Vaccine Hesitance

1.Business Understanding

Context

In 2009, the U.S. conducted the National H1N1 Flu Survey to understand vaccination behaviors during the H1N1 pandemic. This effort mirrors the challenges faced in the COVID-19 era. Understanding the factors that influence vaccine uptake can help public health officials design better vaccine access strategies, communication campaigns, and policy decisions.

Project Goal

Predict whether a person received the H1N1 flu vaccine based on their background, health behavior, beliefs, and socio-demographics.

This project aims to:

- Help public health departments **identify hesitant populations**
- Guide **targeted awareness campaigns**
- Support **data-driven resource allocation** (e.g., mobile clinics, outreach)
- Inform the design of **future vaccination strategies**

🔷 Key Stakeholders

- **Public health officials** managing vaccination programs
- **Healthcare providers** engaging with patients and communities
- **Policy makers** determining communication and funding priorities
- **Data scientists** supporting health systems and NGOs

🔷 Business Questions

1. Who is most likely to get vaccinated?
2. What demographic or behavioral features are associated with vaccine acceptance or hesitancy?
3. Can we predict unvaccinated individuals **before** a campaign begins?
4. How can public health campaigns be improved based on these insights?

2.Data Understanding

In [4]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

Step 1. Loading the datasets provided

In [6]:
```
# Training set features
df_train_features = pd.read_csv('data/training_set_features.csv')
df_train_features.head()
```

Out[6]:

	respondent_id	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_avo
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	

5 rows × 36 columns

In [7]:
```
# Getting a general feel of what the df_train_features looks like

print(f"The shape of df_train_features is :\n", df_train_features.shape)
print()
print(f"Some of the important features of the dataset", df_train_features.info())
print()
# print(f"Snapshot of what the numeric data looks like \n", feature_labels_df.descr
# Check for missing values
print("Missing Values in Features:")
print(df_train_features.isnull().sum().sort_values(ascending=False).head(10))
```

```
The shape of df_train_features is :
 (26707, 36)

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26707 entries, 0 to 26706
Data columns (total 36 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   respondent_id                26707 non-null  int64  
 1   h1n1_concern                 26615 non-null  float64
 2   h1n1_knowledge               26591 non-null  float64
 3   behavioral_antiviral_meds    26636 non-null  float64
 4   behavioral_avoidance         26499 non-null  float64
 5   behavioral_face_mask         26688 non-null  float64
 6   behavioral_wash_hands        26665 non-null  float64
 7   behavioral_large_gatherings  26620 non-null  float64
 8   behavioral_outside_home      26625 non-null  float64
 9   behavioral_touch_face        26579 non-null  float64
 10  doctor_recc_h1n1             24547 non-null  float64
 11  doctor_recc_seasonal         24547 non-null  float64
 12  chronic_med_condition        25736 non-null  float64
 13  child_under_6_months         25887 non-null  float64
 14  health_worker                25903 non-null  float64
 15  health_insurance             14433 non-null  float64
 16  opinion_h1n1_vacc_effective  26316 non-null  float64
 17  opinion_h1n1_risk            26319 non-null  float64
 18  opinion_h1n1_sick_from_vacc  26312 non-null  float64
 19  opinion_seas_vacc_effective  26245 non-null  float64
 20  opinion_seas_risk            26193 non-null  float64
 21  opinion_seas_sick_from_vacc  26170 non-null  float64
 22  age_group                    26707 non-null  object 
 23  education                    25300 non-null  object 
 24  race                         26707 non-null  object 
 25  sex                          26707 non-null  object 
 26  income_poverty               22284 non-null  object 
 27  marital_status               25299 non-null  object 
 28  rent_or_own                  24665 non-null  object 
 29  employment_status            25244 non-null  object 
 30  hhs_geo_region               26707 non-null  object 
 31  census_msa                   26707 non-null  object 
 32  household_adults             26458 non-null  float64
 33  household_children           26458 non-null  float64
 34  employment_industry          13377 non-null  object 
 35  employment_occupation        13237 non-null  object 
dtypes: float64(23), int64(1), object(12)
memory usage: 7.3+ MB
Some of the important features of the dataset None

Missing Values in Features:
employment_occupation    13470
employment_industry      13330
health_insurance         12274
income_poverty            4423
doctor_recc_seasonal      2160
doctor_recc_h1n1          2160
rent_or_own               2042
```

```
employment_status         1463
marital_status            1408
education                 1407
dtype: int64
```

In [8]:
```
# looking into the labels dataset
df_train_labels =  pd.read_csv('data/training_set_labels.csv')
df_train_labels.head()
```

Out[8]:

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

In [9]:
```
# Getting a general of what the df_train_features looks like

print(f"The shape of df_train_labels is :\n", df_train_labels.shape)
print()
print(f"Some of the important features of the dataset", df_train_labels.info())
print()
# print(f"Snapshot of what the numeric data looks like \n", df_train_labels.describ
# Check for missing values
print("Missing Values in Features:")
print(df_train_labels.isnull().sum().sort_values(ascending=False).head(10))
```

```
The shape of df_train_labels is :
 (26707, 3)

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26707 entries, 0 to 26706
Data columns (total 3 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   respondent_id     26707 non-null  int64
 1   h1n1_vaccine      26707 non-null  int64
 2   seasonal_vaccine  26707 non-null  int64
dtypes: int64(3)
memory usage: 626.1 KB
Some of the important features of the dataset None

Missing Values in Features:
respondent_id       0
h1n1_vaccine        0
seasonal_vaccine    0
dtype: int64
```

In [10]:
```
# Test set features
# This particular dataset will act as the useen data our models
```

```
df_test_features = pd.read_csv('data/test_set_features.csv')
df_test_features.head()
```

Out[10]:

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

5 rows × 36 columns

In [11]:

```
# Getting a general of what the df_test_features looks like

print(f"The shape of df_train_labels is :\n", df_test_features.shape)
print()
print(f"Some of the important features of the dataset", df_test_features.info())
print()
# print(f"Snapshot of what the numeric data looks like \n", df_test_features.descri
# Check for missing values
print("Missing Values in Features:")
print(df_test_features.isnull().sum().sort_values(ascending=False).head(10))
```

```
The shape of df_train_labels is :
 (26708, 36)

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26708 entries, 0 to 26707
Data columns (total 36 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   respondent_id                26708 non-null  int64
 1   h1n1_concern                 26623 non-null  float64
 2   h1n1_knowledge               26586 non-null  float64
 3   behavioral_antiviral_meds    26629 non-null  float64
 4   behavioral_avoidance         26495 non-null  float64
 5   behavioral_face_mask         26689 non-null  float64
 6   behavioral_wash_hands        26668 non-null  float64
 7   behavioral_large_gatherings  26636 non-null  float64
 8   behavioral_outside_home      26626 non-null  float64
 9   behavioral_touch_face        26580 non-null  float64
 10  doctor_recc_h1n1             24548 non-null  float64
 11  doctor_recc_seasonal         24548 non-null  float64
 12  chronic_med_condition        25776 non-null  float64
 13  child_under_6_months         25895 non-null  float64
 14  health_worker                25919 non-null  float64
 15  health_insurance             14480 non-null  float64
 16  opinion_h1n1_vacc_effective  26310 non-null  float64
 17  opinion_h1n1_risk            26328 non-null  float64
 18  opinion_h1n1_sick_from_vacc  26333 non-null  float64
 19  opinion_seas_vacc_effective  26256 non-null  float64
 20  opinion_seas_risk            26209 non-null  float64
 21  opinion_seas_sick_from_vacc  26187 non-null  float64
 22  age_group                    26708 non-null  object
 23  education                    25301 non-null  object
 24  race                         26708 non-null  object
 25  sex                          26708 non-null  object
 26  income_poverty               22211 non-null  object
 27  marital_status               25266 non-null  object
 28  rent_or_own                  24672 non-null  object
 29  employment_status            25237 non-null  object
 30  hhs_geo_region               26708 non-null  object
 31  census_msa                   26708 non-null  object
 32  household_adults             26483 non-null  float64
 33  household_children           26483 non-null  float64
 34  employment_industry          13433 non-null  object
 35  employment_occupation        13282 non-null  object
dtypes: float64(23), int64(1), object(12)
memory usage: 7.3+ MB
Some of the important features of the dataset None

Missing Values in Features:
employment_occupation    13426
employment_industry      13275
health_insurance         12228
income_poverty            4497
doctor_recc_seasonal      2160
doctor_recc_h1n1          2160
rent_or_own               2036
```

```
employment_status        1471
marital_status           1442
education                1407
dtype: int64
```

Step 2: Data Cleaning and Preprocessing

Before proceeding to analysis, the raw data was thoroughly reviewed and cleaned to ensure consistency, reliability, and readiness for modeling.

Objectives

- Prepare the dataset for bivariate and multivariate analysis.
- Standardize formats and handle missing or inconsistent entries.
- Implement reusable, object-oriented code for cleaning workflows.

Cleaning Workflow

The following steps were taken:

1. **Initial Exploration**
    - Loaded and previewed the dataset structure.
    - Checked shape, column names, and data types.
2. **Handling Missing Values and Inconsistencies**
    - Identified and quantified missing values across columns.
    - Filled missing values:
        - Numeric columns → median
        - Categorical columns → mode
        - Text/object columns → `"Unknown"`
3. **Type Conversion**
    - Converted appropriate `float` and `object` columns with limited unique values to `category` dtype to optimize memory and modeling.
4. **Code Reusability**
    - Implemented a custom class `VaccineDataCleaner` using Object-Oriented Programming (OOP) principles to:
        - Merge features and labels
        - Clean and prepare the dataset
        - Return a clean, analysis-ready DataFrame

The cleaned dataset (`df_clean`) is now ready for:

- Exploratory Data Analysis (EDA)

- Bivariate and multivariate visualizations
- Feature selection and model training

In [13]:
```
from data_cleaning import VaccineDataCleaner
```

In [14]:
```
# implementing VaccineDataCleaner on the dataset

cleaner = VaccineDataCleaner(df_train_features, df_train_labels)
cleaner.fill_missing()
cleaner.convert_types()

# returning the final cleaned dataframe
df_clean = cleaner.get_cleaned_data()
df_clean.head()
```

Out[14]:

	respondent_id	h1n1_concern	h1n1_knowledge	behavioral_antiviral_meds	behavioral_av
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	

5 rows × 38 columns

In [15]:
```
# Getting a general of what the df_clean looks like

print(f"The shape of df_train_labels is :\n", df_clean.shape)
print()
print(f"Some of the important features of the dataset", df_clean.info())
print()
# print(f"Snapshot of what the numeric data looks like \n", df_clean.describe())
# Check for missing values
print("Missing Values in Features:")
print(df_clean.isnull().sum().sort_values(ascending=False).head(10))
```

```
The shape of df_train_labels is :
 (26707, 38)

<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                 26707 non-null  category
 2   h1n1_knowledge               26707 non-null  category
 3   behavioral_antiviral_meds    26707 non-null  category
 4   behavioral_avoidance         26707 non-null  category
 5   behavioral_face_mask         26707 non-null  category
 6   behavioral_wash_hands        26707 non-null  category
 7   behavioral_large_gatherings  26707 non-null  category
 8   behavioral_outside_home      26707 non-null  category
 9   behavioral_touch_face        26707 non-null  category
 10  doctor_recc_h1n1             26707 non-null  category
 11  doctor_recc_seasonal         26707 non-null  category
 12  chronic_med_condition        26707 non-null  category
 13  child_under_6_months         26707 non-null  category
 14  health_worker                26707 non-null  category
 15  health_insurance             26707 non-null  category
 16  opinion_h1n1_vacc_effective  26707 non-null  category
 17  opinion_h1n1_risk            26707 non-null  category
 18  opinion_h1n1_sick_from_vacc  26707 non-null  category
 19  opinion_seas_vacc_effective  26707 non-null  category
 20  opinion_seas_risk            26707 non-null  category
 21  opinion_seas_sick_from_vacc  26707 non-null  category
 22  age_group                    26707 non-null  category
 23  education                    26707 non-null  category
 24  race                         26707 non-null  category
 25  sex                          26707 non-null  category
 26  income_poverty               26707 non-null  category
 27  marital_status               26707 non-null  category
 28  rent_or_own                  26707 non-null  category
 29  employment_status            26707 non-null  category
 30  hhs_geo_region               26707 non-null  category
 31  census_msa                   26707 non-null  category
 32  household_adults             26707 non-null  category
 33  household_children           26707 non-null  category
 34  employment_industry          26707 non-null  object
 35  employment_occupation        26707 non-null  object
 36  h1n1_vaccine                 26707 non-null  int64
 37  seasonal_vaccine             26707 non-null  int64
dtypes: category(33), int64(3), object(2)
memory usage: 1.9+ MB
Some of the important features of the dataset None

Missing Values in Features:
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
dtype: int64
```

