Final Project Submission

Please fill out:

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- Blog post URL:

Introduction and Business Case

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. The stakeholders for this study are public health officials responsible for determining vaccination strategy.

The goal of this project is too 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 where we will be investigating if a respondent received the Seasonal flu vaccine.

In this study, we will predict whether a participant will get the seasonal flu vaccine. We will optimize on identifying the most amount of people who need a vaccine, at the expense of erroneously identifying people who have already got the vaccine. In data science terms, we will optimize on reducing the amount of false negatives.

The rationale here is that most people who die from the flu are unvaccinated. Ensuring that people are vaccinated will save lives.

Data Understanding

- There are three sets of CSVs provided as part of this study.
- Two of the CSVs are for modeling training, and one is for model testing.
- A train - test split has already been done for us, but we will perform a train - test split on the training data anyway.
- The CSV 'training set features' provides columns we can use to target whether a participant got the Flu Vaccine or not
- The CSV training set labels contains the target column.

Steps to Get the Dataset

Here are the steps to replicate the data

- Go to [https://www.kaggle.com/datasets/imdevskp/h1n1-swine-flu-2009-pandemic-dataset (https://www.kaggle.com/datasets/imdevskp/h1n1-swine-flu-2009-pandemic-dataset)](https://www.kaggle.com/datasets/imdevskp/h1n1-swine-flu-2009-pandemic-dataset)
- Download data.csv
- The data is already separated into a training and testing set
- Features of the data described in training_set_labels.csv

Training Data Set

* The training data set with the features contain 26,707 entries with 35 different columns. The columns are listed out below.

Target Training Data Set

- The target feature set contains 26707 entries with 3 columns:
  - Respondent ID
  - H1N1 Vaccine Status
  - Seasonal Flu Vaccine Status

For this study, we are predicting whether the H1N1 Vaccine was used. The 0s in the H1N1 column indicate that the vaccine was not taken. 1 indicates that it was.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
# Surpress warning errors

import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
X = pd.read_csv('training_set_features.csv', index_col='respondent_id')
y = pd.read_csv('training_set_labels.csv',index_col='respondent_id') #1
```

In [4]:
```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26707 entries, 0 to 26706
Data columns (total 35 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 
dtypes: float64(23), object(12)
memory usage: 7.3+ MB
```

In [5]:
```
y.head(5)
```

Out[5]:

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

In [6]:
```
y.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26707 entries, 0 to 26706
Data columns (total 2 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   h1n1_vaccine      26707 non-null  int64
 1   seasonal_vaccine  26707 non-null  int64
dtypes: int64(2)
memory usage: 625.9 KB
```

In [7]:
```
y["h1n1_vaccine"].value_counts()
```

Out[7]:
```
0    21033
1     5674
Name: h1n1_vaccine, dtype: int64
```

In [8]:
```
y["seasonal_vaccine"].value_counts()
```

Out[8]:
```
0    14272
1    12435
Name: seasonal_vaccine, dtype: int64
```

Since there is a better mix of data for the seasonal vaccine, we are dropping the h1n1 vaccine column

In [9]:
```
y.drop(columns = ["h1n1_vaccine"],axis=0,inplace=True)
```

In [10]:
```
y
```

Out[10]:

respondent_id	seasonal_vaccine
0	0
1	1
2	0
3	1
4	0
...	...
26702	0
26703	0
26704	1
26705	0
26706	0

26707 rows × 1 columns

Exploratory Data Analysis

Created several slices of the data to explore multiple relationships

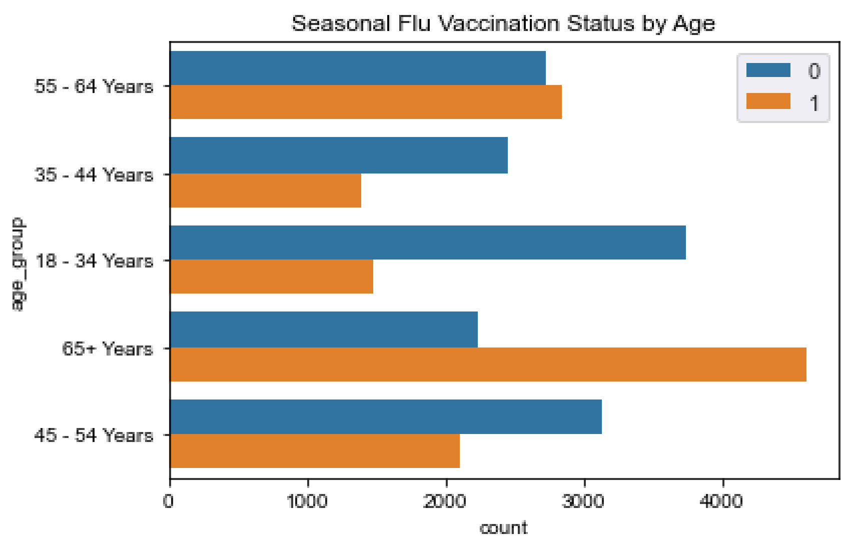
- First created a graph comparing the vaccination status of patients based on age
- Second compared education level against vaccination status
- Compared race to vaccination status
- Compared gender to vaccination status

In [11]:
```
# Merging data columns to perform exploratory data analysis

seas_df = pd.merge(X,y,on = y.index)
```

In [12]:
```
# Compare Age against Vaccination Status
```

In [13]:
```
# Creating a histogram of the proportion of participants who were vacci

