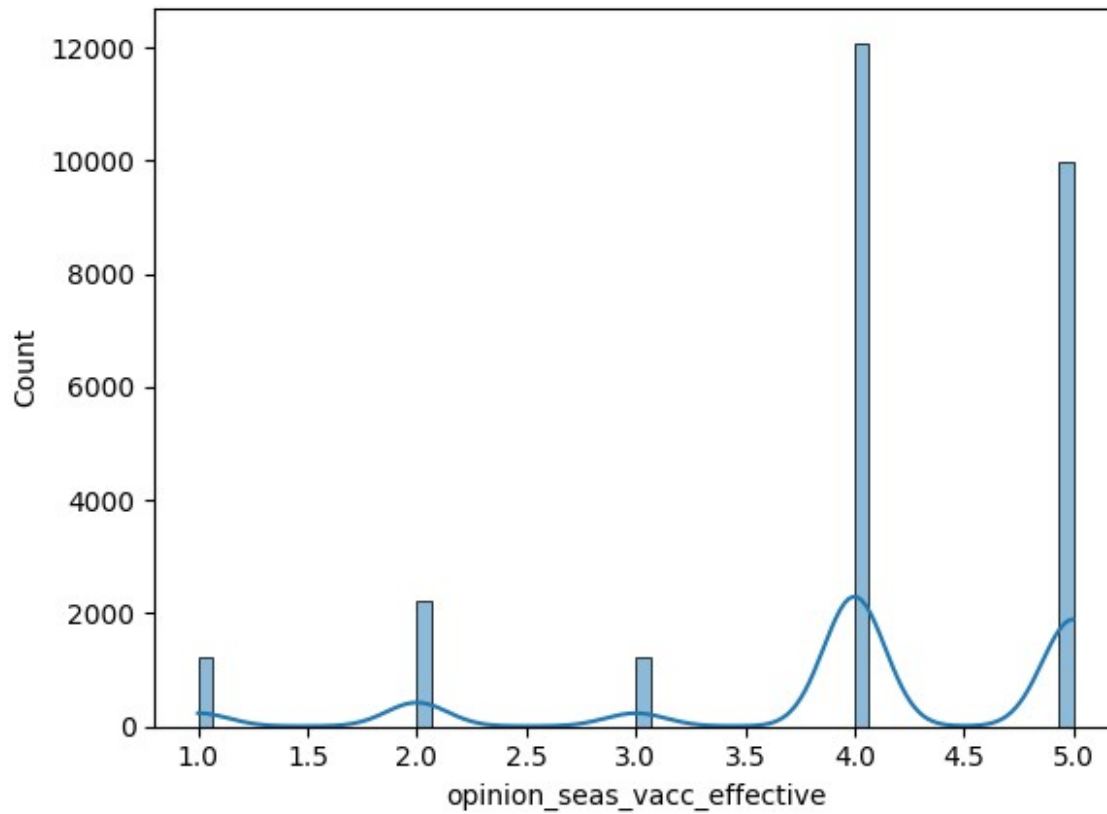
```
sns.boxplot(data=df, x='h1n1_concern')
<Axes: xlabel='h1n1_concern'>
```



```
sns.histplot(data=df, x='opinion_h1n1_vacc_effective', kde=True)
<Axes: xlabel='opinion_h1n1_vacc_effective', ylabel='Count'>
```