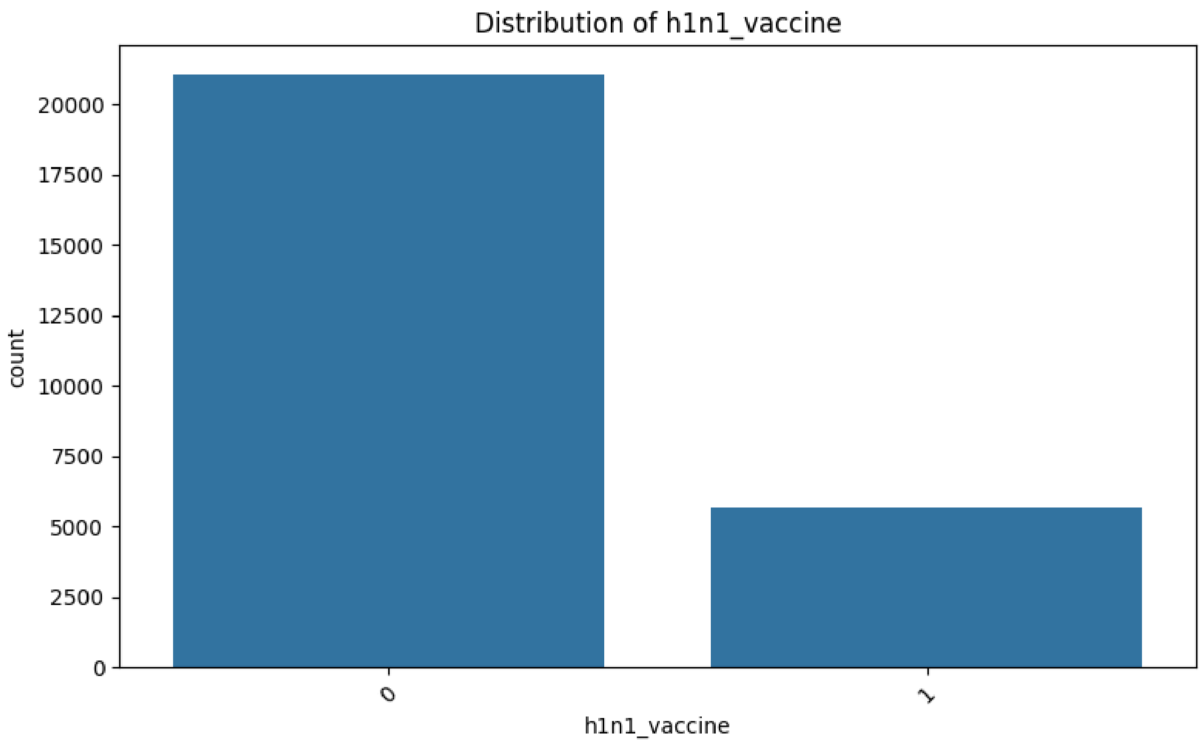
Step 3: Exploratory Data Analysis (EDA)

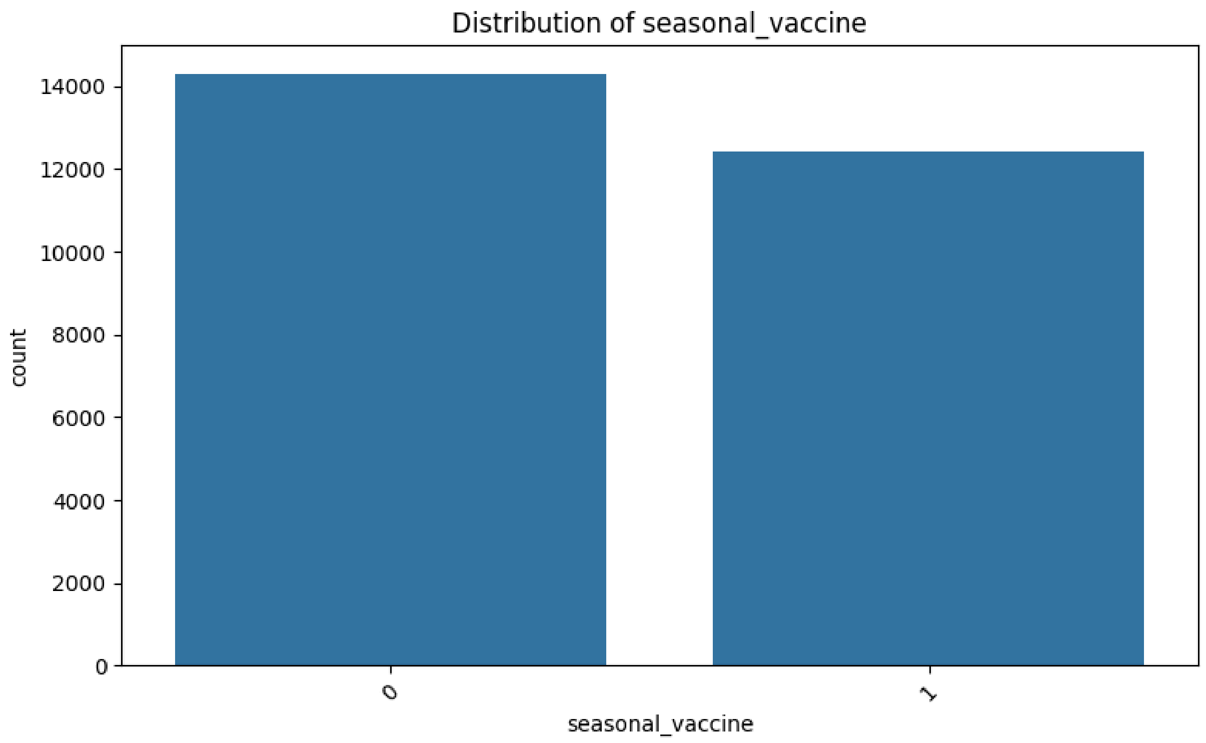
This section begins the EDA process using a custom `VaccineEDA` class to explore variable distributions, relationships, and patterns relevant to vaccine uptake.

In [17]:
```
from EDA import VaccineEDA
```

We ca start by looking at the distribution of the two target variales, from the **df_train_labels**

In [19]:
```
eda = VaccineEDA(df_clean)

eda.plot_bar('h1n1_vaccine'), eda.plot_bar('seasonal_vaccine')
```





Out[19]:
```
(None, None)
```

From the two plots above we can see that almost half of the sampled population recieved the seasoal flu vaccine but less than 30% received the H1N1 vaccine. The seasonal vaccine has class balance while the H1N1 is quite imbalanced.

- *Next we can assess whether the two target variables are independent*

In [21]:
```python
pd.crosstab(
    df_clean["h1n1_vaccine"], df_clean["seasonal_vaccine"], margins=True, normalize
)
```

Out[21]:

seasonal_vaccine h1n1_vaccine	0	1	All
0	0.497810	0.289737	0.787546
1	0.036582	0.175871	0.212454
All	0.534392	0.465608	1.000000

Ordinal Encoding and Correlation Analysis

To prepare the data for correlation analysis and modeling:

- **Applied Ordinal Encoding**
  All remaining categorical columns were converted to numeric format using `OrdinalEncoder`, which assigns integer values to each category. This is important because correlation requires numeric input.

- **Dropped object columns**
  These columns are non-numeric and not suitable for correlation analysis.

In [23]:
```
from sklearn.preprocessing import OrdinalEncoder

encoder = OrdinalEncoder()
df_encoded = df_clean.copy()
categorical_cols = df_encoded.select_dtypes(include='category').columns
df_encoded[categorical_cols] = encoder.fit_transform(
    df_encoded[categorical_cols])

# intention is to drop the columns employment_industry and employment_occupation
# since they may prove diffficult to encode
df_encoded = df_encoded.drop(columns=['employment_industry', 'employment_occupation
```

Select Top 10 Correlated Features

The top 10 features with the highest absolute correlation to the target features selected for further exploration.

In [25]:
```
# Now compute correlation with the target = h1n1_vaccine
correlations = df_encoded.corr()
target_col = 'h1n1_vaccine'
correlations[target_col].drop(labels=[target_col]).sort_values(ascending=False).hea
```

Out[25]:
```
doctor_recc_h1n1               0.394086
seasonal_vaccine               0.377143
opinion_h1n1_risk              0.320580
opinion_h1n1_vacc_effective    0.267352
opinion_seas_risk              0.255874
doctor_recc_seasonal           0.218976
opinion_seas_vacc_effective    0.177799
health_worker                  0.168056
h1n1_concern                   0.121574
h1n1_knowledge                 0.117771
Name: h1n1_vaccine, dtype: float64
```

- ***The most significant factor for getting the H1N1 vaccine is doctor's recommendation followed closely by whether the individual has already gotten the seasonal flu vaccine***

In [27]:
```
# Now compute correlation with the target = sesonal_vaccine
correlations = df_encoded.corr()
target_col1 = 'seasonal_vaccine'
correlations[target_col1].drop(labels=[target_col1]).sort_values(ascending=False).h
```

```
Out[27]: opinion_seas_risk              0.386916
         h1n1_vaccine                   0.377143
         doctor_recc_seasonal           0.360696
         opinion_seas_vacc_effective    0.358869
         age_group                      0.277454
         opinion_h1n1_risk              0.215650
         opinion_h1n1_vacc_effective    0.203187
         doctor_recc_h1n1               0.198560
         chronic_med_condition          0.169465
         h1n1_concern                   0.154488
         Name: seasonal_vaccine, dtype: float64
```

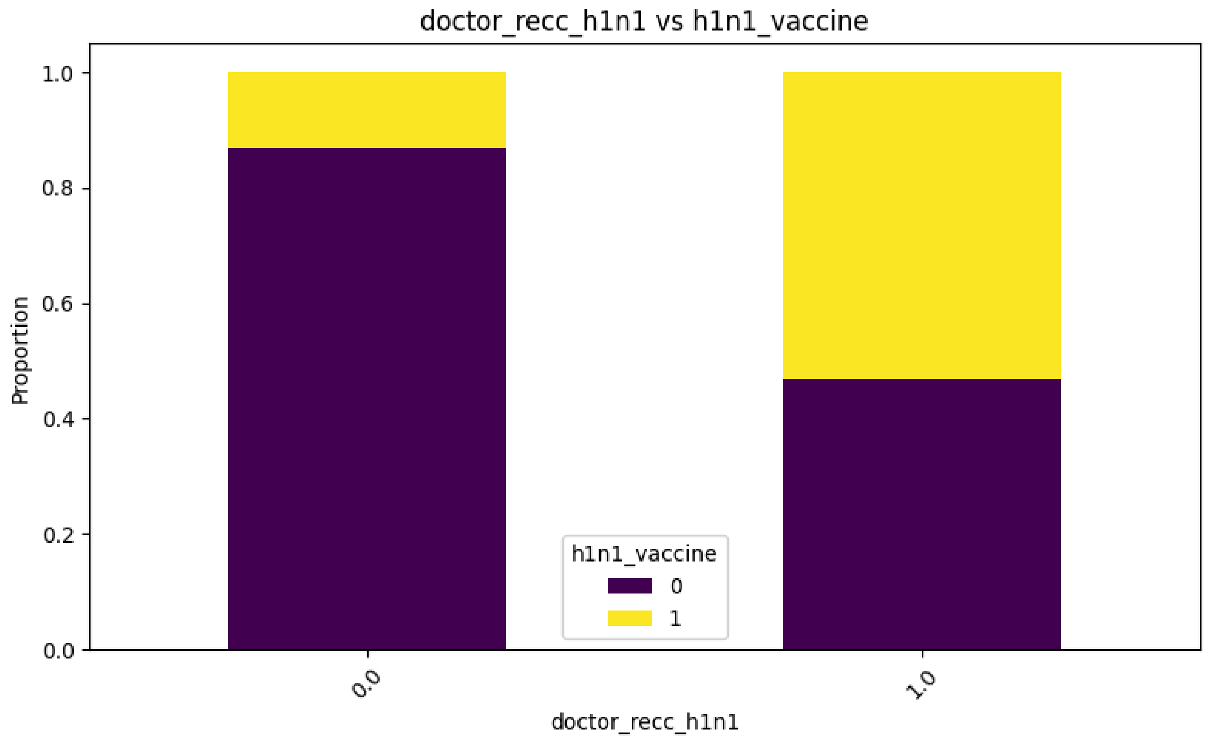
Next Step – Crosstab Analysis

For each of the top correlated features:

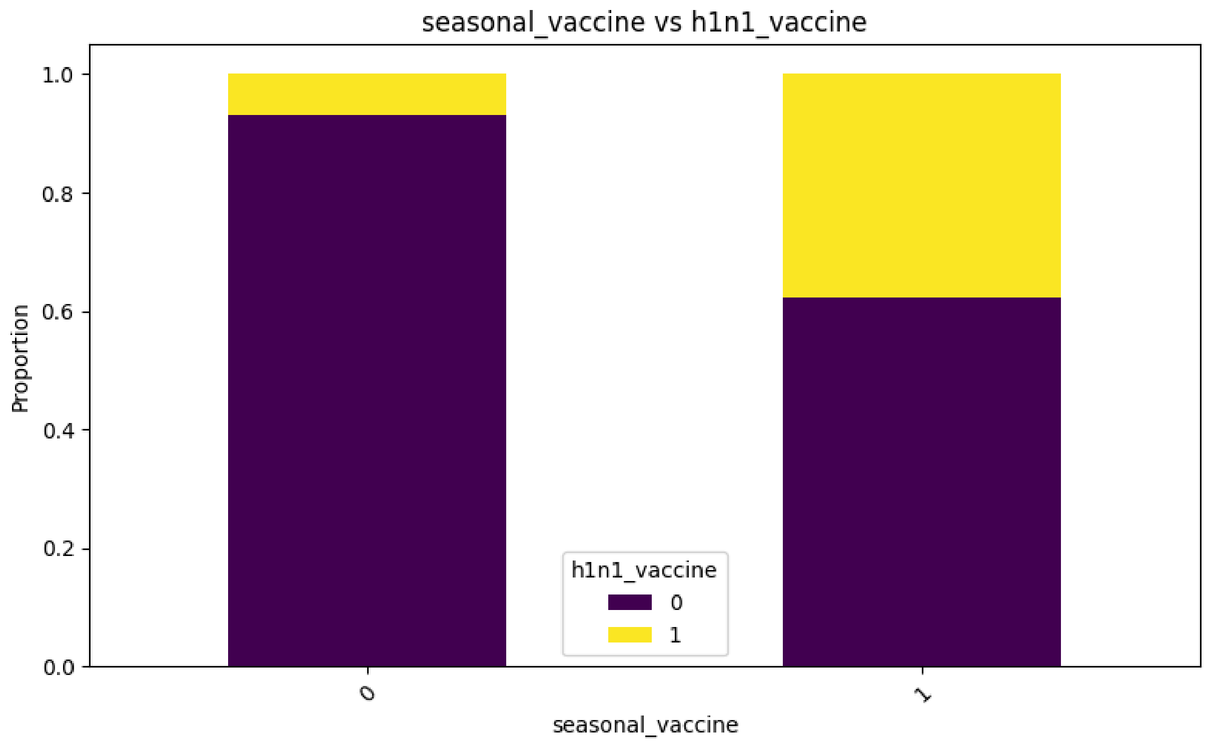
- A crosstab will be created showing the relationship between feature values and vaccine uptake (`0` = not vaccinated, `1` = vaccinated).
- These visualizations will help identify which features may be strong predictors for modeling.

```
In [29]: # Step 1: Create dictionary of top correlated features per target
         top_corr_dict = {}

         for target in ['h1n1_vaccine', 'seasonal_vaccine']:
             top_corr = df_encoded.corr()[target] \
                 .drop(labels=[target]) \
                 .abs() \
                 .sort_values(ascending=False) \
                 .head(10) \
                 .index.tolist()

             top_corr_dict[target] = top_corr

         # Step 2: Loop through and plot using
         for target, feature_list in top_corr_dict.items():
             print(f" Crosstab plots for target: `{target}`")
             for feature in feature_list:
                 eda.crosstab_plot(feature, target)
```

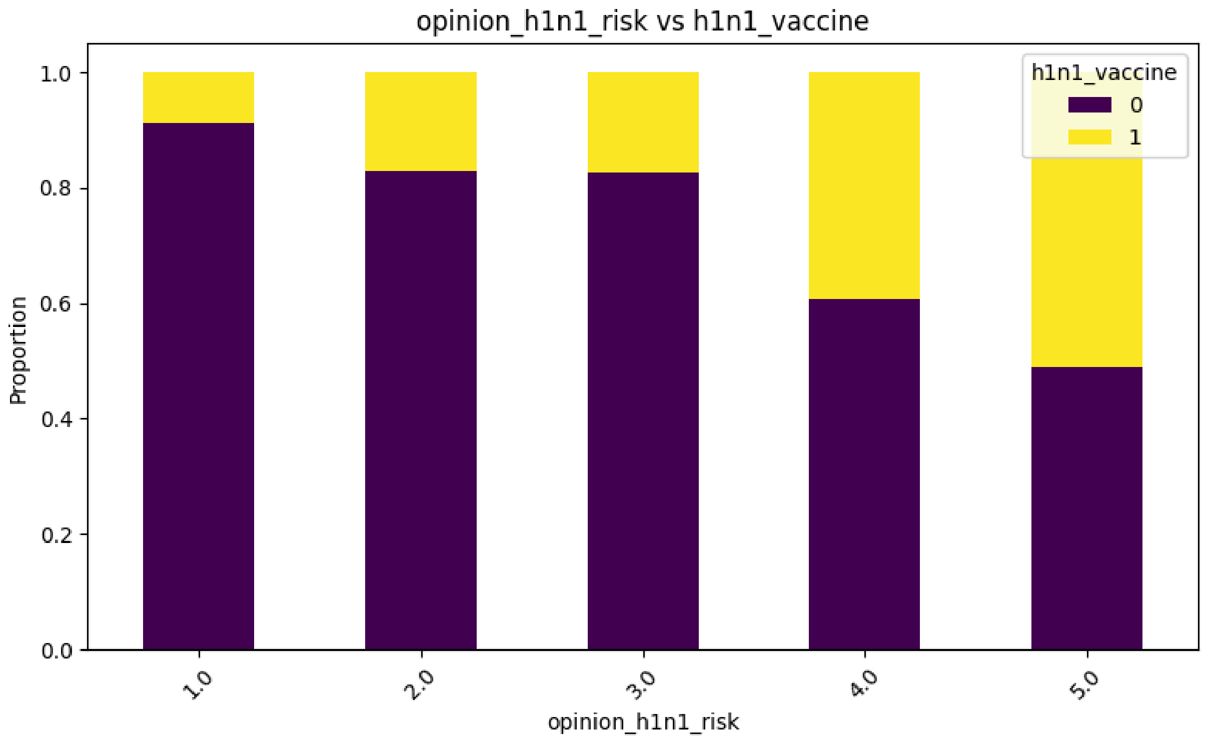
```
 Crosstab plots for target: `h1n1_vaccine`
h1n1_vaccine              0         1
doctor_recc_h1n1
0.0                0.868773  0.131227
1.0                0.467641  0.532359
```



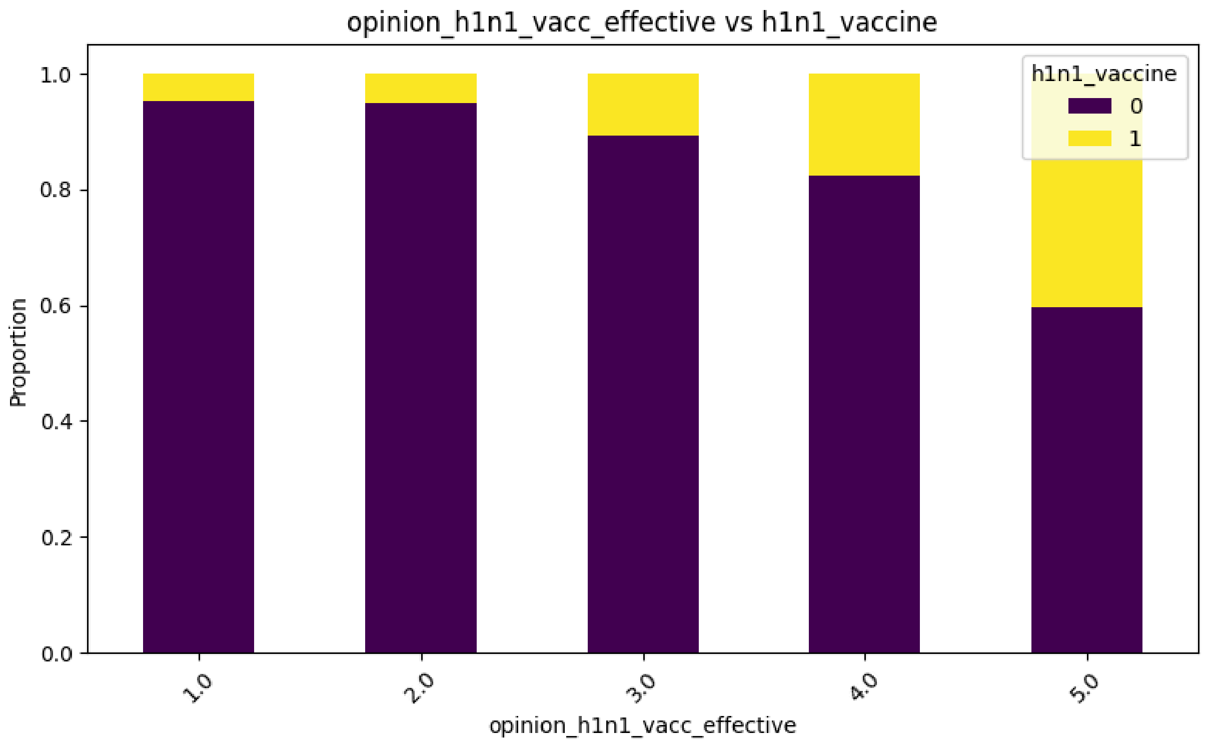
```
h1n1_vaccine              0         1
seasonal_vaccine
0                  0.931544  0.068456
1                  0.622276  0.377724
```



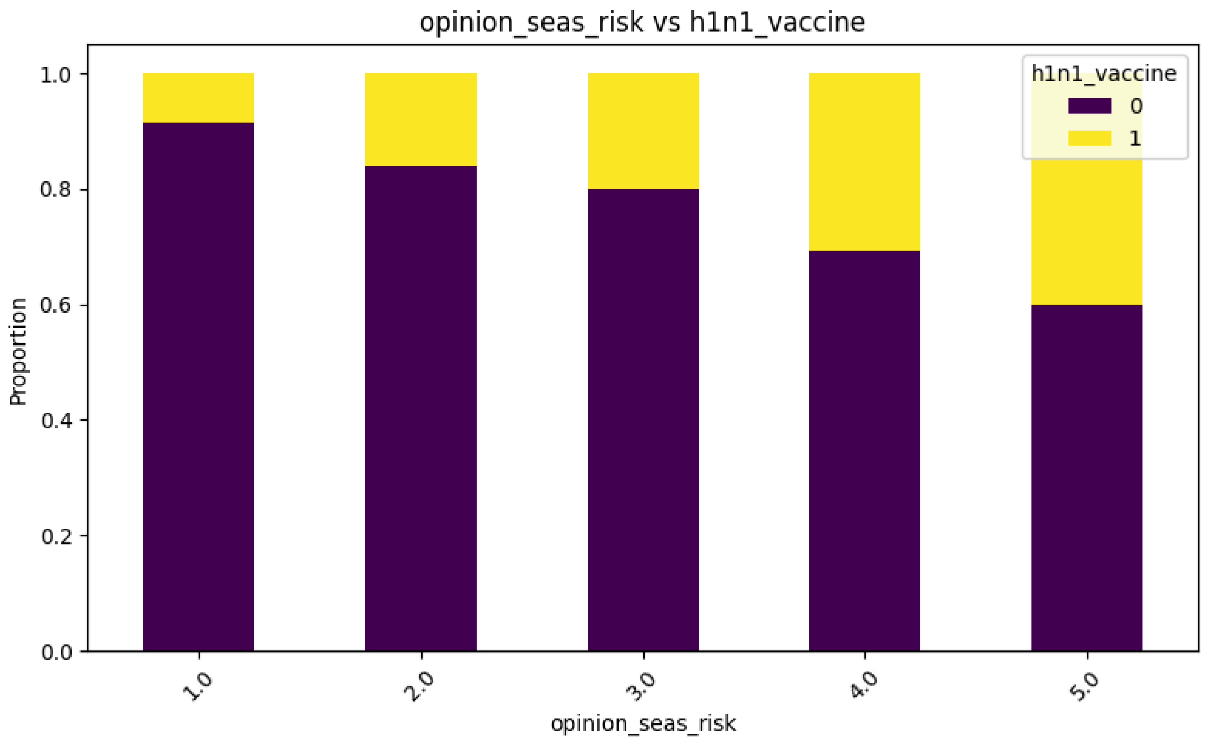
```
h1n1_vaccine              0         1
opinion_h1n1_risk
1.0                0.911660  0.088340
2.0                0.830018  0.169982
3.0                0.826321  0.173679
4.0                0.607898  0.392102
5.0                0.489143  0.510857
```