sns.countplot(y=seas_df['age_group'],hue=seas_df['seasonal_vaccine'],da
sns.set(rc={'figure.figsize':(15,15)})
plt.xticks()
plt.title('Seasonal Flu Vaccination Status by Age')
plt.legend(loc=1)
```

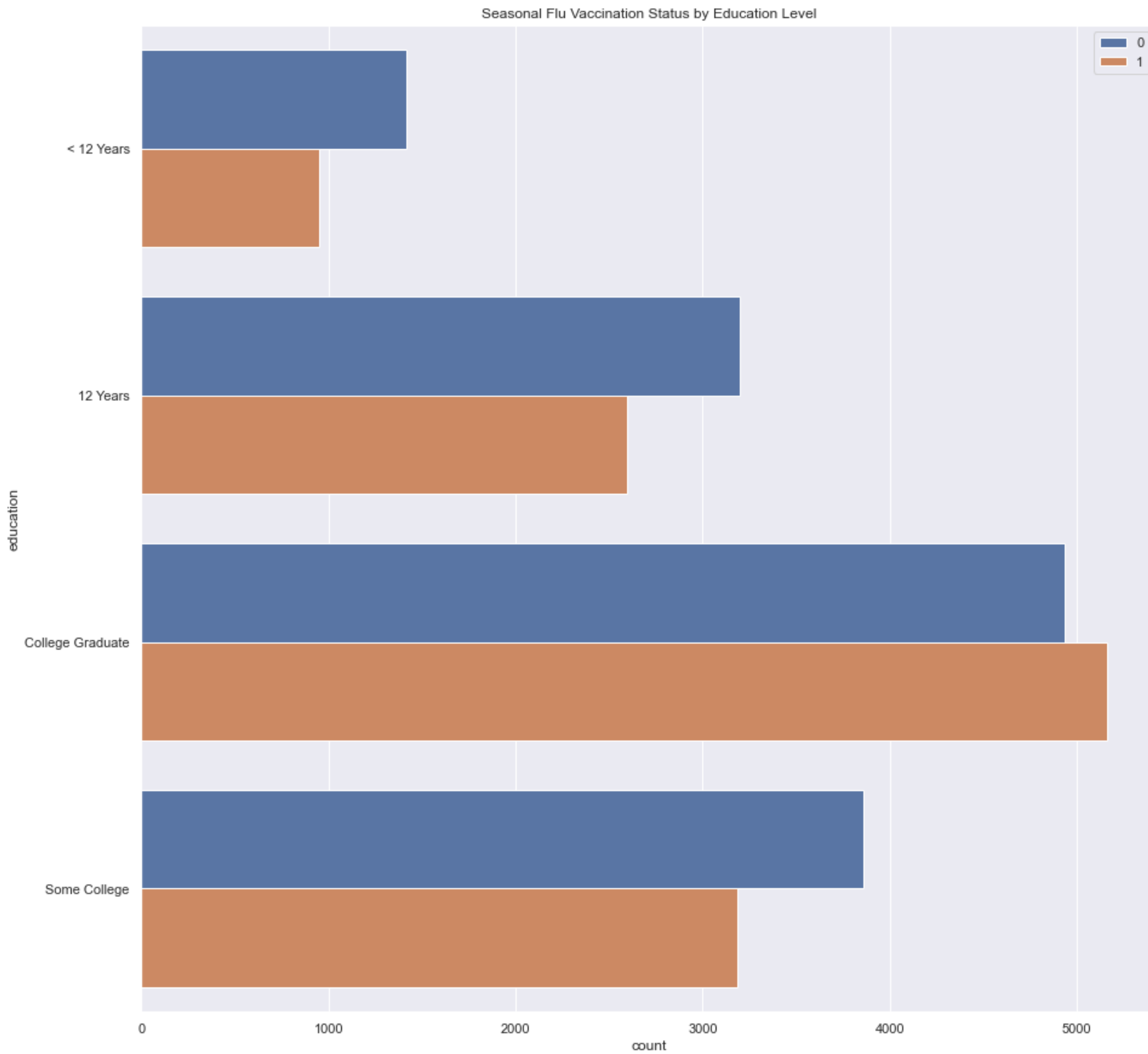
Out[13]:
```
<matplotlib.legend.Legend at 0x7fd0f7f4d400>
```



In [14]:
```
# Compare Education Level Against Vaccination Status
```

In [15]:
```
sns.countplot(y=seas_df['education'],hue=seas_df['seasonal_vaccine'],da
sns.set(rc={'figure.figsize':(15,15)})
plt.xticks()
plt.title('Seasonal Flu Vaccination Status by Education Level')
plt.legend(loc=1)
```

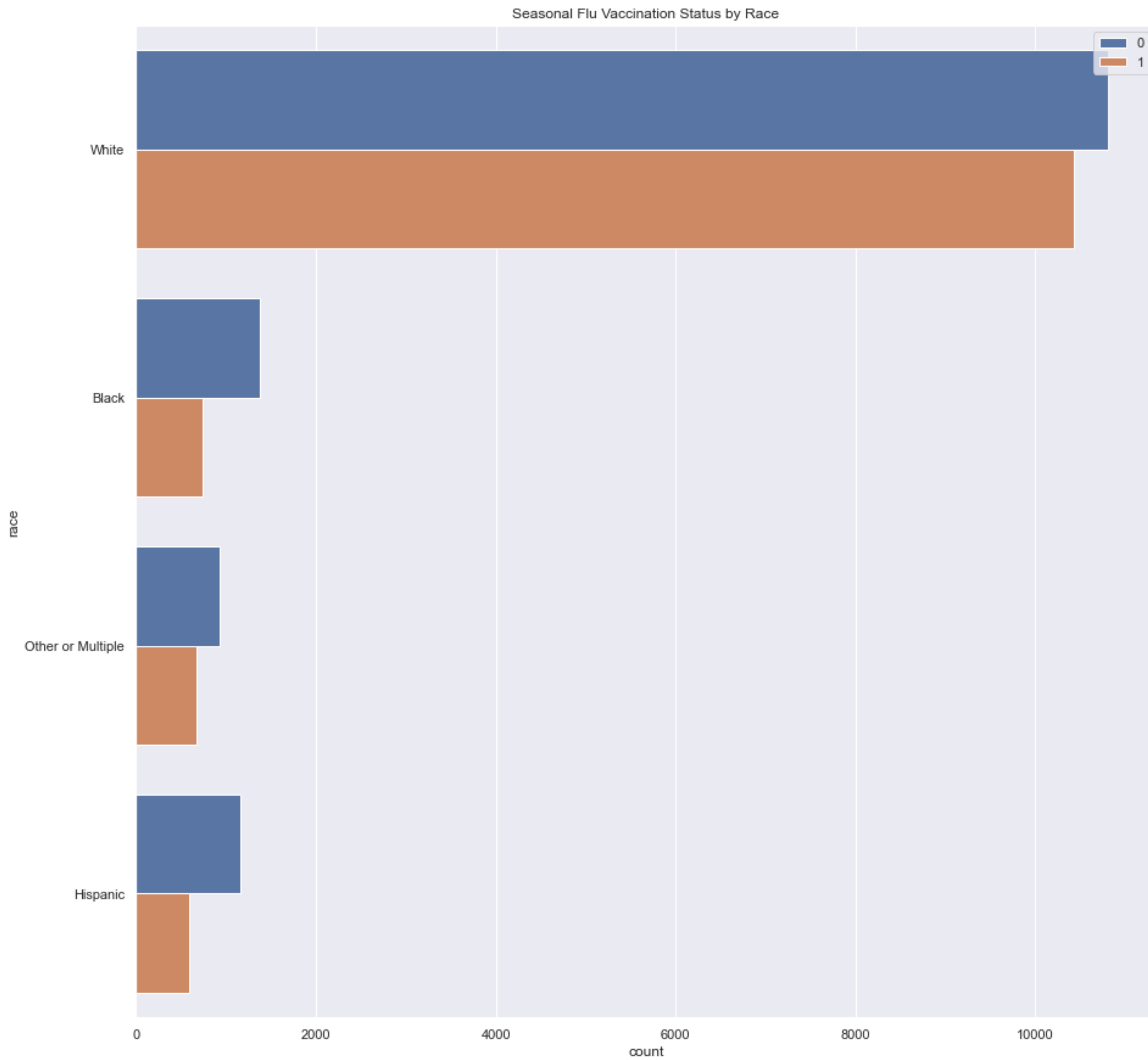
Out[15]: <matplotlib.legend.Legend at 0x7fd0f6fe1130>



In [16]:
```