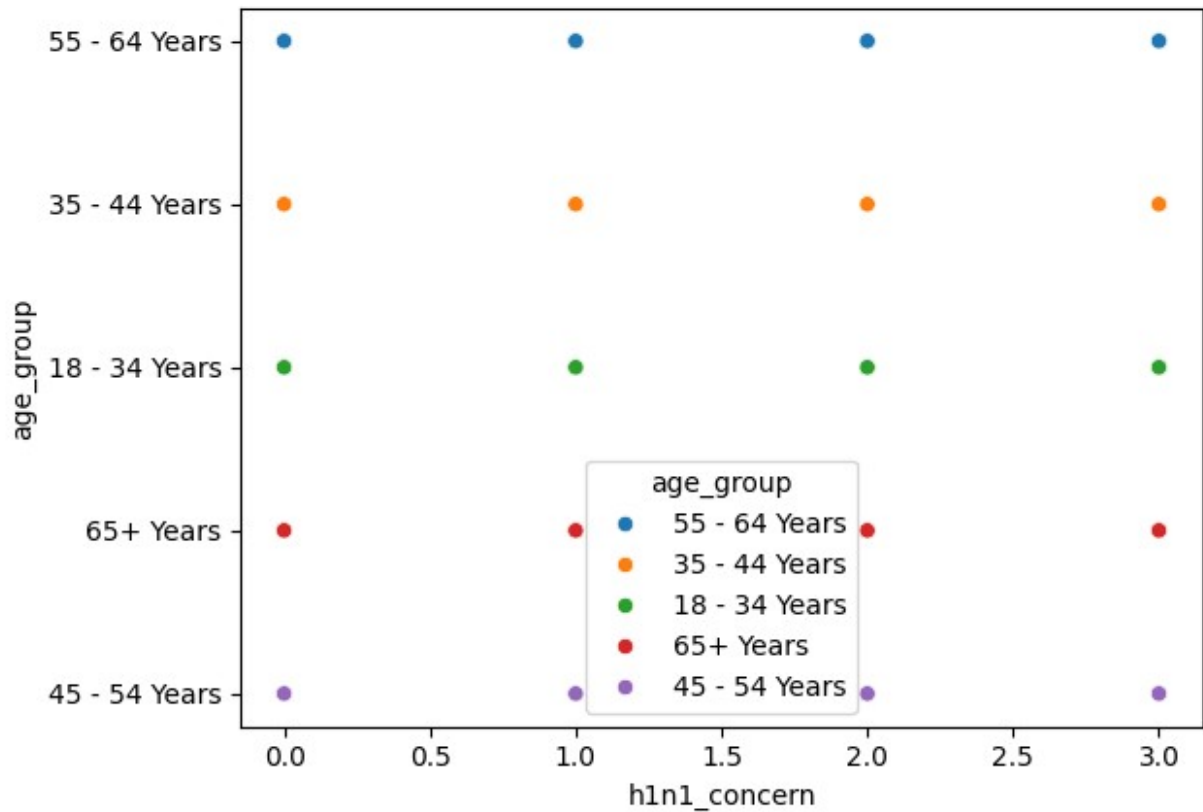
```
sns.histplot(data=df, x='opinion_seas_vacc_effective', kde=True)  
<Axes: xlabel='opinion_seas_vacc_effective', ylabel='Count'>
```