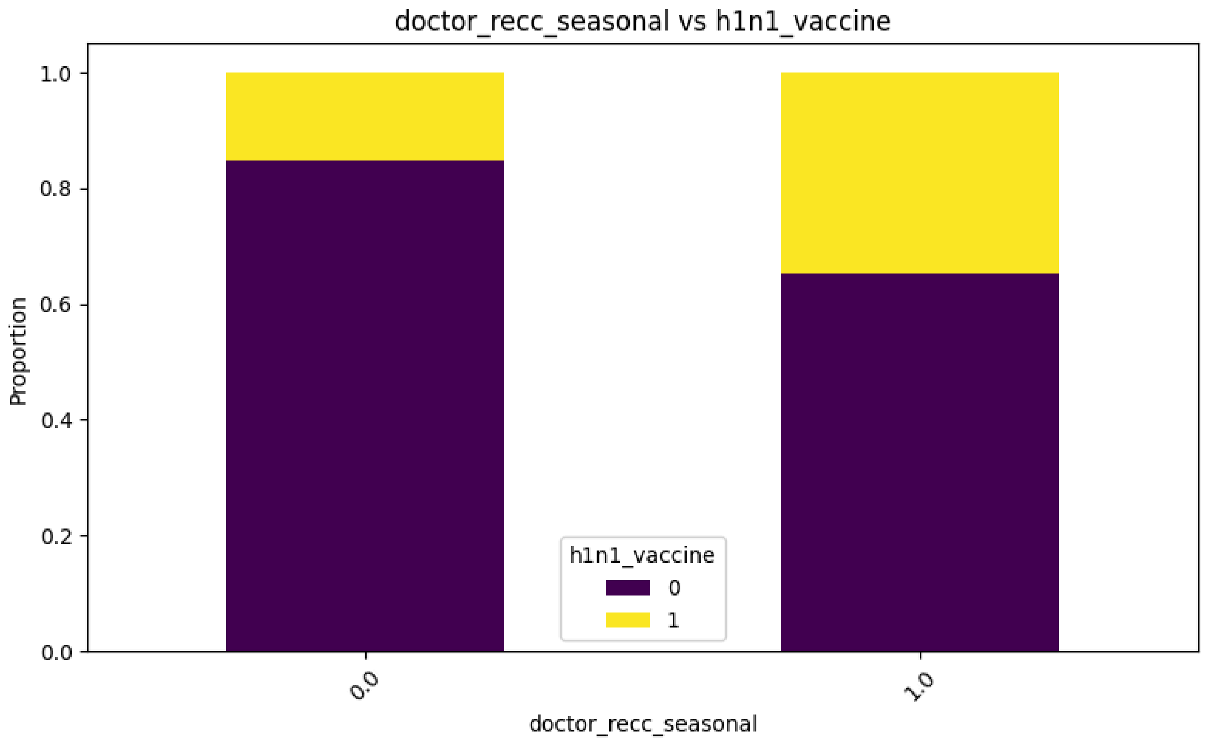
```
h1n1_vaccine                          0         1
opinion_h1n1_vacc_effective
1.0                            0.952596  0.047404
2.0                            0.948870  0.051130
3.0                            0.894347  0.105653
4.0                            0.823008  0.176992
5.0                            0.595172  0.404828
```



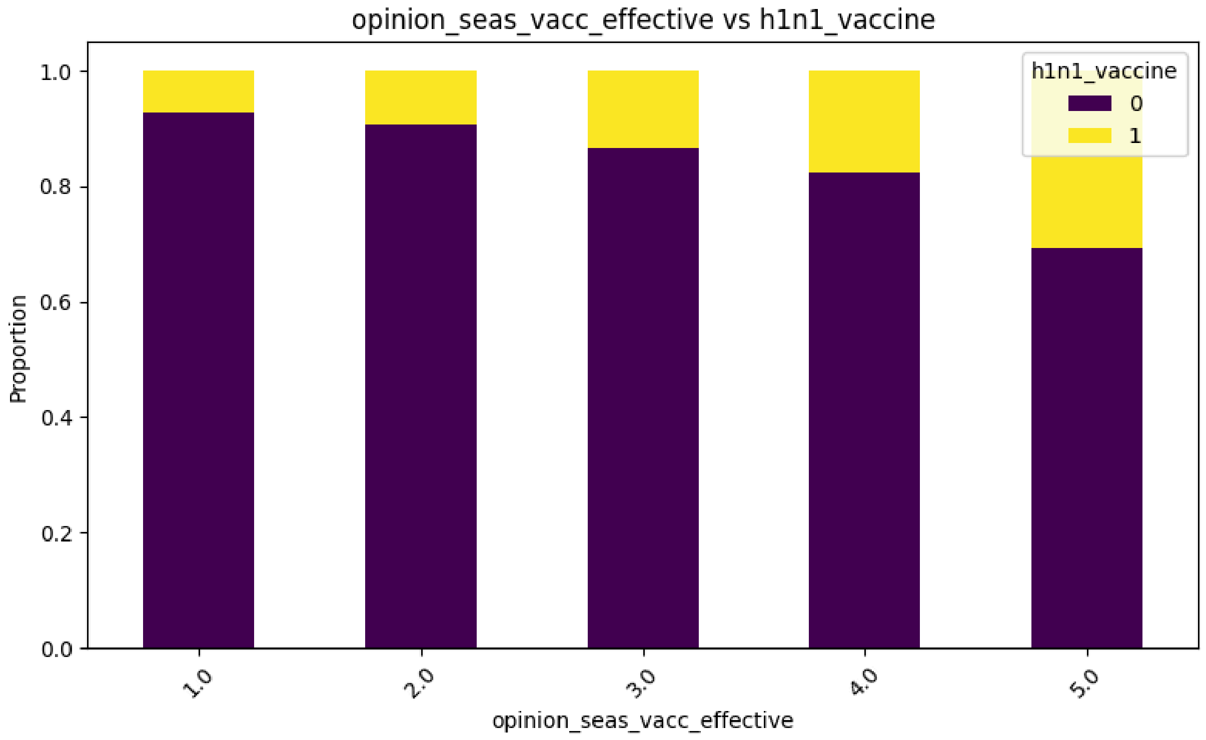
```
h1n1_vaccine             0         1
opinion_seas_risk
1.0               0.915300  0.084700
2.0               0.839987  0.160013
3.0               0.799114  0.200886
4.0               0.693971  0.306029
5.0               0.600406  0.399594
```



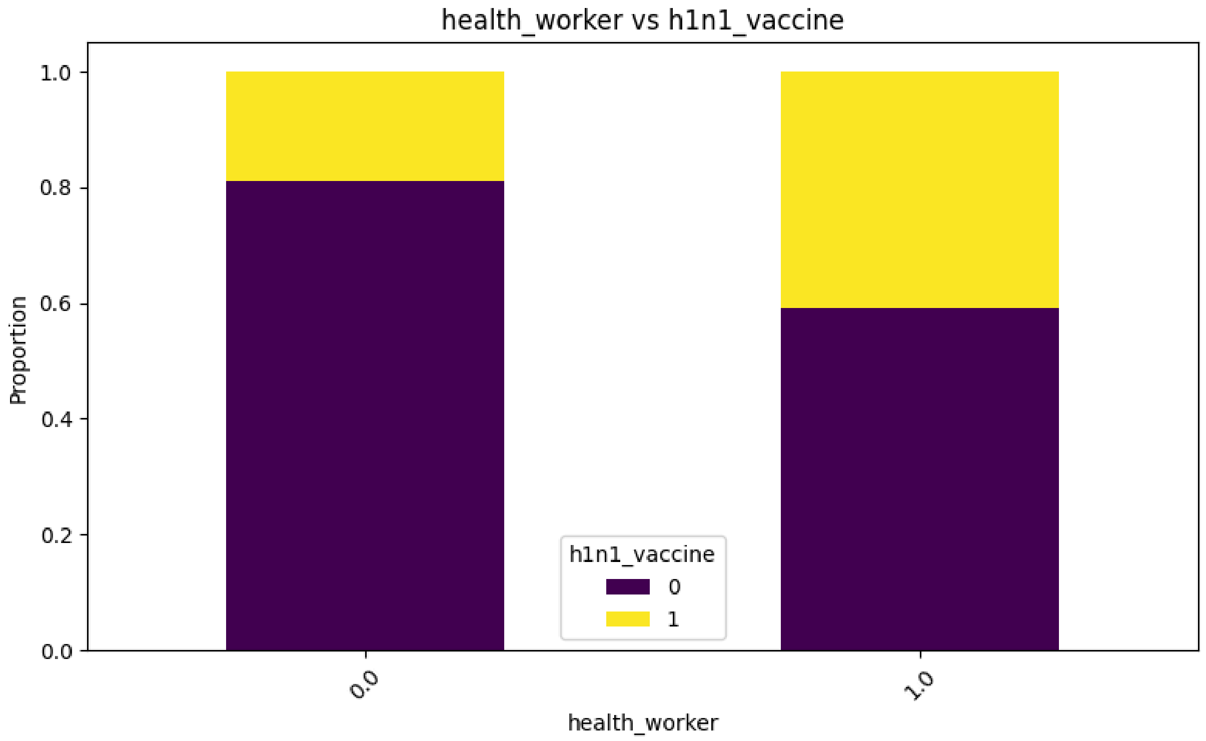
```
h1n1_vaccine              0         1
doctor_recc_seasonal
0.0                0.846613  0.153387
1.0                0.651717  0.348283
```



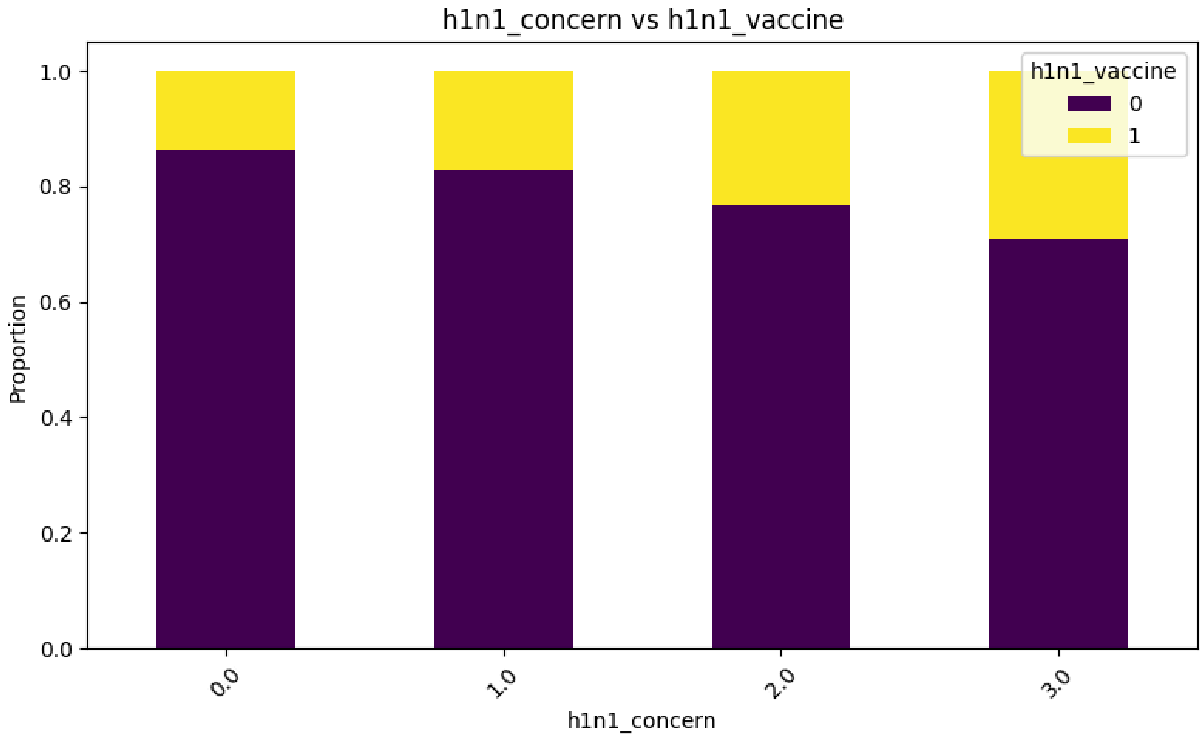
```
h1n1_vaccine                        0         1
opinion_seas_vacc_effective
1.0                          0.927109  0.072891
2.0                          0.907072  0.092928
3.0                          0.866776  0.133224
4.0                          0.822843  0.177157
5.0                          0.691567  0.308433
```