# Compare Race to Seasonal Vaccination Status
```

In [17]:
```
sns.countplot(y=seas_df['race'],hue=seas_df['seasonal_vaccine'],data=se
sns.set(rc={'figure.figsize':(15,15)})
plt.xticks()
plt.title('Seasonal Flu Vaccination Status by Race')
plt.legend(loc=1)
```

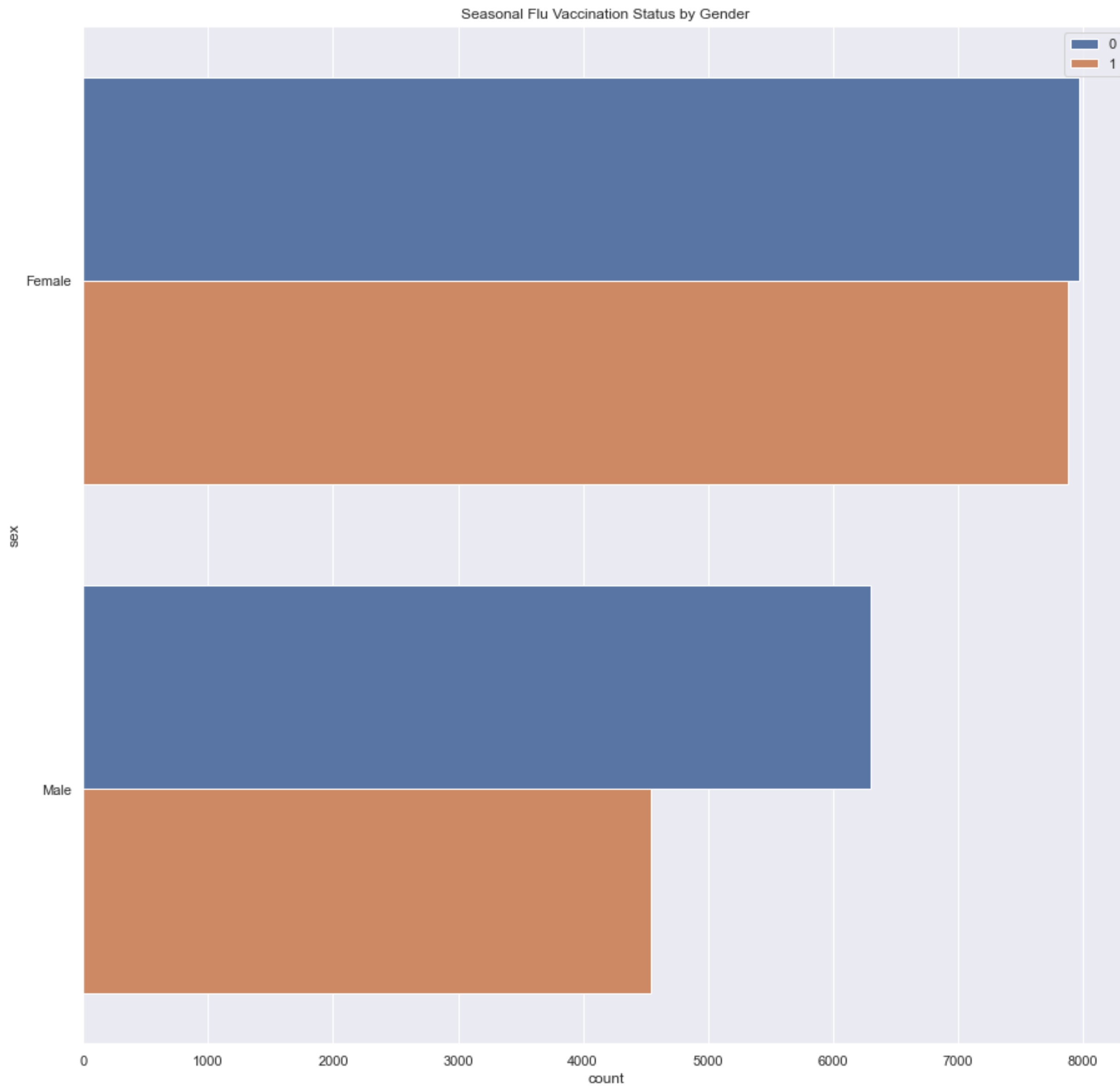
Out[17]: <matplotlib.legend.Legend at 0x7fd0f8c31220>



In [18]:
```
# Compare Gender to Vaccination Status
```

In [19]:
```
sns.countplot(y=seas_df['sex'],hue=seas_df['seasonal_vaccine'],data=sea
sns.set(rc={'figure.figsize':(15,15)})
plt.xticks()
plt.title('Seasonal Flu Vaccination Status by Gender')
plt.legend(loc=1)
```

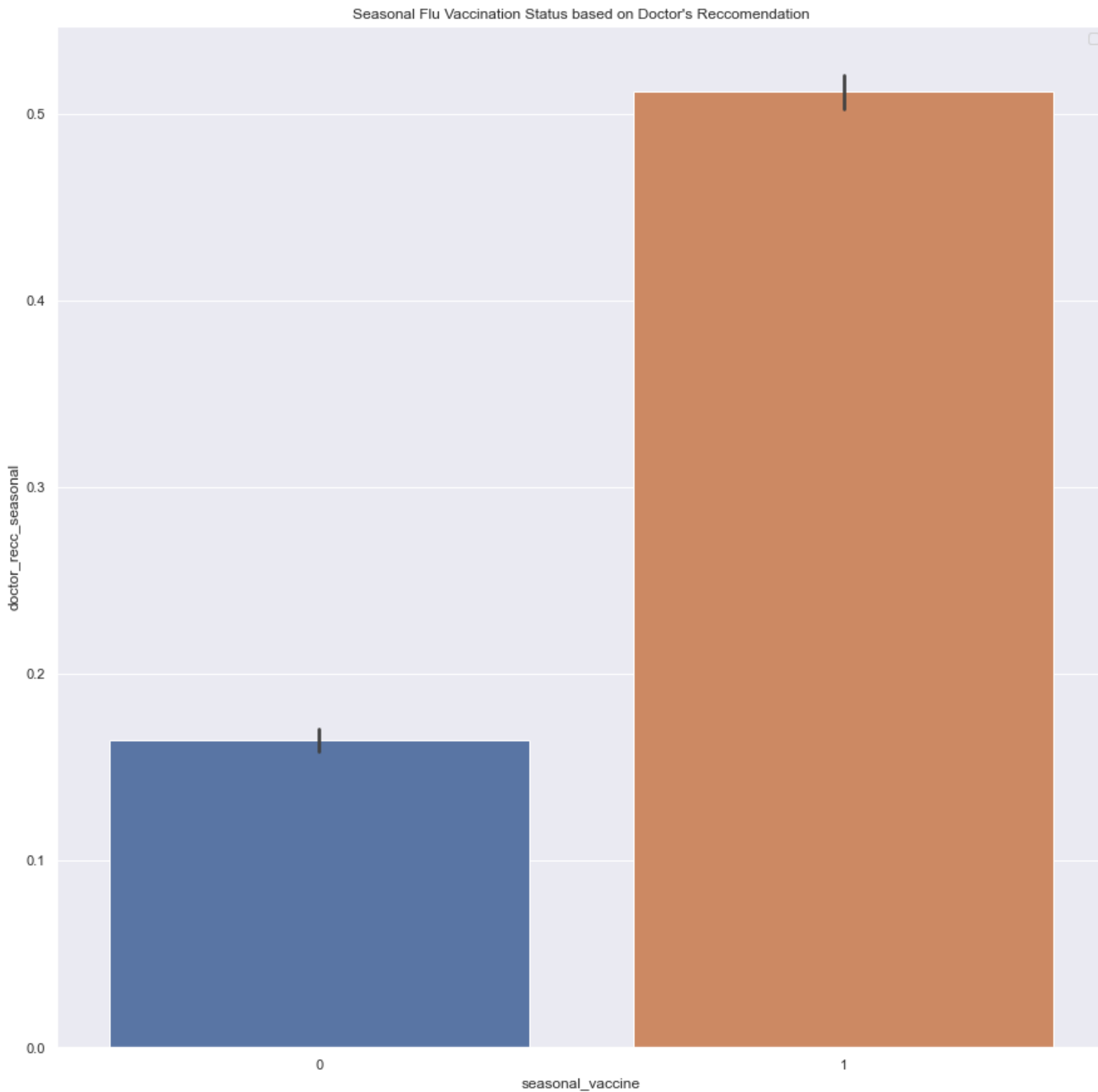
Out[19]: <matplotlib.legend.Legend at 0x7fd0f903b430>



In [20]:

```
sns.barplot(x = seas_df['seasonal_vaccine'], y = seas_df['doctor_recc_s
plt.xticks()
plt.title("Seasonal Flu Vaccination Status based on Doctor's Reccomenda
plt.legend(loc=1)
plt.show()
```

```
No handles with labels found to put in legend.
```



Data Preparation

Here is the process we followed for data preparation

- Dropped columns not related to Seasonal: 'h1n1_concern', 'h1n1_knowledge','doctor_recc_h1n1','opinion_h1n1_vacc_effective', 'opinion_h1n1_risk','opinion_h1n1_sick_from_vacc',
- Drop Columns: health insurance, employment_industry, employment occupation, income_povery

- drop rows: h1n1_, *behavioral*_, opinion_h1n1_vacc_effective, opinion_h1n1_risk, opinion_h1n1_sick_from_vacc, household_adults, household_children
- fill with median: doctor_recc_*, health_worker
- fill with mode: chronic_med_cond, child_under_6_months, health_worker, education, marital_status, rent_or_own,employment_status

In [21]:
```
X.isna().sum()
```

Out[21]:
```
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
dtype: int64
```

In [22]:
```
X.columns
```

Out[22]:
```
Index(['h1n1_concern', 'h1n1_knowledge', 'behavioral_antiviral_meds',
       'behavioral_avoidance', 'behavioral_face_mask', 'behavioral_wash_h
ands',
       'behavioral_large_gatherings', 'behavioral_outside_home',
       'behavioral_touch_face', 'doctor_recc_h1n1', 'doctor_recc_seasona
l',
       'chronic_med_condition', 'child_under_6_months', 'health_worker',
       'health_insurance', 'opinion_h1n1_vacc_effective', 'opinion_h1n1_r
isk',
       'opinion_h1n1_sick_from_vacc', 'opinion_seas_vacc_effective',
       'opinion_seas_risk', 'opinion_seas_sick_from_vacc', 'age_group',
       'education', 'race', 'sex', 'income_poverty', 'marital_status',
       'rent_or_own', 'employment_status', 'hhs_geo_region', 'census_ms
a',
       'household_adults', 'household_children', 'employment_industry',
       'employment_occupation'],
      dtype='object')
```

In [23]:
```
#drop columns not related to Seasonal: 'h1n1_concern', 'h1n1_knowledge'
# Drop Columns: health insurance, employment_industry, employment occup
# drop rows: h1n1_*, behavioral_*, opinion_h1n1_vacc_effective, opinion
#household_adults, household_children

# fill with median: doctor_recc_*, health_worker
# fill with mode: chronic_med_cond, child_under_6_months, health_worker



```

In [24]:
```
# List of columns dropped related to seasonal vaccine