## Bivariate analysis

```
sns.scatterplot(data=df, x= 'h1n1_concern', y='age_group',  
hue='age_group')
```

```
<Axes: xlabel='h1n1_concern', ylabel='age_group'>
```



```
# data
opinion_response = df[
    ['opinion_h1n1_vacc_effective',
     'opinion_h1n1_risk',
     'opinion_h1n1_sick_from_vacc',
     'opinion_seas_vacc_effective',
     'opinion_seas_risk',
     'opinion_seas_sick_from_vacc']
]

# Create a DataFrame
opinion_response = pd.DataFrame(opinion_response)

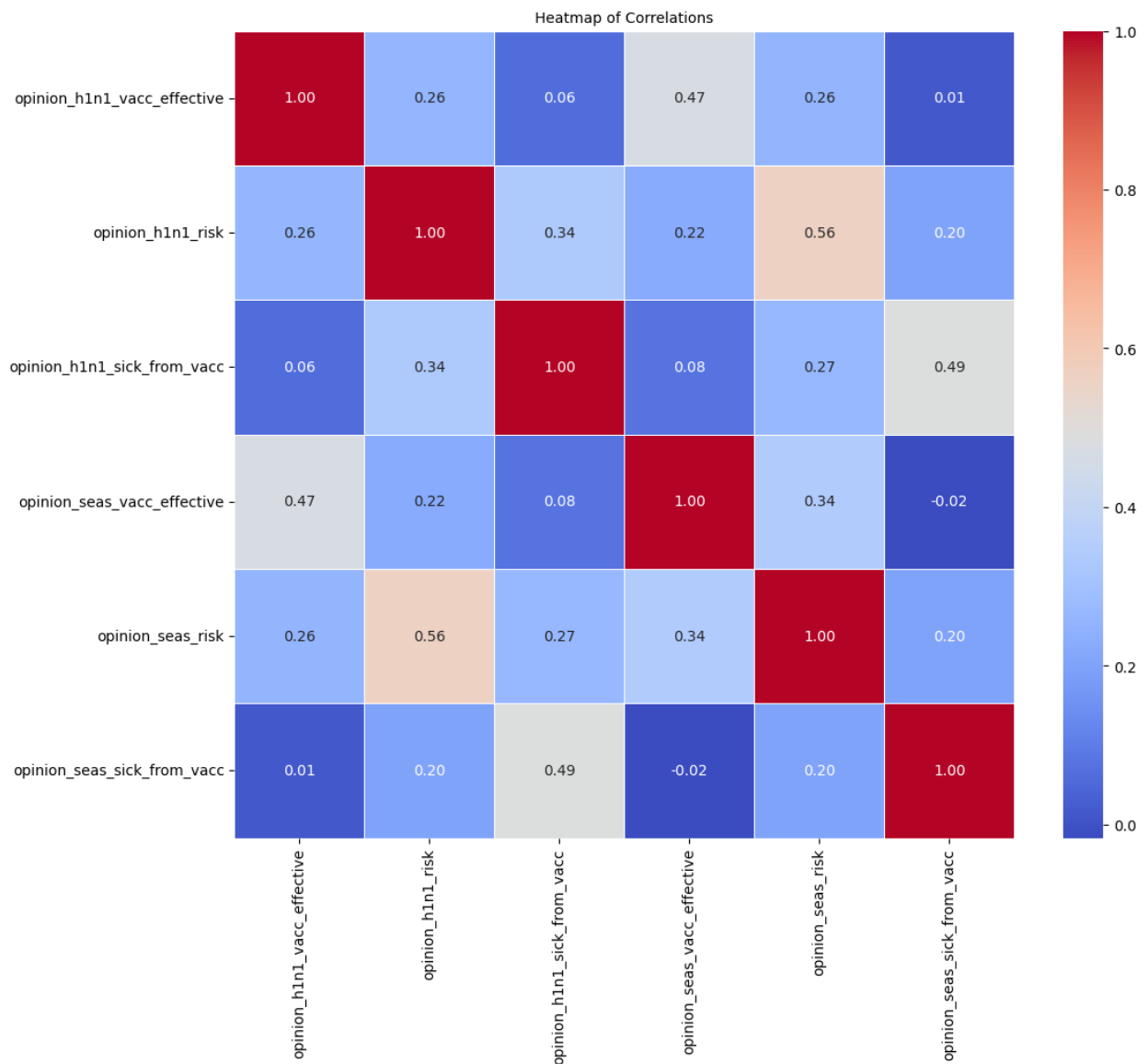
# Compute the correlation matrix
correlation_matrix = opinion_response.corr()

# Create a heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm",
            fmt=".2f", linewidths=0.5)

# Add titles and labels
# Add titles and labels
```



```
plt.title('Heatmap of Correlations', fontsize=10)
plt.show()
```



```
# data
behavior_response = df[
    ['behavioral_wash_hands',
     'behavioral_large_gatherings',
     'behavioral_antiviral_meds',
     'behavioral_avoidance',
     'behavioral_face_mask',
     'behavioral_outside_home',
     'behavioral_touch_face']
]
```

```

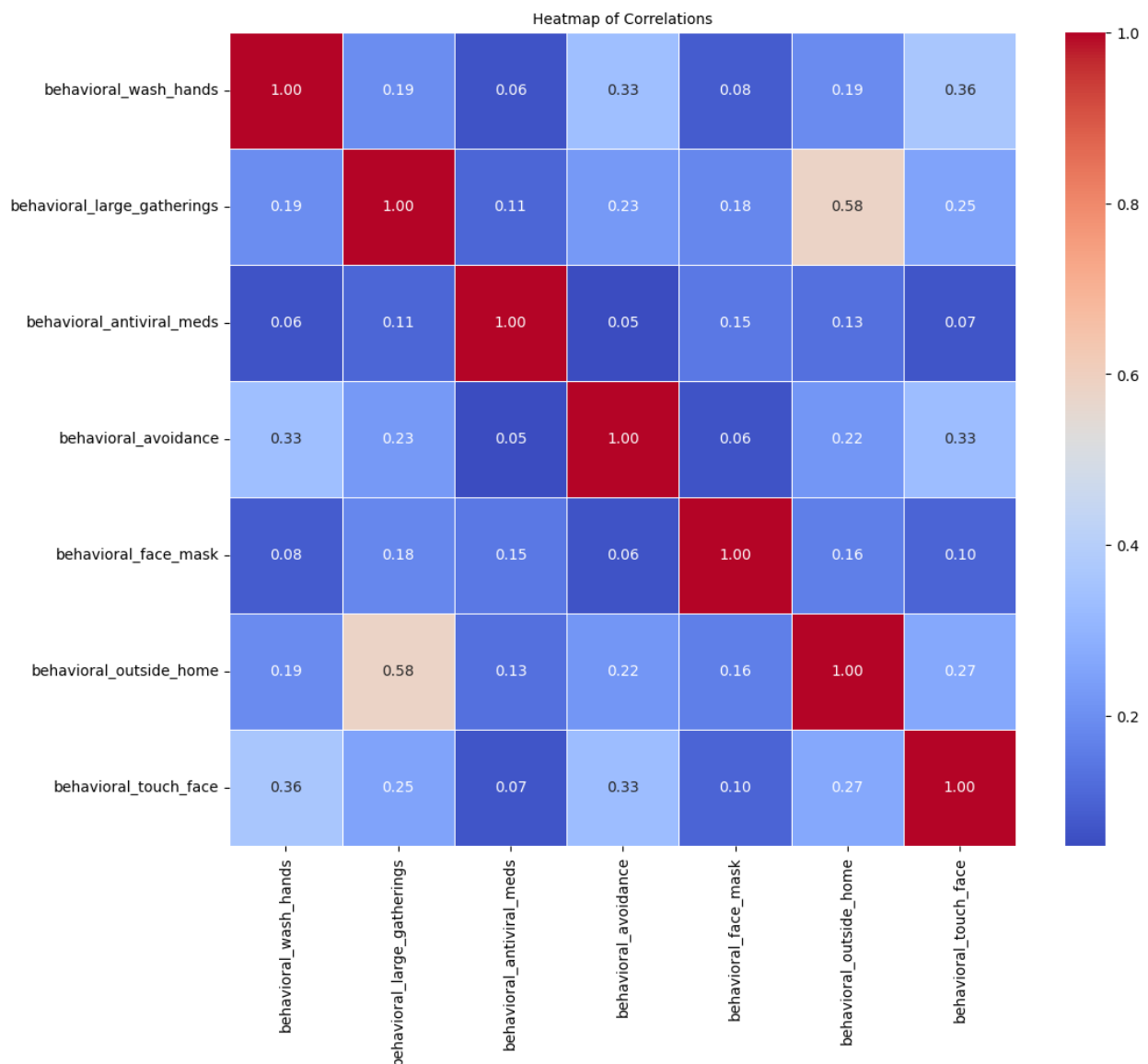
# Create a DataFrame
behavior_response = pd.DataFrame(behavior_response)

# Compute the correlation matrix
correlation_matrix = behavior_response.corr()

# Create a heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap="coolwarm",
fmt=".2f", linewidths=0.5)

# Add titles and labels
# Add titles and labels
plt.title('Heatmap of Correlations', fontsize=10)
plt.show()