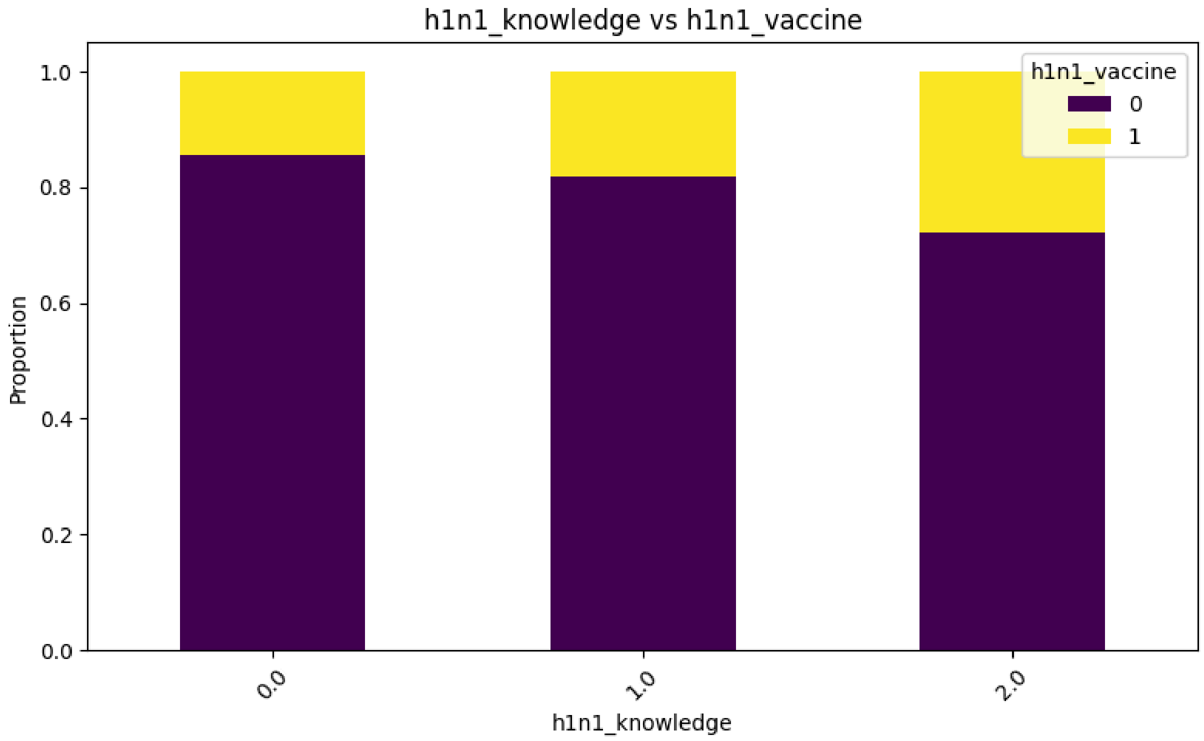
```
h1n1_vaccine          0         1
health_worker
0.0            0.811534  0.188466
1.0            0.590548  0.409452
```



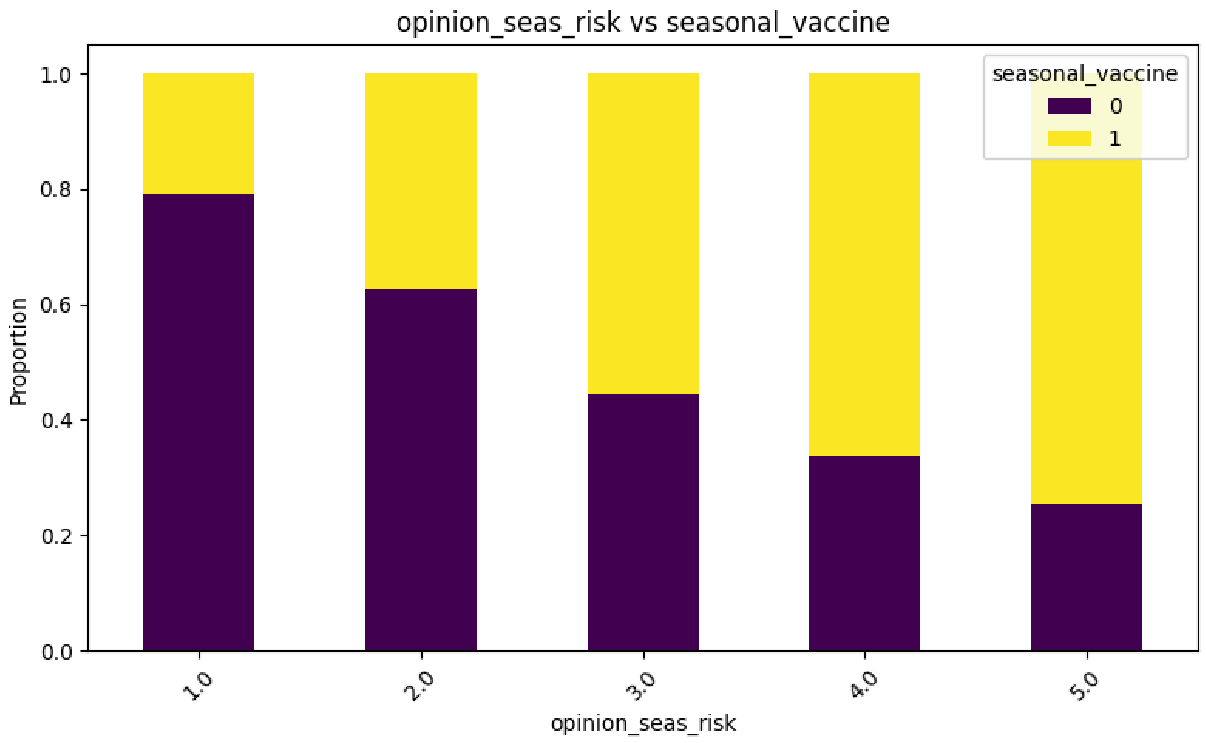
```
h1n1_vaccine         0         1
h1n1_concern
0.0           0.864381  0.135619
1.0           0.828652  0.171348
2.0           0.766664  0.233336
3.0           0.707907  0.292093
```



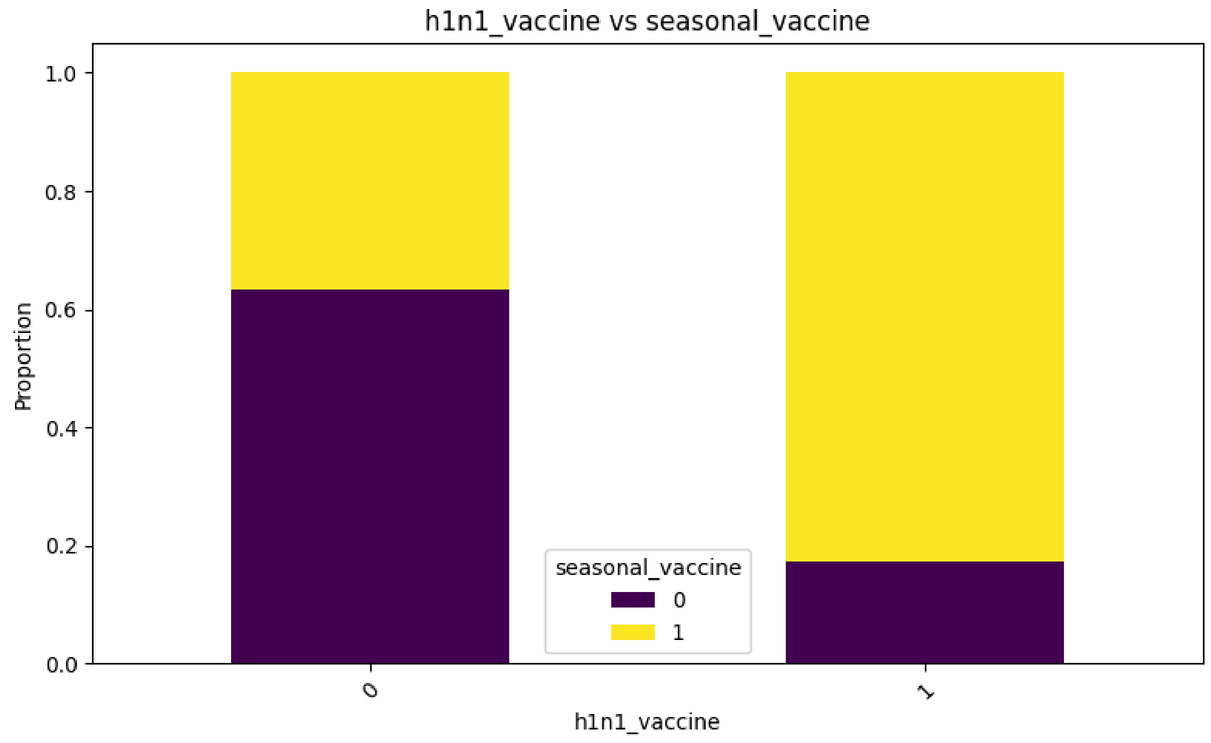
```
h1n1_vaccine          0         1
h1n1_knowledge
0.0            0.855946  0.144054
1.0            0.818200  0.181800
2.0            0.721935  0.278065
```



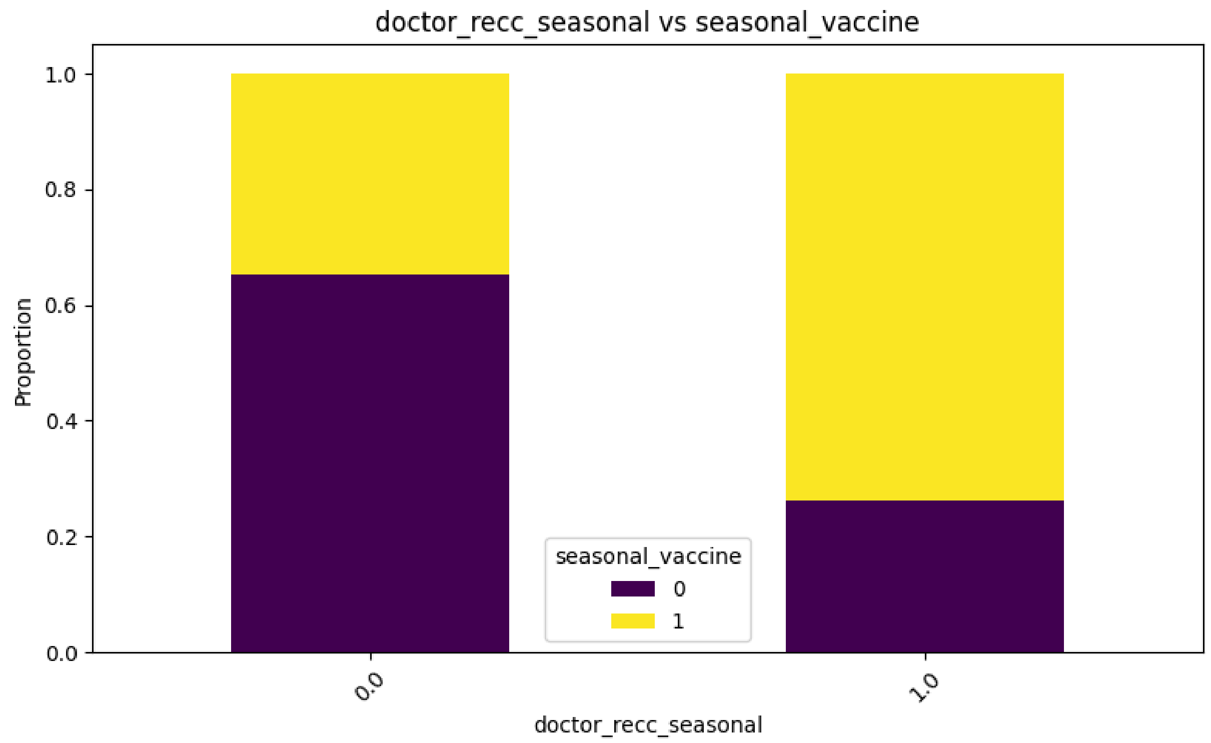
```
 Crosstab plots for target: `seasonal_vaccine`
seasonal_vaccine         0         1
opinion_seas_risk
1.0               0.790593  0.209407
2.0               0.625898  0.374102
3.0               0.443131  0.556869
4.0               0.336566  0.663434
5.0               0.255240  0.744760
```