H1N1_Columns_Dropped = ['h1n1_concern', 'h1n1_knowledge','doctor_recc_h

```

In [25]:
```
# List of Columns Dropped because they have large amounts of data missi

Column_Dropped_High_Data_Loss = ["health_insurance", "employment_indust
```

In [26]:
```
stof Columns where we are dropping columns with NA

_Row_Columns = ['behavioral_avoidance', 'behavioral_face_mask', 'behavioral_
'behavioral_large_gatherings', 'behavioral_outside_home','behavioral_tou
'opinion_seas_sick_from_vacc', 'household_children', 'household_adults']

```

In [27]:
```python
# List of columns where we fill missing values with the median and Mode

Fill_Median = ['health_worker']
Fill_Mode = ['chronic_med_condition', 'child_under_6_months', 'health_w

```

In [28]:
```python
# First drop seasonal columns

X = X.drop(H1N1_Columns_Dropped,axis = 1)

X.columns
```

Out[28]:
```
Index(['behavioral_antiviral_meds', 'behavioral_avoidance',
       'behavioral_face_mask', 'behavioral_wash_hands',
       'behavioral_large_gatherings', 'behavioral_outside_home',
       'behavioral_touch_face', 'doctor_recc_seasonal',
       'chronic_med_condition', 'child_under_6_months', 'health_worker',
       'health_insurance', 'opinion_seas_vacc_effective', 'opinion_seas_r
isk',
       'opinion_seas_sick_from_vacc', 'age_group', 'education', 'race',
'sex',
       'income_poverty', 'marital_status', 'rent_or_own', 'employment_sta
tus',
       'hhs_geo_region', 'census_msa', 'household_adults',
       'household_children', 'employment_industry', 'employment_occupatio
n'],
      dtype='object')
```

In [29]:
```python
# Drop columns that have mostly NA rows

X = X.drop(Column_Dropped_High_Data_Loss,axis = 1)

X.columns
```

Out[29]:
```
Index(['behavioral_antiviral_meds', 'behavioral_avoidance',
       'behavioral_face_mask', 'behavioral_wash_hands',
       'behavioral_large_gatherings', 'behavioral_outside_home',
       'behavioral_touch_face', 'doctor_recc_seasonal',
       'chronic_med_condition', 'child_under_6_months', 'health_worker',
       'opinion_seas_vacc_effective', 'opinion_seas_risk',
       'opinion_seas_sick_from_vacc', 'age_group', 'education', 'race',
'sex',
       'marital_status', 'rent_or_own', 'employment_status', 'hhs_geo_reg
ion',
       'census_msa', 'household_adults', 'household_children'],
      dtype='object')
```

In [30]:

```
# Fill columns with median

for col in Fill_Median:
    X[col].fillna(X[col].median(),inplace = True)

X[Fill_Median].isna().sum()
```

Out[30]:

```
health_worker    0
dtype: int64
```

In [31]:

```
# Fill columns with Mode

for col in Fill_Mode:
    X[col].fillna(X[col].mode()[0],inplace=True)

X[Fill_Mode].isna().sum()
```

Out[31]:

```
chronic_med_condition    0
child_under_6_months     0
health_worker            0
education                0
marital_status           0
rent_or_own              0
employment_status        0
dtype: int64
```

In [32]:

```
# Finally drop rows in columns that have minimal data missing

X.dropna(axis=0,inplace=True)

X[Drop_Row_Columns].isna().sum()
```

Out[32]:

```
behavioral_avoidance           0
behavioral_face_mask           0
behavioral_wash_hands          0
behavioral_large_gatherings    0
behavioral_outside_home        0
behavioral_touch_face          0
opinion_seas_vacc_effective    0
opinion_seas_risk              0
opinion_seas_sick_from_vacc    0
household_children             0
household_adults               0
dtype: int64
```

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

Out[33]:
```
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_seasonal           0
chronic_med_condition          0
child_under_6_months           0
health_worker                  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
marital_status                 0
rent_or_own                    0
employment_status              0
hhs_geo_region                 0
census_msa                     0
household_adults               0
household_children             0
dtype: int64
```

In [34]:
```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 23574 entries, 0 to 26706
Data columns (total 25 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   behavioral_antiviral_meds    23574 non-null  float64
 1   behavioral_avoidance         23574 non-null  float64
 2   behavioral_face_mask         23574 non-null  float64
 3   behavioral_wash_hands        23574 non-null  float64
 4   behavioral_large_gatherings  23574 non-null  float64
 5   behavioral_outside_home      23574 non-null  float64
 6   behavioral_touch_face        23574 non-null  float64
 7   doctor_recc_seasonal         23574 non-null  float64
 8   chronic_med_condition        23574 non-null  float64
 9   child_under_6_months         23574 non-null  float64
 10  health_worker                23574 non-null  float64
 11  opinion_seas_vacc_effective  23574 non-null  float64
 12  opinion_seas_risk            23574 non-null  float64
 13  opinion_seas_sick_from_vacc  23574 non-null  float64
 14  age_group                    23574 non-null  object 
 15  education                    23574 non-null  object 
 16  race                         23574 non-null  object 
 17  sex                          23574 non-null  object 
 18  marital_status               23574 non-null  object 
 19  rent_or_own                  23574 non-null  object 
 20  employment_status            23574 non-null  object 
 21  hhs_geo_region               23574 non-null  object 
 22  census_msa                   23574 non-null  object 
 23  household_adults             23574 non-null  float64
 24  household_children           23574 non-null  float64
dtypes: float64(16), object(9)
memory usage: 4.7+ MB
```

Data Preparation Target Dataframe

- Now let's prepare the data in y. In X we removed a lot of rows with respondant IDs that are still in our target.
- let's ensure X and y have the same respondants in the data set.
- We can do this by inner joining X and y, then only selecting for the "seasonal_vaccine" column

In [35]:
```python
# Currently there are around 26K rows

y.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 26707 entries, 0 to 26706
Data columns (total 1 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   seasonal_vaccine  26707 non-null  int64
dtypes: int64(1)
memory usage: 417.3 KB
```

In [36]:
```python
# Only leave rows that are in X

y = pd.concat(
    [y,X],
    axis=1,
    join ="inner"
)[["seasonal_vaccine"]]

y
```

Out[36]:

	seasonal_vaccine
respondent_id	
0	0
1	1
3	1
4	0
5	0
...	...
26701	0
26702	0
26703	0
26704	1
26706	0

23574 rows × 1 columns

In [37]:
```python
# y now has the same number of rows as X

assert len(y) == len(X)
```

Modeling

- First import libraries

- Train - Test Split the data
- Start with the baseline logistical model

In [38]:
```
from sklearn.model_selection import train_test_split, GridSearchCV, Ran
from sklearn.preprocessing import StandardScaler, OneHotEncoder, Functi
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier, GradientBoostingCl
from sklearn.svm import LinearSVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, p
from sklearn.multioutput import MultiOutputClassifier
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
```

In [39]:
```
## Train Test Split -