```



# Predictive Statistics

## Modeling

- Basleine model
- Refined model
- Evaluation
- Adress class imbalance

```
# Model creation
X=df_new.drop(['h1n1_vaccine','seasonal_vaccine'], axis=1)
y=df_new[['h1n1_vaccine','seasonal_vaccine']]

y.shape

(26707, 2)

from sklearn.model_selection import train_test_split

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

## Scaling

```
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

X_train_scaled.shape

(21365, 33)

y_train.shape

(21365, 2)
```

## Multi-label Classification problem

- Binary Relevance
- Classifier chain
- Label Powerset
- Gradient Boosting
- SGD classifier

# Baseline Model

- Classifier chain Logistic regression

```
from skmultilearn.problem_transform import ClassifierChain
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

chain1 = ClassifierChain(classifier=LogisticRegression())
chain1.fit(X_train_scaled,y_train)
predict_lr = chain1.predict(X_test_scaled)

lr_cc= accuracy_score(y_test,predict_lr)
lr_cc

0.6761512542119057
```

- Binary Relevance + Gradient Boosting

```
from sklearn.ensemble import GradientBoostingClassifier
from skmultilearn.problem_transform import BinaryRelevance

classifier5 = BinaryRelevance(GradientBoostingClassifier())
classifier5.fit(X_train_scaled,y_train)
predictions_gb = classifier5.predict(X_test_scaled)

gb_br= accuracy_score(y_test,predictions_gb)
gb_br

0.6834518906776488
```

- Classifier chain + Gradient boosting

```
classifier2 = ClassifierChain(GradientBoostingClassifier())
classifier2.fit(X_train_scaled,y_train)
predictions_CC = classifier2.predict(X_test_scaled)

gb_CC= accuracy_score(y_test,predictions_CC)
gb_CC

0.6840134780980907
```

- Label powerset + Gradient Boosting

```
from skmultilearn.problem_transform import LabelPowerset

model = LabelPowerset(GradientBoostingClassifier())
model_1 = model.fit(X_train_scaled, y_train)
predictions_nb_ps1 = model.predict(X_test_scaled)

nb_ps= accuracy_score(y_test,predictions_nb_ps1)
nb_ps
```

0.690565331336578

## Othermodels

- Binary Relevance + KNN