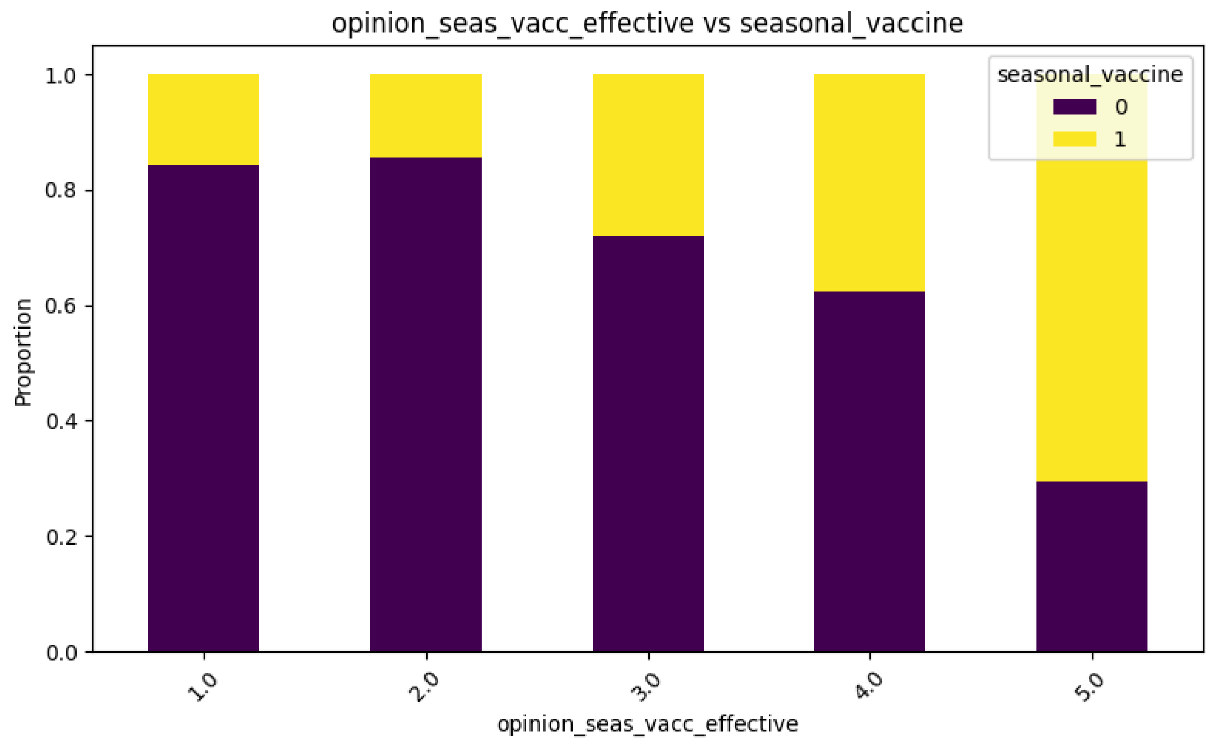
```
seasonal_vaccine        0         1
h1n1_vaccine
0                0.632102  0.367898
1                0.172189  0.827811
```



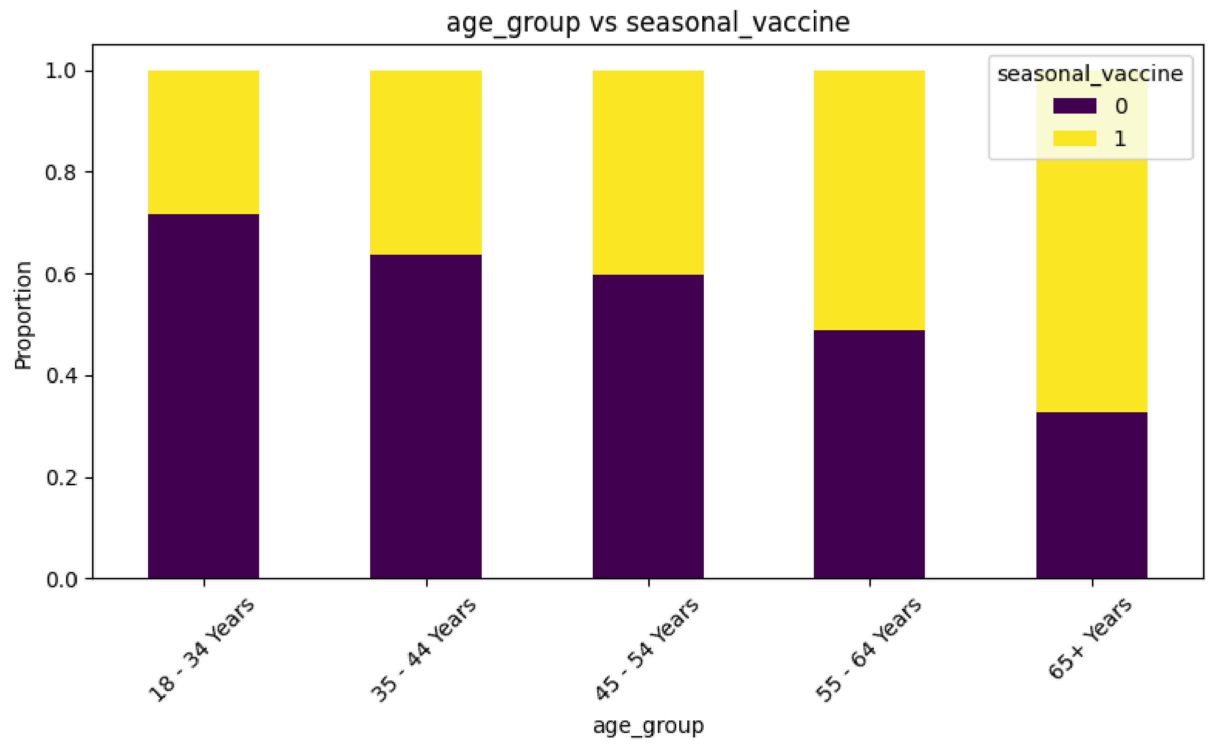
```
seasonal_vaccine              0         1
doctor_recc_seasonal
0.0                    0.653038  0.346962
1.0                    0.261552  0.738448
```



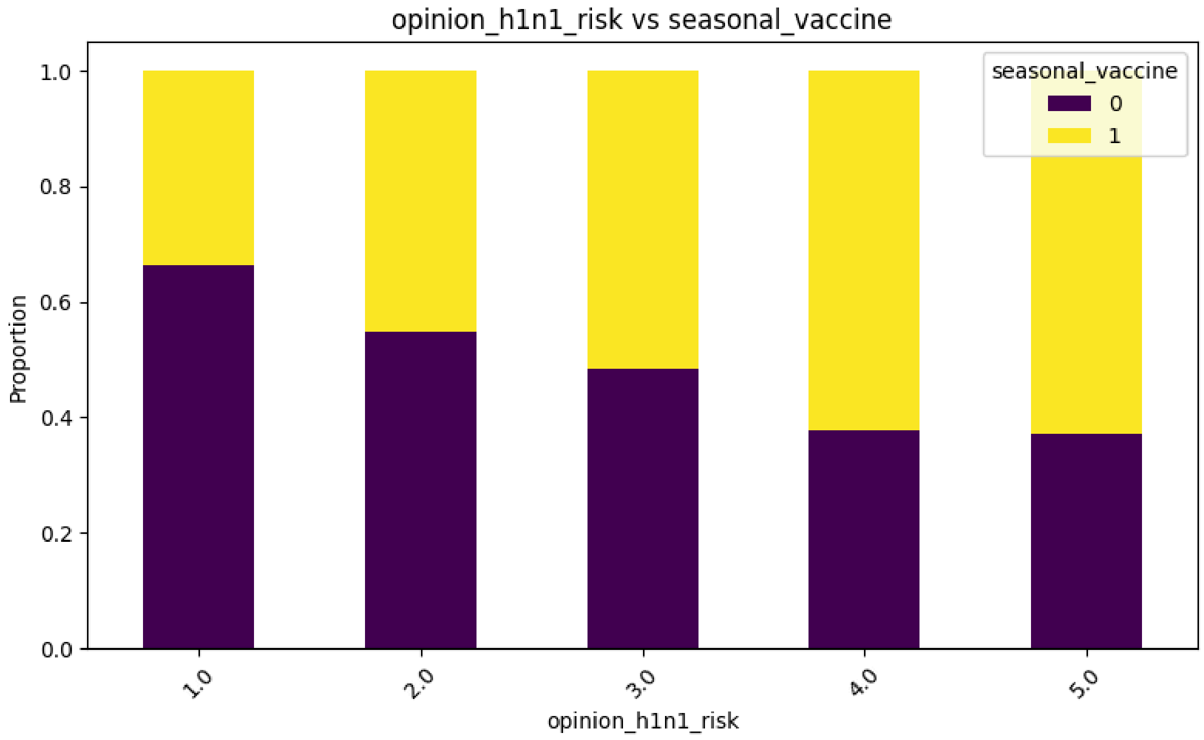
```
seasonal_vaccine                     0         1
opinion_seas_vacc_effective
1.0                           0.841933  0.158067
2.0                           0.854488  0.145512
3.0                           0.720395  0.279605
4.0                           0.623439  0.376561
5.0                           0.295297  0.704703
```



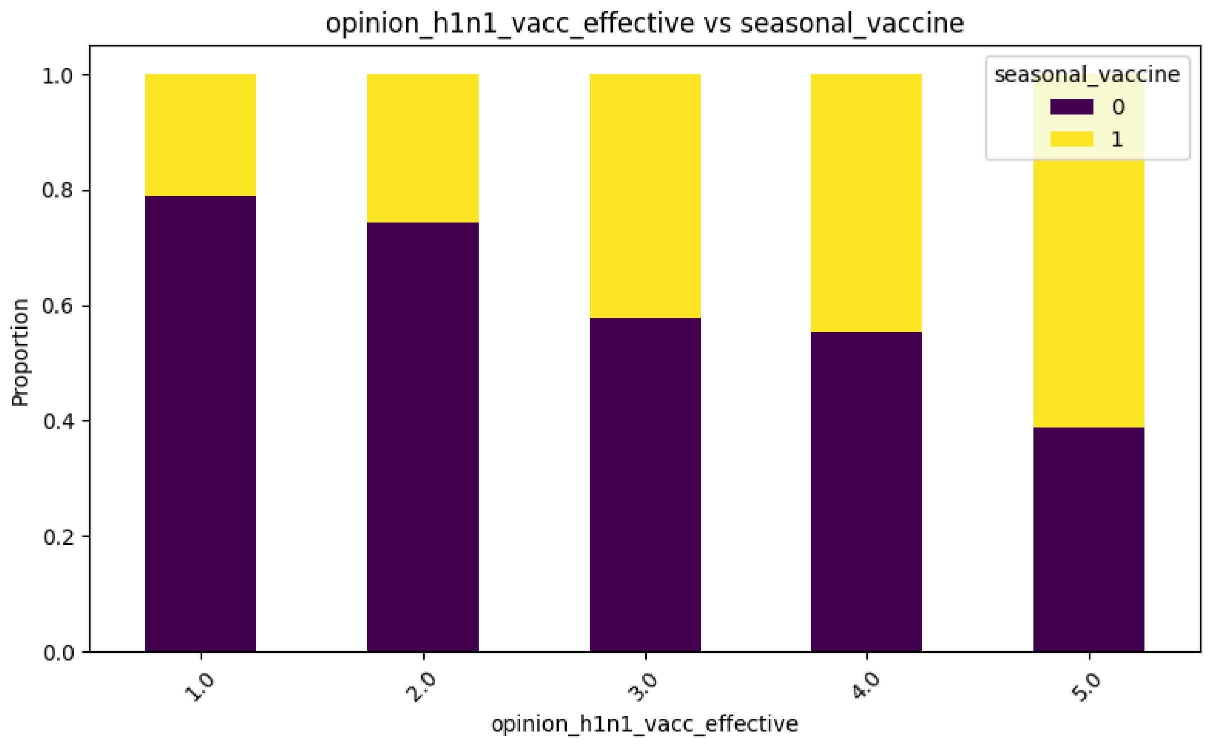
```
seasonal_vaccine         0         1
age_group
18 - 34 Years     0.715436  0.284564
35 - 44 Years     0.637474  0.362526
45 - 54 Years     0.598702  0.401298
55 - 64 Years     0.488765  0.511235
65+ Years         0.326319  0.673681
```



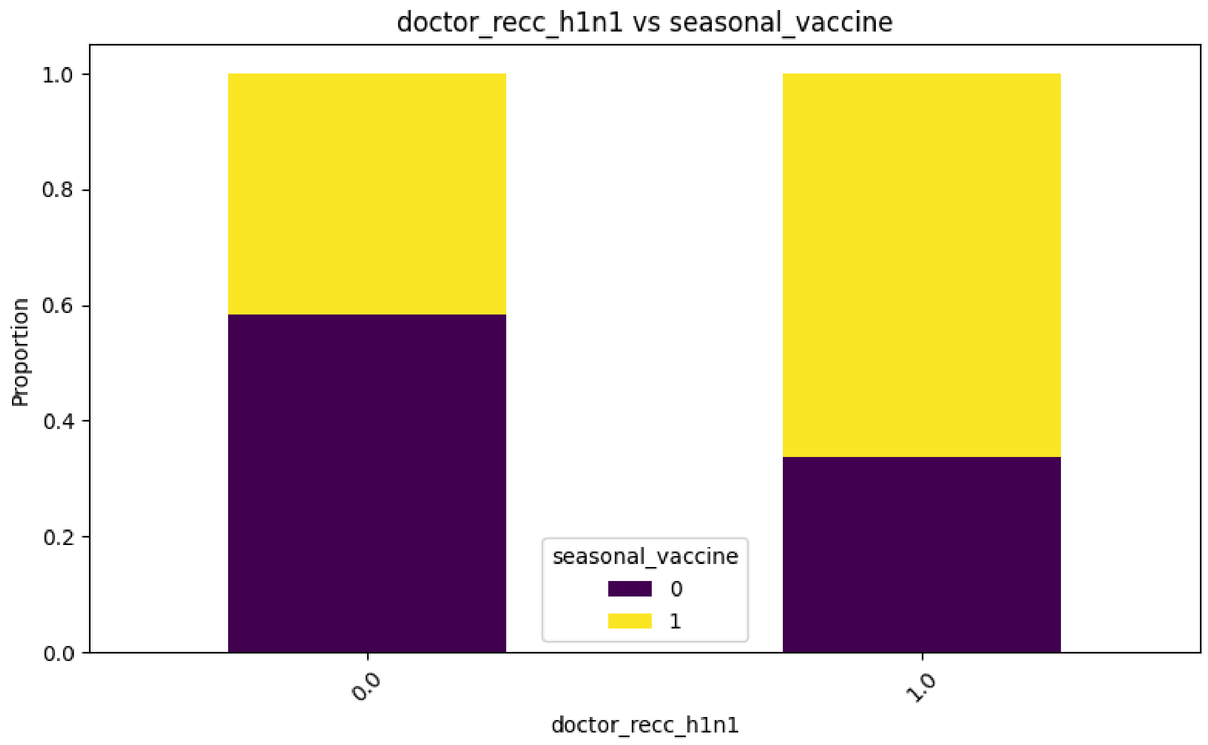
```
seasonal_vaccine          0         1
opinion_h1n1_risk
1.0               0.664332  0.335668
2.0               0.547492  0.452508
3.0               0.483438  0.516562
4.0               0.376159  0.623841
5.0               0.373143  0.626857
```



