In [7]:
```python
# Import necessary libraries
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report, roc_curve, auc
import statsmodels.api as sm
import matplotlib.pyplot as plt
```

In [13]:
```python
# Load the dataset
data_path = "C:\\Users\\nihar\\OneDrive\\Desktop\\Bootcamp\\SCMA 632\\DataSet\\NSSO68.csv"
try:
    data = pd.read_csv(data_path, low_memory=False)
    print("Data loaded successfully")
except FileNotFoundError:
    print(f"File not found at path: {data_path}")
except Exception as e:
    print(f"An error occurred while loading the data: {e}")
```

```
Data loaded successfully
```

In [39]:
```python
# Ensure the data is loaded
if 'data' in locals():
    # Create the Target variable
    data['non_veg'] = np.where(data[['eggsno_q', 'fishprawn_q', 'goatmeat_q', 'beef_q', 'pork_q', 'chicken_q', 'othrbirds_q']].sum(axis=1) > 0, 1, 0)
```

In [41]:
```python
# Get the value counts of non_veg
non_veg_values = data['non_veg'].value_counts()
print(non_veg_values)
```

```
non_veg
1    68590
0    33072
Name: count, dtype: int64
```

In [43]:
```python
# Ensure the dataset contains both levels of the target variable
if data['non_veg'].nunique() < 2:
    raise ValueError("The dataset does not contain both levels of the target variable 'non_veg'.")
```

In [45]:
```python
# Define the dependent variable (non_veg) and independent variables
y = data['non_veg']
X = data[['HH_type', 'Religion', 'Social_Group', 'Regular_salary_earner', 'Possess_ration_card', 'Sex', 'Age', 'Marital_Status', 'Education', 'Meals_At_Home', 'Region', 'hhdsz', 'NIC_2008', 'NCO_2004']]
```

In [47]:
```python
# Convert relevant columns to categorical
X = pd.get_dummies(X, drop_first=True)
```

In [53]:
```python
# Combine the dependent and independent variables into one dataframe
combined_data = pd.concat([y, X], axis=1)
```

In [55]:
```python
# Inspect the combined data
print(combined_data.info())
print(combined_data.head())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 101662 entries, 0 to 101661
Data columns (total 15 columns):
 #   Column                 Non-Null Count   Dtype  
---  ------                 --------------   -----  
 0   non_veg                101662 non-null  int32  
 1   HH_type                101635 non-null  float64
 2   Religion               101659 non-null  float64
 3   Social_Group           101648 non-null  float64
 4   Regular_salary_earner  101650 non-null  float64
 5   Possess_ration_card    101649 non-null  float64
 6   Sex                    101662 non-null  int64  
 7   Age                    101662 non-null  int64  
 8   Marital_Status         101660 non-null  float64
 9   Education              101655 non-null  float64
 10  Meals_At_Home          100443 non-null  float64
 11  Region                 101662 non-null  int64  
 12  hhdsz                  101662 non-null  int64  
 13  NIC_2008               94151 non-null   float64
 14  NCO_2004               94175 non-null   float64
dtypes: float64(10), int32(1), int64(4)
memory usage: 11.2 MB
None
   non_veg  HH_type  Religion  Social_Group  Regular_salary_earner  \
0        1      2.0       1.0           3.0                    1.0   
1        1      2.0       3.0           9.0                    1.0   
2        1      1.0       1.0           9.0                    1.0   
3        1      2.0       3.0           9.0                    1.0   
4        1      1.0       1.0           9.0                    2.0   

   Possess_ration_card  Sex  Age  Marital_Status  Education  Meals_At_Home  \
0                  1.0    1   50             2.0        8.0           59.0   
1                  1.0    2   40             3.0       12.0           56.0   
2                  1.0    1   45             2.0        7.0           60.0   
3                  1.0    1   75             3.0        6.0           60.0   
4                  1.0    1   30             2.0        7.0           59.0   

   Region  hhdsz  NIC_2008  NCO_2004  
0       2      5   47510.0     411.0  
1       2      2   85102.0     331.0  
2       2      5   49219.0     121.0  
3       2      3   49231.0     911.0  
4       2      4   45403.0     121.0  
```

In [57]:
```python
# Remove rows with missing values
combined_data = combined_data.dropna()
```

In [59]:
```python
# Split the data into training and testing sets
train_data, test_data = train_test_split(combined_data, test_size=0.2, random_state=123, stratify=combined_data['non_veg'])
```

In [61]:
```python
# Fit the probit regression model on the training data
X_train = train_data.drop('non_veg', axis=1)
y_train = train_data['non_veg']
X_test = test_data.drop('non_veg', axis=1)
y_test = test_data['non_veg']
```