```
from sklearn.neighbors import KNeighborsClassifier

classifier3 = BinaryRelevance(KNeighborsClassifier())
classifier3.fit(X_train_scaled,y_train)
predictions_rf = classifier3.predict(X_test_scaled)

rf_br= accuracy_score(y_test,predictions_rf)
rf_br

0.5990265818045676
```

- Binary Relevance + Logistic Regression

```
classifier1 = BinaryRelevance(LogisticRegression())
classifier1.fit(X_train_scaled,y_train)
predictions_lr = classifier1.predict(X_test_scaled)

lr_br=accuracy_score(y_test,predictions_lr)
lr_br

0.6718457506551854
```

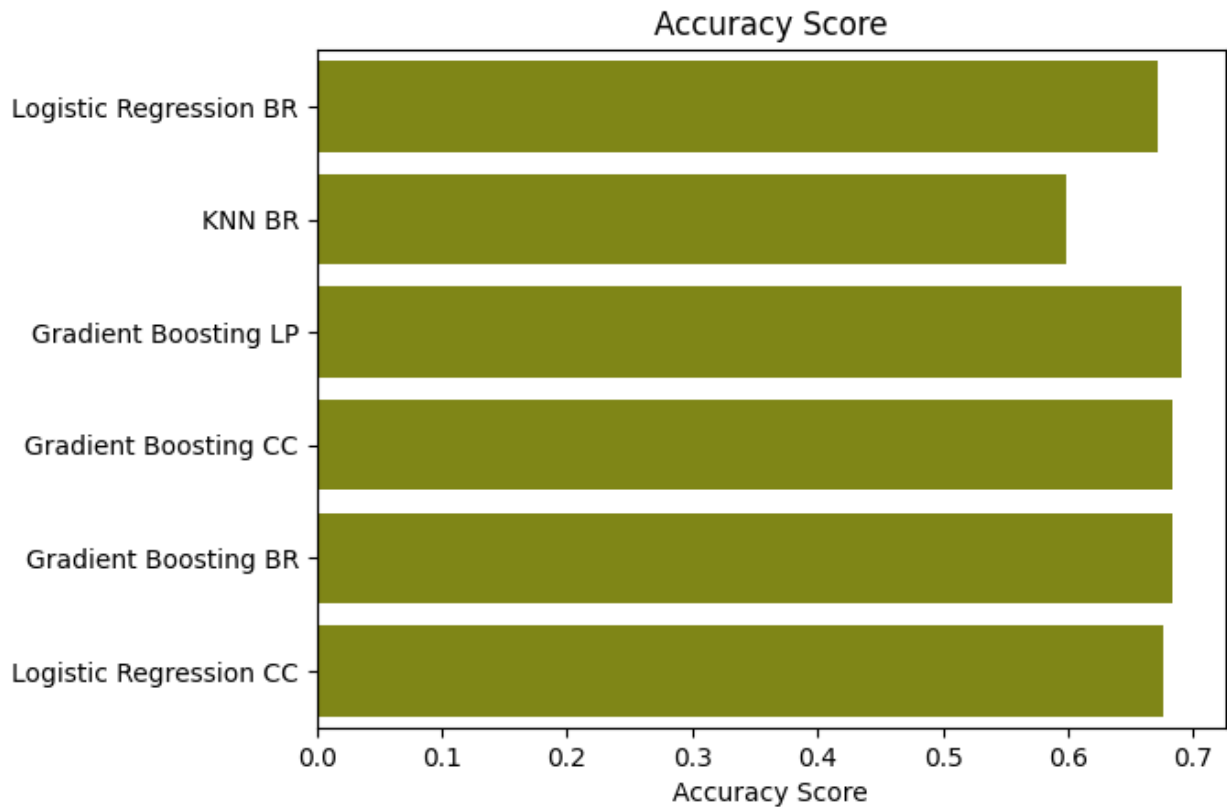
## Evaluation and insights

- Report metrics
- Analyze feature importance
- Interpretation

## Model Performance

```
Accuracy_Score = [lr_br,rf_br,nb_ps,gb_CC,gb_br,lr_cc]
Models = ['Logistic Regression BR', 'KNN BR', 'Gradient Boosting LP',
          'Gradient Boosting CC',
          'Gradient Boosting BR', 'Logistic Regression CC']

sns.barplot(x=Accuracy_Score, y=Models, color="xkcd:baby poop green")
plt.xlabel('Accuracy Score')
plt.title('Accuracy Score')
plt.show()
```



## Hypertuning for the best model

- Label powerset + Gradient boosting

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.ensemble import GradientBoostingClassifier
from skmultilearn.problem_transform import LabelPowerset
from sklearn.metrics import make_scorer, accuracy_score
from scipy.stats import uniform, randint

# Define the parameter distribution
param_distributions = {
    'classifier__learning_rate': uniform(0.01, 0.3), # Learning rate
    'classifier__n_estimators': randint(100, 500), # Number of
trees
    'classifier__max_depth': randint(3, 10), # Maximum tree
depth
    'classifier__min_samples_split': randint(2, 20), # Minimum
samples to split
    'classifier__min_samples_leaf': randint(1, 10), # Minimum
samples per leaf
}

# Wrap GradientBoostingClassifier with LabelPowerset
```

```

base_classifier = GradientBoostingClassifier()
model = LabelPowerSet(classifier=base_classifier)

# RandomizedSearchCV setup
random_search = RandomizedSearchCV(
    estimator=model,
    param_distributions=param_distributions,
    scoring=make_scorer(accuracy_score),
    n_iter=30, # Number of parameter settings sampled
    cv=3,      # Cross-validation folds
    verbose=2,
    random_state=42,
    n_jobs=-1
)