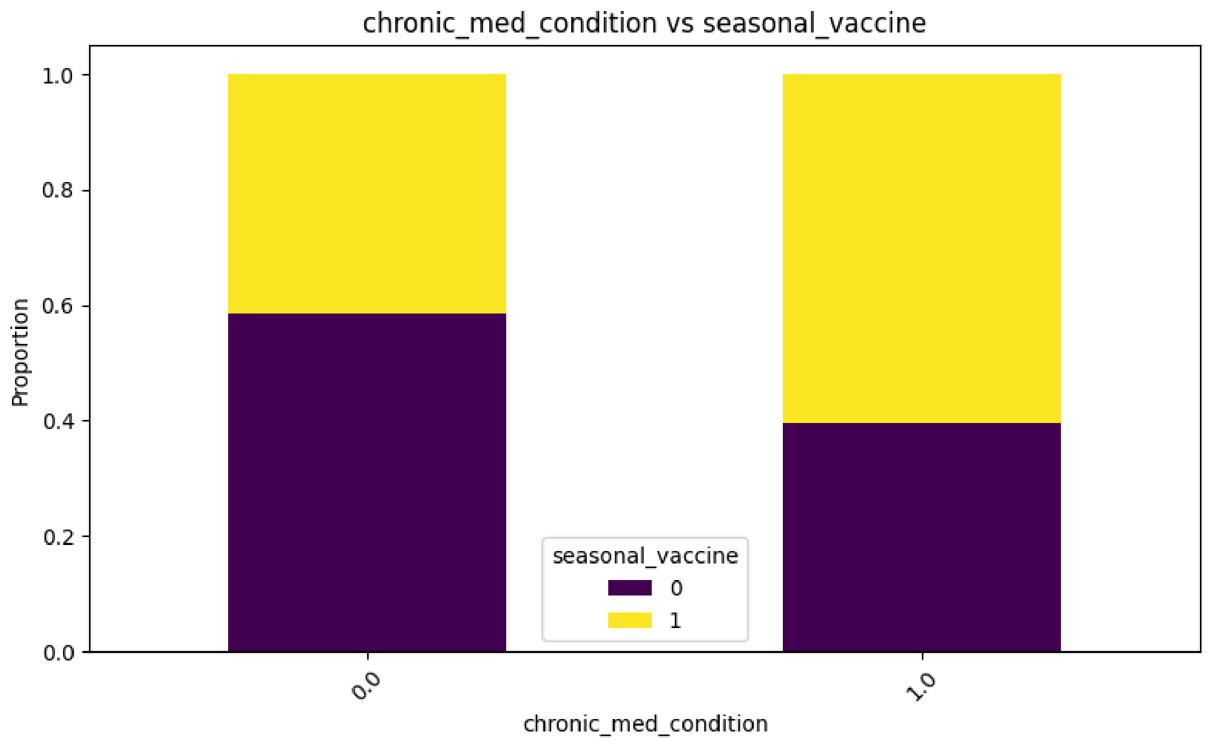
```
seasonal_vaccine                    0         1
opinion_h1n1_vacc_effective
1.0                          0.788939  0.211061
2.0                          0.743272  0.256728
3.0                          0.577387  0.422613
4.0                          0.553835  0.446165
5.0                          0.387664  0.612336
```



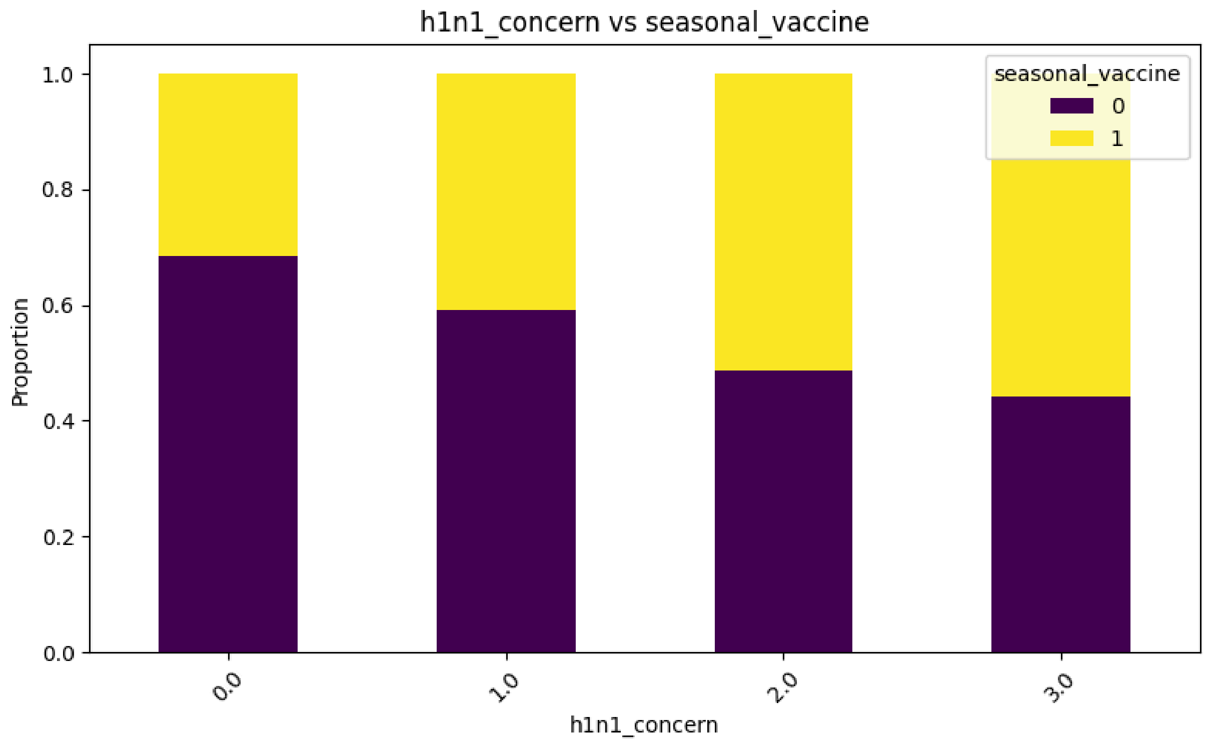
```
seasonal_vaccine          0         1
doctor_recc_h1n1
0.0               0.584300  0.415700
1.0               0.337833  0.662167
```



```
seasonal_vaccine              0         1
chronic_med_condition
0.0                    0.586187  0.413813
1.0                    0.396433  0.603567
```

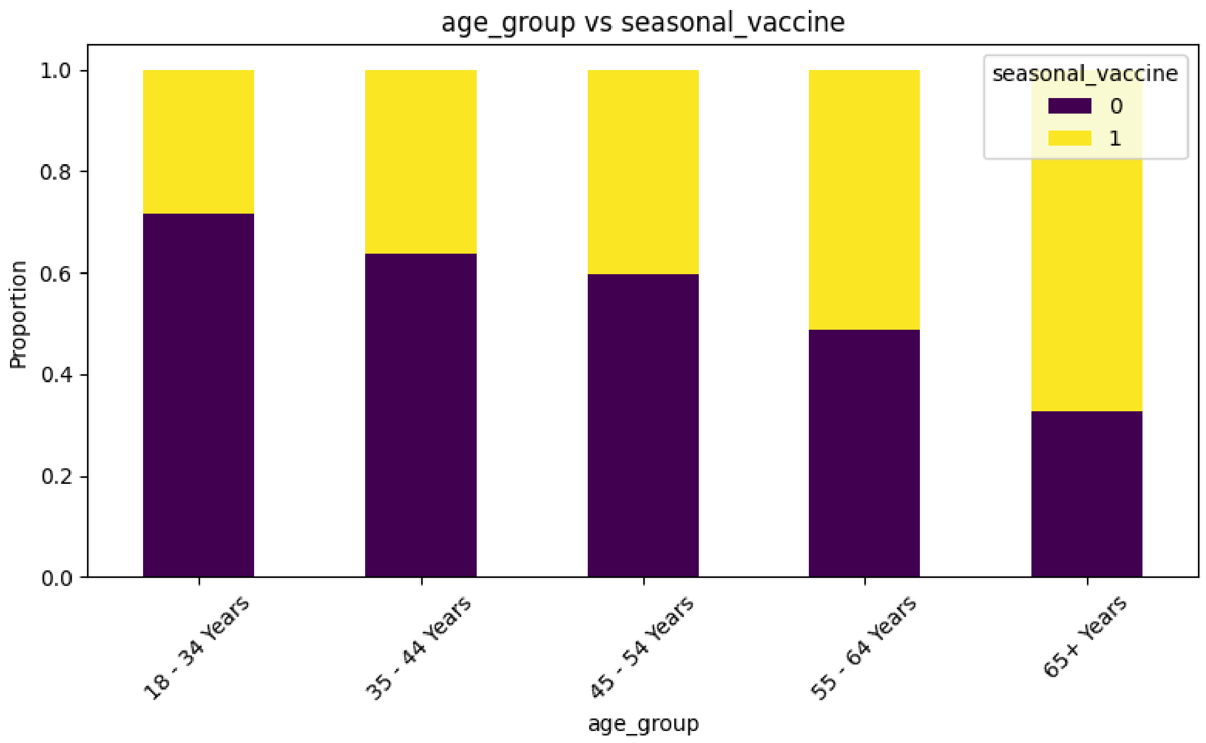


```
seasonal_vaccine         0         1
h1n1_concern
0.0               0.683859  0.316141
1.0               0.590090  0.409910
2.0               0.486079  0.513921
3.0               0.440427  0.559573
```



```
In [30]: eda.crosstab_plot('age_group', 'seasonal_vaccine')
```

```
seasonal_vaccine         0         1
age_group
18 - 34 Years     0.715436  0.284564
35 - 44 Years     0.637474  0.362526
45 - 54 Years     0.598702  0.401298
55 - 64 Years     0.488765  0.511235
65+ Years         0.326319  0.673681
```



Step 4: Modeling – Predicting Vaccine Uptake

With the data cleaned, encoded, and explored, we now move into the **modeling phase**.

In this section, we aim to:

- Define our features (`X`) and target (`y`)
- Split the dataset into training and test sets
- Train baseline classification models (e.g., Logistic Regression, Decision Tree)
- Evaluate model performance using metrics such as **accuracy, precision, recall, and F1-score**
- Use confusion matrices and classification reports for deeper insight

We will begin with simple baseline models and progressively improve using:

- Hyperparameter tuning
- Cross-validation
- Feature engineering

Our goal: Build an effective model to predict whether a person received the **H1N1 vaccine** or the **Seasonal flu vaccine**, based on their characteristics, behaviors, and opinions.

In [32]:
```
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.linear_model import LinearRegression, LogisticRegression, RidgeCV, Las
from sklearn.model_selection import cross_val_score
from sklearn.preprocessing import PolynomialFeatures
from sklearn.cluster import KMeans
from sklearn.metrics import confusion_matrix
from sklearn.tree import DecisionTreeClassifier

# imports from VaccineModel class
from modelling import VaccineModel
# from sklearn.linear_model import LogisticRegression
# from sklearn.tree import DecisionTreeClassifier
# from sklearn.pipeline import Pipeline
# from sklearn.preprocessing import StandardScaler
# from sklearn.model_selection import train_test_split
# from sklearn.metrics import (
#     accuracy_score, precision_score, recall_score,
#     f1_score, confusion_matrix, classification_report
# )
```

Baseline Modeling: Logistic Regression vs. Decision Tree

To establish a benchmark, we start training two baseline models on the encoded dataset:

- **Logistic Regression**: A linear model suitable for binary classification
- **Decision Tree**: A non-linear, rule-based model that can capture interactions

He we use baseline parameters for both and evaluate performance using accuracy, precision, recall, and F1-score. This helps us compare model complexity vs. predictive performance in future iterations.