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.2,

```

Baseline model

- A logistical Regression model will be used as the baseline model.
- Two forms of the model were evaluated. One that used OHE and one that did not.
- Data scaled using a standard scaler after these methods.
- Train-test split occurs after transformation methods to prevent data lost.

In [40]:
```
X_train.columns
```

Out[40]:
```
Index(['behavioral_antiviral_meds', 'behavioral_avoidance',
       'behavioral_face_mask', 'behavioral_wash_hands',
       'behavioral_large_gatherings', 'behavioral_outside_home',
       'behavioral_touch_face', 'doctor_recc_seasonal',
       'chronic_med_condition', 'child_under_6_months', 'health_worker',
       'opinion_seas_vacc_effective', 'opinion_seas_risk',
       'opinion_seas_sick_from_vacc', 'age_group', 'education', 'race',
'sex',
       'marital_status', 'rent_or_own', 'employment_status', 'hhs_geo_reg
ion',
       'census_msa', 'household_adults', 'household_children'],
      dtype='object')
```

In [41]:
```
numeric_columns = list(X_train.columns[X_train.dtypes == 'float64'].val
object_columns = list(X_train.columns[X_train.dtypes == 'object'].value
```

In [42]:
```
X_train_object = X_train[object_columns]
X_test_object = X_test[object_columns]

ohe = OneHotEncoder(categories="auto", handle_unknown="ignore", sparse=F

X_train_ohe = pd.DataFrame(ohe.fit_transform(X_train_object), columns=oh
X_test_ohe = pd.DataFrame(ohe.transform(X_test_object), columns=ohe.get_

X_train_ohe = pd.concat([X_train[numeric_columns], X_train_ohe], axis=1)
X_test_ohe = pd.concat([X_test[numeric_columns], X_test_ohe], axis=1)
```

In [43]:
```
# Instantiate a LogisticRegression with random_state=42
log_reg = LogisticRegression(solver="liblinear")

baseline_model = log_reg.fit(X_train_ohe, y_train)

# Make predictions on test data
y_pred = baseline_model.predict(X_test_ohe)

# Calculate the ROC-AUC score
roc_auc = roc_auc_score(y_test, y_pred)
print("ROC-AUC score: ", roc_auc)
```

```
ROC-AUC score:  0.7789120090838635
```

In [44]:
```
## Compare against model that does not use the OHE method
```

In [45]:
```
log_reg = LogisticRegression(solver="liblinear")

baseline_model = log_reg.fit(X_train[numeric_columns], y_train)

# Make predictions on test data
y_pred = baseline_model.predict(X_test[numeric_columns])

# Calculate the ROC-AUC score
roc_auc = roc_auc_score(y_test, y_pred)
print("ROC-AUC score: ", roc_auc)
```

```
ROC-AUC score:  0.756862462375863
```

In [46]:
```
## Our model did slightly better without the categorical columns since
```

In [47]:
```
## Standardization and Scaling
```

In [48]:
```
#scaling the Dataset

ss = StandardScaler()

X_scaled = ss.fit_transform(X[numeric_columns])
X_scaled = pd.DataFrame(X,columns=numeric_columns)
X_scaled
```

Out[48]:

respondent_id	behavioral_antiviral_meds	behavioral_avoidance	behavioral_face_mask	behavioral_was
0	0.0	0.0	0.0	
1	0.0	1.0	0.0	
3	0.0	1.0	0.0	
4	0.0	1.0	0.0	
5	0.0	1.0	0.0	
...	...	...	...	
26701	0.0	0.0	0.0	
26702	0.0	1.0	0.0	
26703	0.0	1.0	0.0	
26704	0.0	1.0	1.0	
26706	0.0	1.0	0.0	

23574 rows × 16 columns

In [49]:
```
# Since we've lost rows from scaling the data, we need to create y-scal

y_scaled = pd.concat(
    [y,X_scaled[numeric_columns]],
    axis=1,
    join ="inner"
)[["seasonal_vaccine"]]

y_scaled.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 23574 entries, 0 to 26706
Data columns (total 1 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   seasonal_vaccine  23574 non-null  int64
dtypes: int64(1)
memory usage: 368.3 KB
```

In [50]:
```
assert len(X_scaled) == len(y_scaled) #X_scaled and y_scaled are not th
```

In [51]:
```
## Train Test Split for scaling

X_train_s, X_test_s, y_train_s, y_test_s = train_test_split(X_scaled, y
```

In [52]:
```
# Create Baseline model for Seasonal Flu Vaccine
baseline_model.fit(X_train_s, y_train_s)