```

```

# Fit the search
random_search.fit(X_train_scaled, y_train)

```

```

# Best model and parameters
best_model = random_search.best_estimator_
best_params = random_search.best_params_
print("Best Parameters:", best_params)

```

```

# Evaluate performance on test data
predictions_nb_ps = best_model.predict(X_test_scaled)
accuracy = accuracy_score(y_test, predictions_nb_ps)
print("Accuracy on Test Set:", accuracy)

```

Fitting 3 folds for each of 30 candidates, totalling 90 fits

```

C:\Users\DELL\AppData\Local\Packages\
PythonSoftwareFoundation.Python.3.12_qbz5n2kfra8p0\LocalCache\local-
packages\Python312\site-packages\sklearn\model_selection\
_search.py:1102: UserWarning: One or more of the test scores are non-
finite: [nan nan nan nan nan nan nan nan nan nan nan nan nan nan nan
nan nan nan
nan nan nan nan nan nan nan nan nan nan nan nan]
warnings.warn(

```

```

Best Parameters: {'classifier__learning_rate':
np.float64(0.12236203565420874), 'classifier__max_depth': 7,
'classifier__min_samples_leaf': 8, 'classifier__min_samples_split': 8,
'classifier__n_estimators': 221}
Accuracy on Test Set: 0.6722201422688132

```

```

from sklearn.metrics import accuracy_score, precision_score,
recall_score, f1_score, roc_auc_score, classification_report, roc_curve

```

```

# Evaluate on test data
predictions_nb_ps = model_1.predict(X_test_scaled)

```

```
# Calculate metrics
nb_ps_accuracy = accuracy_score(y_test, predictions_nb_ps)
nb_ps_precision = precision_score(y_test, predictions_nb_ps,
average='weighted') # Use 'weighted' for multilabel
nb_ps_recall = recall_score(y_test, predictions_nb_ps,
average='weighted')
nb_ps_f1 = f1_score(y_test, predictions_nb_ps, average='weighted')
```

```
# Print results
print("Accuracy:", nb_ps_accuracy)
print("Precision:", nb_ps_precision)
print("Recall:", nb_ps_recall)
print("f1_score:", nb_ps_f1)
```

```
Accuracy: 0.690565331336578
Precision: 0.7503850457154486
Recall: 0.6467467187936331
f1_score: 0.6940706211013609
```

```
print(classification_report(y_test, predictions_nb_ps))
```

	precision	recall	f1-score	support
0	0.65	0.51	0.57	1130
1	0.80	0.71	0.75	2451
micro avg	0.75	0.65	0.70	3581
macro avg	0.72	0.61	0.66	3581
weighted avg	0.75	0.65	0.69	3581
samples avg	0.32	0.32	0.31	3581

```
C:\Users\DELL\AppData\Local\Packages\
PythonSoftwareFoundation.Python.3.12_qbz5n2kfra8p0\LocalCache\local-
packages\Python312\site-packages\sklearn\metrics\
_classification.py:1531: UndefinedMetricWarning: Precision is ill-
defined and being set to 0.0 in samples with no predicted labels. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
C:\Users\DELL\AppData\Local\Packages\
PythonSoftwareFoundation.Python.3.12_qbz5n2kfra8p0\LocalCache\local-
packages\Python312\site-packages\sklearn\metrics\
_classification.py:1531: UndefinedMetricWarning: Recall is ill-defined
and being set to 0.0 in samples with no true labels. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))
C:\Users\DELL\AppData\Local\Packages\
PythonSoftwareFoundation.Python.3.12_qbz5n2kfra8p0\LocalCache\local-
packages\Python312\site-packages\sklearn\metrics\
```



```

_classification.py:1531: UndefinedMetricWarning: F-score is ill-
defined and being set to 0.0 in samples with no true nor predicted
labels. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, f"{metric.capitalize()} is",
len(result))

# Ensure y_test and predictions_nb_ps are numpy arrays
y_test = np.array(y_test.toarray()) if not isinstance(y_test,
np.ndarray) else y_test
predictions_nb_ps = np.array(predictions_nb_ps.toarray()) if not
isinstance(predictions_nb_ps, np.ndarray) else predictions_nb_ps

roc_auc = roc_auc_score(y_test, predictions_nb_ps)

roc_auc

np.float64(0.7476184114825843)