Baseline Modelling for H1N1

In [35]:
```
# Logistic regression is set as default in VaccineModel class

h1n1_lr_base = VaccineModel(df_encoded, target='h1n1_vaccine', scale=True)
h1n1_lr_base.split_data()
h1n1_lr_base.train_model()
h1n1_lr_base.evaluate()
```

```
 Evaluation for `h1n1_vaccine` using Pipeline:

Accuracy: 0.8356420816173717
Precision: 0.6848920863309352
Recall: 0.4193832599118943
F1 Score: 0.5202185792349727

Confusion Matrix:
[[3988  219]
 [ 659  476]]

Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.95      0.90      4207
           1       0.68      0.42      0.52      1135

    accuracy                           0.84      5342
   macro avg       0.77      0.68      0.71      5342
weighted avg       0.82      0.84      0.82      5342
```

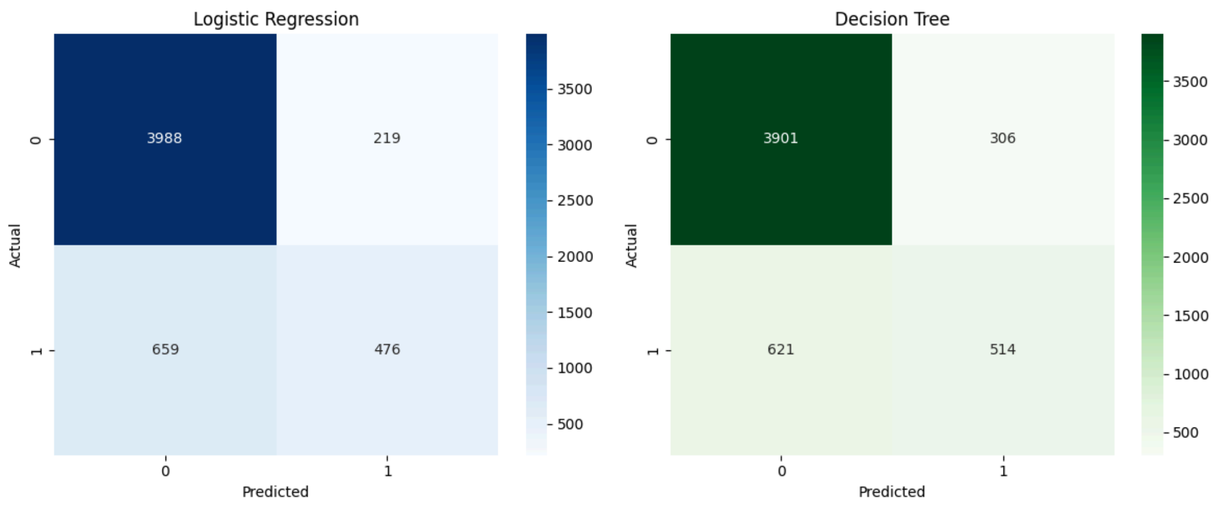
In [36]:
```python
# Decision Tree
tree_model = DecisionTreeClassifier(max_depth=5, random_state=42)

h1n1_tree_base = VaccineModel(df_encoded, target='h1n1_vaccine', model=tree_model)
h1n1_tree_base.split_data()
h1n1_tree_base.train_model()
h1n1_tree_base.evaluate()
```

```
 Evaluation for `h1n1_vaccine` using DecisionTreeClassifier:

Accuracy: 0.8264694870834893
Precision: 0.6268292682926829
Recall: 0.452863436123348
F1 Score: 0.5258312020460358

Confusion Matrix:
[[3901  306]
 [ 621  514]]

Classification Report:
              precision    recall  f1-score   support

           0       0.86      0.93      0.89      4207
           1       0.63      0.45      0.53      1135

    accuracy                           0.83      5342
   macro avg       0.74      0.69      0.71      5342
weighted avg       0.81      0.83      0.82      5342
```

Confusion Matrix Visualiation

In [38]:
```python
def plot_confusion_matrices(y_true_lr, y_pred_lr, y_true_tree, y_pred_tree, labels=
    fig, axes = plt.subplots(1, 2, figsize=(12, 5))
    # Logistic Regression
    cm_lr = confusion_matrix(y_true_lr, y_pred_lr, labels=labels)
    sns.heatmap(cm_lr, annot=True, fmt='d', cmap='Blues', ax=axes[0])
    axes[0].set_title("Logistic Regression")
    axes[0].set_xlabel("Predicted")
    axes[0].set_ylabel("Actual")

    # Decision Tree
    cm_tree = confusion_matrix(y_true_tree, y_pred_tree, labels=labels)
    sns.heatmap(cm_tree, annot=True, fmt='d', cmap='Greens', ax=axes[1])
    axes[1].set_title("Decision Tree")
    axes[1].set_xlabel("Predicted")
    axes[1].set_ylabel("Actual")

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

In [39]:
```
# plot confusion matrix for H1N1 vaccine compaing LogReg and decisiontree
plot_confusion_matrices(
    y_true_lr=h1n1_lr_base.y_test,
    y_pred_lr=h1n1_lr_base.y_pred,
    y_true_tree=h1n1_tree_base.y_test,
    y_pred_tree=h1n1_tree_base.y_pred
)
```



Baseline model Evaluation for H1N1 vaccine

Metric	Logistic Regression	Decision Tree
Accuracy	83.6%	82.6%
Precision	0.685	0.627
Recall	0.419	0.453
F1 Score	0.520	0.526

Classification Report for Logistic Regression:

- Class 0 (Not Vaccinated): Precision 0.86 | Recall 0.95 | F1 Score 0.90
- Class 1 (Vaccinated): Precision 0.68 | Recall 0.42 | F1 Score 0.52

Confusion Matrix | | Predicted 0 | Predicted 1 | |---------------|-------------|-------------| | **Actual 0** | 3988 | 306 | | **Actual 1** | 621 | 514 |

Classification Report for Decision Tree:

- Class 0 (Not Vaccinated): Precision 0.86 | Recall 0.93 | F1 Score 0.89
- Class 1 (Vaccinated): Precision 0.63 | Recall 0.45 | F1 Score 0.53

Confusion Matrix

	Predicted 0	**Predicted 1**
Actual 0	3901	219
Actual 1	659	476

Key Insights

- Logistic Regression has slightly **higher precision and accuracy**, but **lower recall**.
- Decision Tree offers a **better balance** between precision and recall, resulting in a slightly better F1 score.
- Both models struggle with predicting the vaccinated group (class 1), suggesting the need for addressing class imbalance or testing other algorithms

Baseline Modelling for Seasonal Vaccine

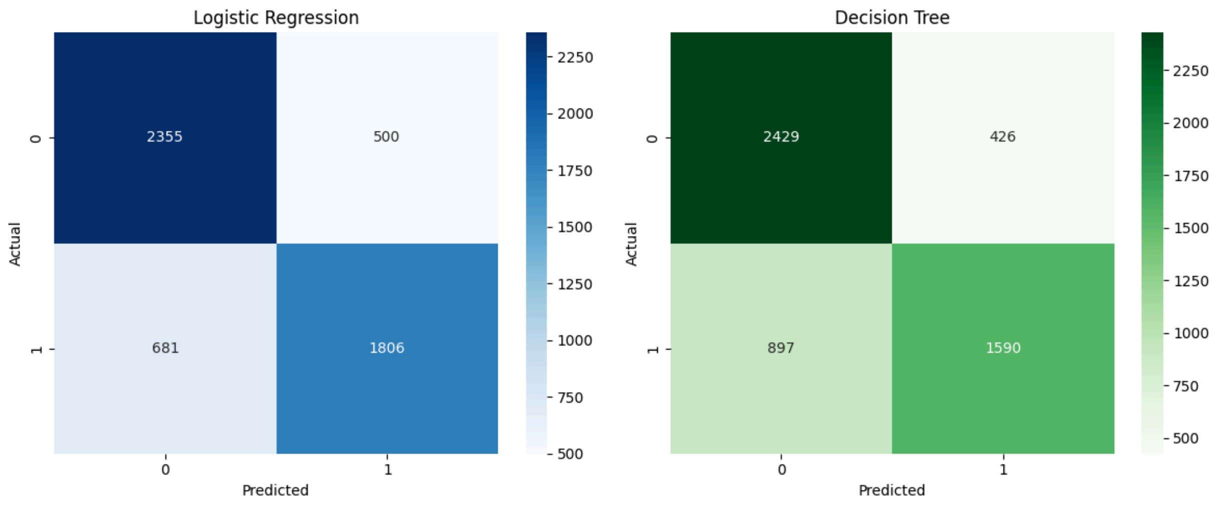
In [46]:
```python
# Logistic regression is set as default in VaccineModel class

seasonal_lr_base = VaccineModel(df_encoded, target='seasonal_vaccine', scale=True)
seasonal_lr_base.split_data()
seasonal_lr_base.train_model()
seasonal_lr_base.evaluate()
```

```
 Evaluation for `seasonal_vaccine` using Pipeline:

Accuracy: 0.7789217521527517
Precision: 0.7831743278404163
Recall: 0.7261761158021713
F1 Score: 0.7535989985395368

Confusion Matrix:
[[2355  500]
 [ 681 1806]]

Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.82      0.80      2855
           1       0.78      0.73      0.75      2487

    accuracy                           0.78      5342
   macro avg       0.78      0.78      0.78      5342
weighted avg       0.78      0.78      0.78      5342
```

In [48]:
```
# Decision Tree
tree_model1 = DecisionTreeClassifier(max_depth=5, random_state=42)

seasonal_tree_base = VaccineModel(df_encoded, target='seasonal_vaccine', model=tree
seasonal_tree_base.split_data()
seasonal_tree_base.train_model()
seasonal_tree_base.evaluate()
```

```
 Evaluation for `seasonal_vaccine` using DecisionTreeClassifier:

Accuracy: 0.7523399475851741
Precision: 0.7886904761904762
Recall: 0.6393244873341375
F1 Score: 0.7061958694203864

Confusion Matrix:
[[2429  426]
 [ 897 1590]]

Classification Report:
              precision    recall  f1-score   support

           0       0.73      0.85      0.79      2855
           1       0.79      0.64      0.71      2487

    accuracy                           0.75      5342
   macro avg       0.76      0.75      0.75      5342
weighted avg       0.76      0.75      0.75      5342
```

In [50]:
```
# plot confusion matrix for seasnal vaccine compaing LogReg and decisiontree

plot_confusion_matrices(
    y_true_lr=seasonal_lr_base.y_test,
    y_pred_lr=seasonal_lr_base.y_pred,
    y_true_tree=seasonal_tree_base.y_test,
    y_pred_tree=seasonal_tree_base.y_pred
)
```



Key Insights and Reommendations

This analysis of the 2009 H1N1 Flu Survey provided key insights into factors that influence vaccine uptake for both H1N1 and seasonal flu. The findings are valuable for guiding future public health strategies and improving vaccine campaign outcomes.

Key Insights

- **Doctor Recommendations Matter**
  Respondents who received a recommendation from a healthcare provider were **significantly more likely** to get vaccinated. This highlights the crucial role of **trusted messengers** in influencing public behavior.

- **Perceptions of Risk and Effectiveness Drive Behavior**
  Higher **perceived risk** of flu and greater **confidence in vaccine effectiveness** were positively correlated with vaccine uptake. Conversely, fears of **side effects** were associated with hesitancy.

- **Behavioral Factors Provide Predictive Signals**
  Preventive actions such as **mask-wearing, handwashing, and avoiding crowds** were often aligned with vaccine acceptance. These behavioral cues can be early indicators of openness to vaccination.

- **Sociodemographic Patterns are Uneven**
  Vaccine uptake varied by **age group, education level, and employment sector**. Tailoring campaigns to different demographics can improve reach and effectiveness.

- **Model Performance is Promising**
  Both Logistic Regression and Decision Tree classifiers achieved over **82% accuracy**. While Logistic Regression performed slightly better in terms of recall and precision for H1N1 predictions, Decision Trees were easier to interpret and showed comparable F1 scores.

Recommendations for Stakeholders

- **Public Health Officials**
  Target individuals with low vaccine uptake using behavioral and demographic signals. Strengthen community-based strategies and deploy trained communicators.

- **Healthcare Providers**
  Actively discuss vaccine benefits and risks with patients. Provider recommendation is a key driver of acceptance.

- **Policy Makers**
  Invest in educational campaigns that correct misconceptions. Prioritize **health literacy** initiatives and fund **data-driven outreach programs**.

- **Data Scientists & NGOs**
  Build predictive tools into health information systems to **flag high-risk groups** before campaigns launch. Use interpretable models to guide real-time decisions.

By leveraging these insights, vaccination programs can become more strategic, equitable, and impactful.