# Make predictions on test data
y_pred2 = baseline_model.predict(X_test_s)

# Calculate the ROC-AUC score
roc_auc = roc_auc_score(y_test_s, y_pred2)
print("ROC-AUC score: ", roc_auc)
```

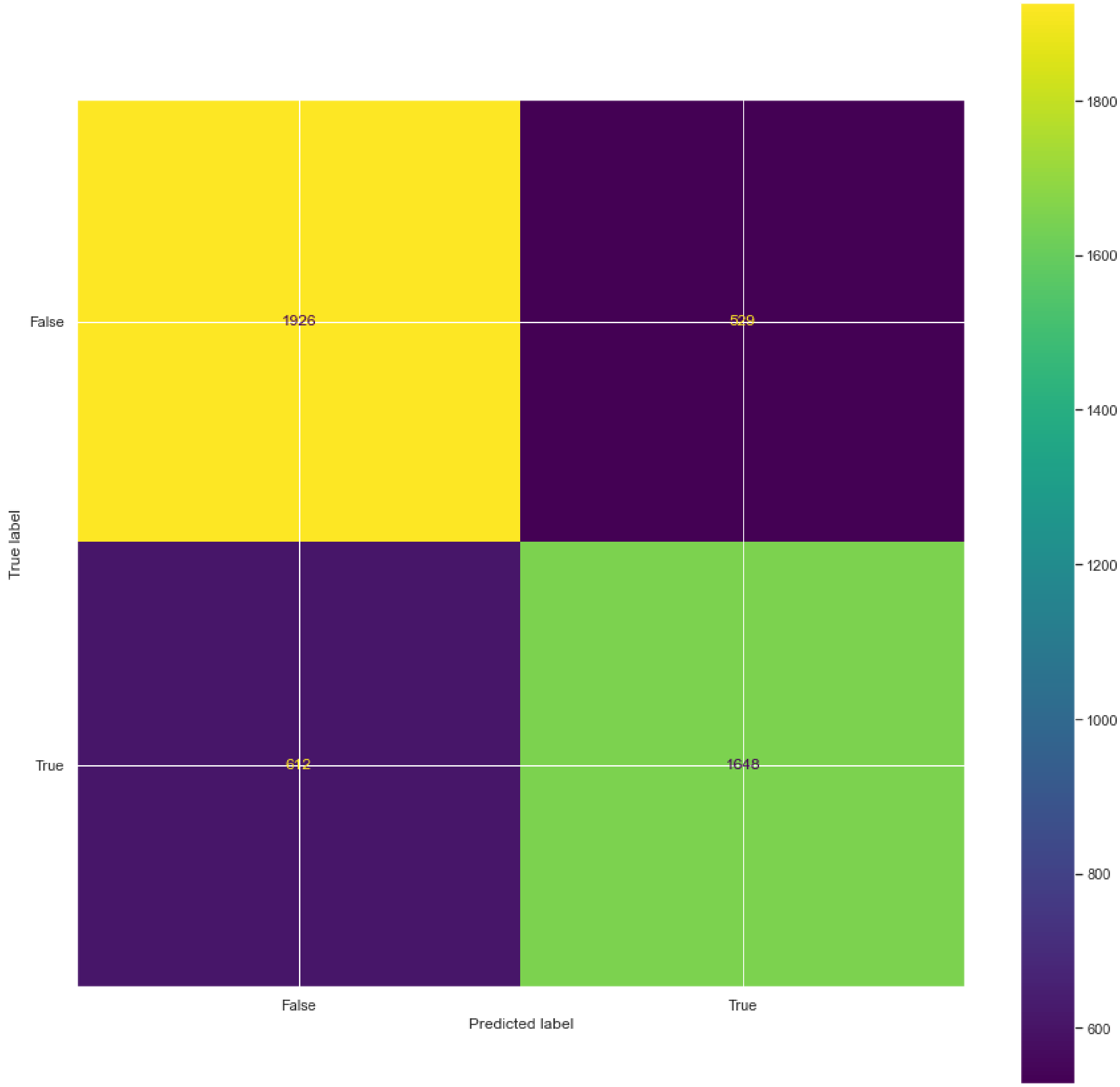
```
ROC-AUC score:  0.756862462375863
```

In [53]:
```
# Scaling does not improve the ROC-AUC score.
```

In [54]:
```
# Calculate the Confusion Matrix Values

cm = confusion_matrix(y_test, y_pred2)
TN, FP, FN, TP = confusion_matrix(y_test_s, y_pred2).ravel()

print('True Positive(TP)  = ', TP)
print('False Positive(FP) = ', FP)
print('True Negative(TN)  = ', TN)
print('False Negative(FN) = ', FN)
```

```
True Positive(TP)  =  1648
False Positive(FP) =  529
True Negative(TN)  =  1926
False Negative(FN) =  612
```

In [55]:
```
from sklearn import metrics

confusion_matrix = metrics.confusion_matrix(y_test_s,y_pred2)

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix = confusic

cm_display.plot()
plt.show()
```



Evaluation of Baseline Model

Our baseline model has identified 1648 as true positive results. The model identified the result as positive and its true value was positive.

It had 529 False positive results. Where the model identified them as positive, but these values were actually negative.

It had 612 False Negative results. Where the model identified them as negative, but they were actually positive.

Finally, it identified 1926 true negatives. These values were negative and the model identified them accurately as negative.

Since we are trying to predict the status of someone needing a vaccine, it's preferable to reduce the number of False negatives. The use of this model would be to determine who needs a vaccination.

If the model flags a false positive, then a person who got vaccinated, would be pinged again for vaccination.

A false negative would go under the radar, potentially not receive a vaccination, which could be detrimental.

Evaluation of Other Models

- Let's evaluate other models to reduce the false negative count of the previous model
- The following models were evaluated in addition to Logistic Regression: Naive Bayes, Support Vector Machines, Decision Trees, Random Forest, and K-Nearest Neighbor.
- We calculated the following metrics to evaluate these models against one-another: accuracy, precision, recall, and Roc-AUC score.

In [56]:
```
# Initialize the other model classifiers such as logistic regression, r
# random forest, and K-nearest neighbors

models = {}

models['Logistic Regression'] = LogisticRegression()

models['Naive Bayes'] = GaussianNB()

models['Support Vector Machines'] = LinearSVC()

models['Decision Trees'] = DecisionTreeClassifier()

models['Random Forest'] = RandomForestClassifier()

models['K-Nearest Neighbor'] = KNeighborsClassifier()

```

In [57]:

```
# loop over each classifier to evaluate poerformance
acc, rec, prec, F1, Roc_Auc = {}, {}, {}, {}, {}

for model in models.keys():

    # Fit the classifier
    models[model].fit(X_train_s, y_train_s)

    # Make predictions
    y_pred3 = models[model].predict(X_test_s)

    # Calculate metrics
    acc[model] = accuracy_score(y_pred3, y_test_s).ravel()
    rec[model] = recall_score(y_pred3, y_test_s).ravel()
    prec[model] = precision_score(y_pred3, y_test_s).ravel()
    F1[model] = f1_score(y_pred3,y_test_s).ravel()
    Roc_Auc[model] = roc_auc_score(y_test_s, y_pred3)
```

In [58]:

```
metrics = pd.DataFrame(index=models.keys(), columns=['Accuracy','Recall
metrics['Accuracy'] = acc.values()
metrics['Recall'] = rec.values()
metrics['Precision'] = prec.values()
metrics['F1 Score'] = F1.values()
metrics['Roc-AUC Score'] = Roc_Auc.values()
metrics
```

Out[58]:

	Accuracy	Recall	Precision	F1 Score
Logistic Regression	(0.7580063626723224,)	(0.7567691601652135,)	(0.7296460176991151,)	(0.7429601261545392,)
Naive Bayes	(0.7257688229056204,)	(0.7117827420061322,)	(0.7190265486725663,)	(0.7153863086066475,)
Support Vector Machines	(0.7571580063626723,)	(0.7584608252202133,)	(0.7238938053097345,)	(0.7407742811863256,)
Decision Trees	(0.6981972428419937,)	(0.6999522216913521,)	(0.6482300884955752,)	(0.6730990121755112,)
Random Forest	(0.7266171792152704,)	(0.7230133210840606,)	(0.6964601769911505,)	(0.7094883930583727,)
K-Nearest Neighbor	(0.7223753976670202,)	(0.7200370198981952,)	(0.6884955752212389,)	(0.7039131418231169,)

In [59]:

```
# Plot features in bar graph
# Convert objects to strings

metrics_num = metrics

for col in metrics:
    if col != 'Roc-AUC Score':
        for val in metrics[col]:
            value = val[0] #Extract the numeric value from the tuple
            metrics_num[col] = value

metrics_num
```

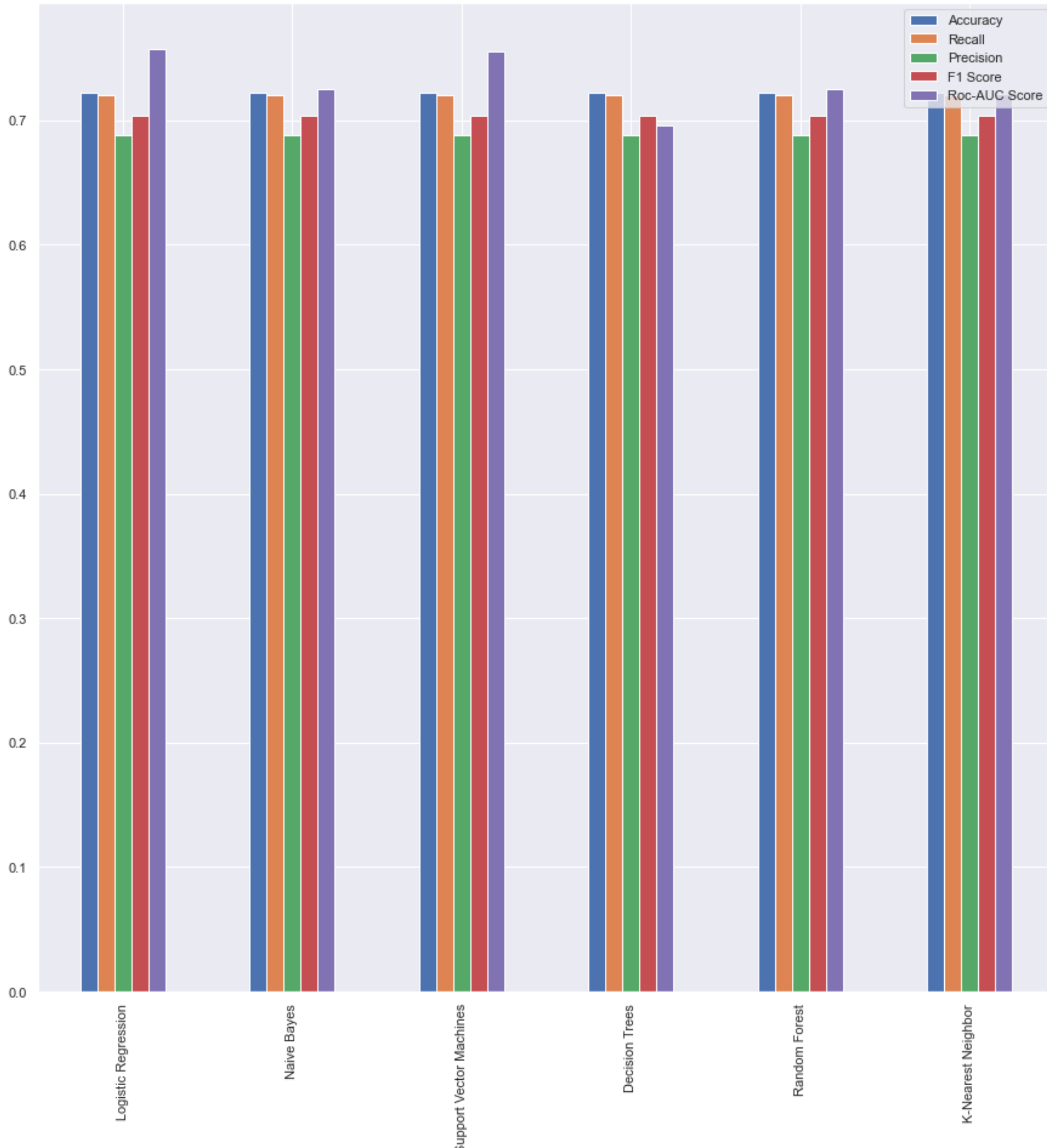
Out[59]:

	Accuracy	Recall	Precision	F1 Score	Roc-AUC Score
Logistic Regression	0.722375	0.720037	0.688496	0.703913	0.756880
Naive Bayes	0.722375	0.720037	0.688496	0.703913	0.725501
Support Vector Machines	0.722375	0.720037	0.688496	0.703913	0.755837
Decision Trees	0.722375	0.720037	0.688496	0.703913	0.696213
Random Forest	0.722375	0.720037	0.688496	0.703913	0.725419
K-Nearest Neighbor	0.722375	0.720037	0.688496	0.703913	0.721030

In [60]:

```
metrics_num.plot.bar()
```

Out[60]: <AxesSubplot:>



Final Model Evaluation

All models have fairly close accuracy, recall, precision, and roc-auc scores. Based on the business problem, we would want to reduce the number of false negatives. A false negative implies that someone was not vaccinated, was predicted to not need a vaccination. That means that this person would be missed if this model would target whom to outreach.

As a result, the logistic regression model and the Support Vector machine model are the top models. Both have accuracy scores of around 76% and recall of 76%.

It seems like the baseline model using logistical regression performed better on the test data with a higher recall and accuracy score. As a result, the final model for this project will be the Logistical regression model.