```

- The curve can not be plotted for a multiclass label

```

from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay,
accuracy_score
import matplotlib.pyplot as plt
import numpy as np

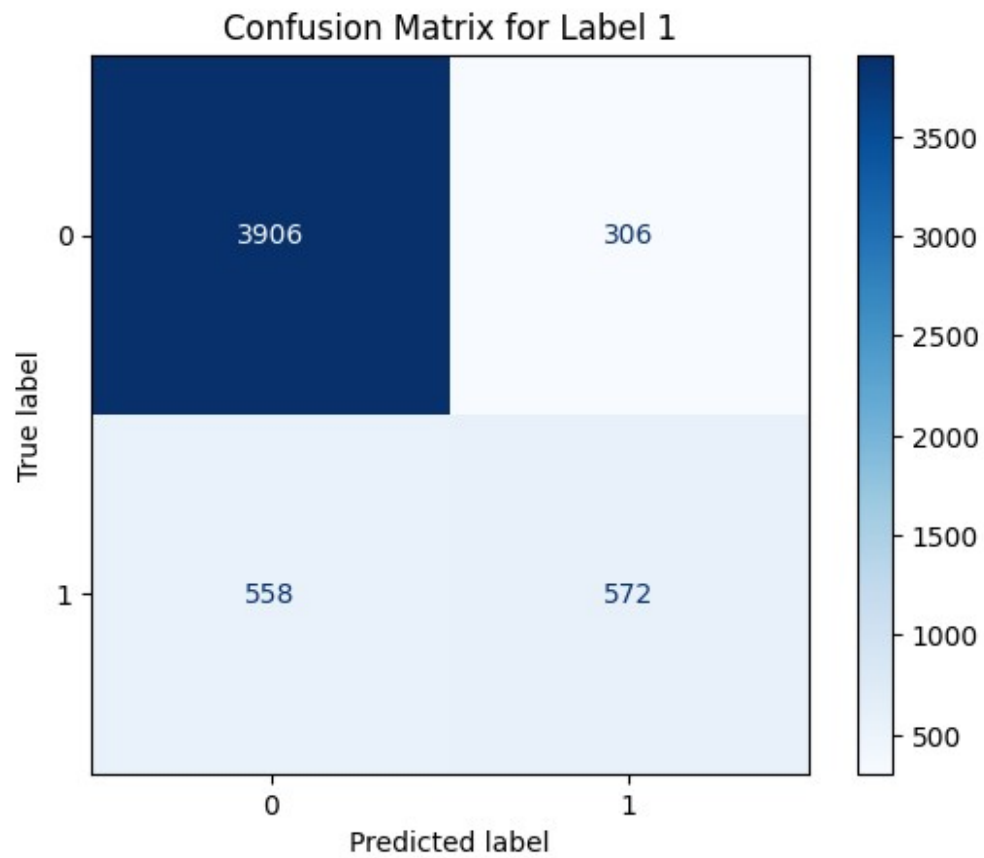
# Ensure y_test and predictions_nb_ps are numpy arrays
y_test = np.array(y_test.toarray()) if not isinstance(y_test,
np.ndarray) else y_test
predictions_nb_ps = np.array(predictions_nb_ps.toarray()) if not
isinstance(predictions_nb_ps, np.ndarray) else predictions_nb_ps

# Create confusion matrices for each label
for i in range(y_test.shape[1]): # Iterate over each label (column)
    cm = confusion_matrix(y_test[:, i], predictions_nb_ps[:, i]) #
    Confusion matrix for label i
    disp = ConfusionMatrixDisplay(confusion_matrix=cm) # Display
    confusion matrix

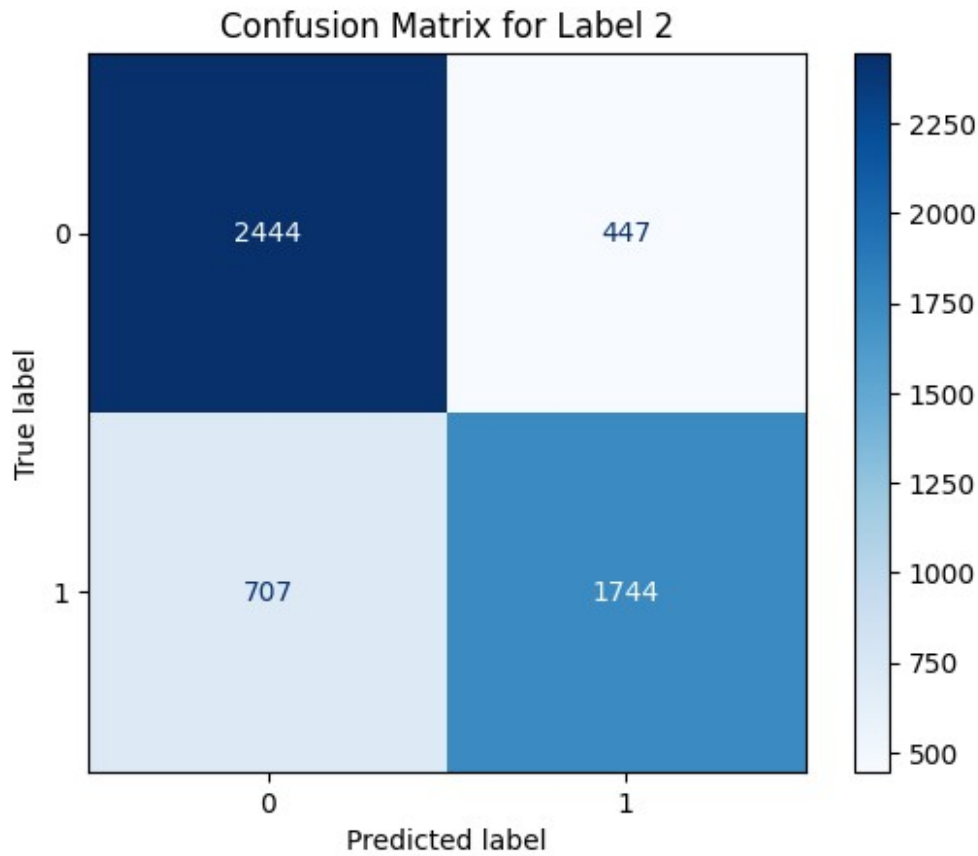
    # Plot
    print(f"Confusion Matrix for Label {i + 1}:")
    disp.plot(cmap="Blues", colorbar=True)
    plt.title(f"Confusion Matrix for Label {i + 1}")
    plt.show()

Confusion Matrix for Label 1:

```



Confusion Matrix for Label 2:



# Project Report

## 1. Modeling Section

### Baseline Model

We started with a baseline Logistic Regression model to establish a benchmark. The model used the default hyperparameters and was trained on preprocessed data, including scaled numeric features and labeled categorical variables. The dataset was split into an 80-20 train-test split to evaluate performance.

### Feature Engineering

Before modeling, the following preprocessing steps were applied:

- **Missing Value Imputation:** Median imputation for numeric features and mode for categorical features.
- **Scaling:** StandardScaler was used for continuous variables.
- **Labeling:** LabelEncoder was applied to categorical variables.

## Model Refinement

- To improve performance, hyperparameter tuning was performed using GridSearchCV for the best performing model which is the LabelPowerset with the GradientBoostingClassifier.

## 2. Evaluation Section

### Metrics Chosen

Given the dataset's multiclass classification problem and potential class imbalance, the following metrics were used:

- **Accuracy:** To measure overall correctness.
- **Precision:** To evaluate the proportion of true positive predictions among all positive predictions.
- **Recall:** To assess the model's ability to detect true positives.
- **F1-Score:** As a balance between precision and recall.
- **ROC-AUC:** To measure the overall ability of the model to distinguish between classes.

### Results

- The baseline Logistic Regression achieved an accuracy of 67% and an F1-score of 0.71 on the test set.
  - The tuned Gradient Boosting gave an accuracy score of 67%
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## 3. Findings Section

- **Feature Importance:** Vaccine awareness, health conditions, and demographics (age, education level) were the most influential features across models.
  - **Model Performance:** While both the Logistic Regression and Gradient Boosting performed comparably, the Gradient Boosting showed greater robustness across different subsets of the data.
  - **Limitations:** The models struggled with certain subpopulations where data was sparse or highly imbalanced, such as older age groups with limited survey responses.
- 

## 4. Recommendations Section

- **Targeted Campaigns:** Public health organizations should focus on populations identified as less likely to vaccinate, such as individuals with lower education levels or limited vaccine awareness.
- **Data-Driven Strategies:** Modifying awareness campaigns to increase education around the benefits of H1N1 and seasonal flu vaccines could improve uptake.

- **Future Improvements:** Collecting more balanced data across diverse demographics will enhance model accuracy and applicability.
- **Model Application:** Use predictions to identify high-risk areas for non-vaccination and allocate resources to these regions.