In [63]:
```python
probit_model = sm.Probit(y_train, sm.add_constant(X_train)).fit()
print(probit_model.summary())
```

```
Optimization terminated successfully.
         Current function value: 0.589410
         Iterations 5
                          Probit Regression Results                          
==============================================================================
Dep. Variable:                non_veg   No. Observations:                74476
Model:                         Probit   Df Residuals:                    74461
Method:                           MLE   Df Model:                           14
Date:                Mon, 01 Jul 2024   Pseudo R-squ.:                 0.05215
Time:                        22:45:32   Log-Likelihood:                -43897.
converged:                       True   LL-Null:                       -46312.
Covariance Type:            nonrobust   LLR p-value:                     0.000
=========================================================================================
                            coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------------------
const                     0.0086      0.062      0.139      0.890      -0.113       0.131
HH_type                   0.0200      0.004      4.791      0.000       0.012       0.028
Religion                  0.1896      0.006     33.638      0.000       0.179       0.201
Social_Group             -0.0461      0.002    -28.644      0.000      -0.049      -0.043
Regular_salary_earner    -0.0354      0.012     -2.864      0.004      -0.060      -0.011
Possess_ration_card       0.0148      0.013      1.129      0.259      -0.011       0.040
Sex                      -0.0361      0.022     -1.609      0.108      -0.080       0.008
Age                      -0.0020      0.000     -4.553      0.000      -0.003      -0.001
Marital_Status           -0.0117      0.018     -0.660      0.509      -0.047       0.023
Education                -0.0109      0.002     -6.544      0.000      -0.014      -0.008
Meals_At_Home             0.0104      0.000     33.208      0.000       0.010       0.011
Region                   -0.0782      0.004    -21.250      0.000      -0.085      -0.071
hhdsz                    -0.0052      0.002     -2.238      0.025      -0.010      -0.001
NIC_2008               2.315e-06   2.03e-07     11.415      0.000    1.92e-06    2.71e-06
NCO_2004               7.082e-05   2.42e-05      2.926      0.003    2.34e-05       0.000
=========================================================================================
```

In [65]:
```python
# Predict probabilities on the test data
predicted_probs = probit_model.predict(sm.add_constant(X_test))
```

In [67]:
```python
# Convert probabilities to binary predictions using a threshold of 0.5
predicted_classes = np.where(predicted_probs > 0.5, 1, 0)
```

In [69]:
```python
# Confusion Matrix
conf_matrix = confusion_matrix(y_test, predicted_classes)
print(conf_matrix)
```

```
[[  639  5198]
 [  417 12366]]
```

In [71]:
```python
# Classification Report
class_report = classification_report(y_test, predicted_classes)
print(class_report)
```

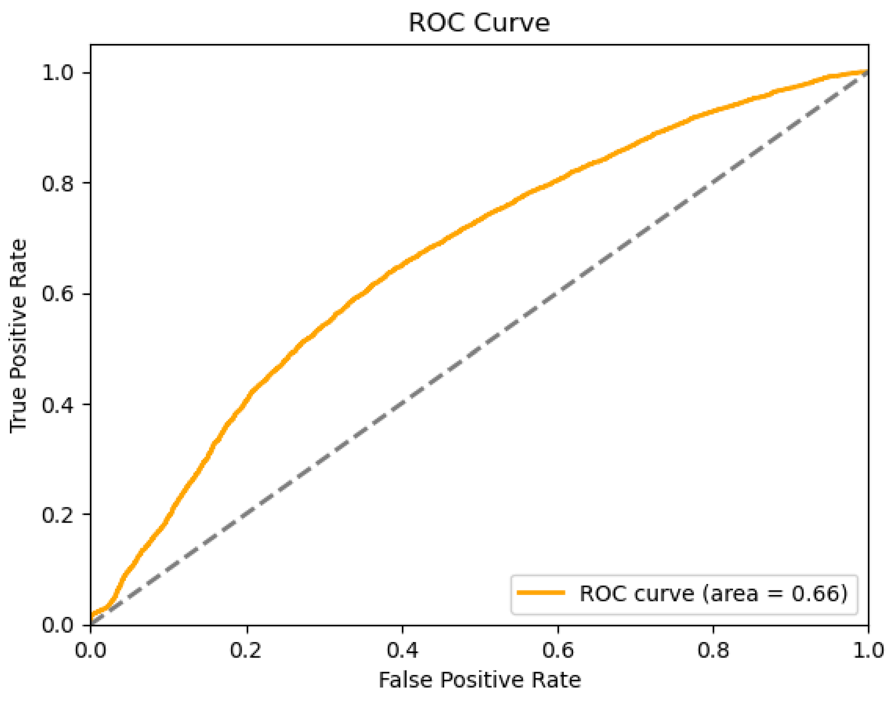
```
              precision    recall  f1-score   support

           0       0.61      0.11      0.19      5837
           1       0.70      0.97      0.81     12783

    accuracy                           0.70     18620
   macro avg       0.65      0.54      0.50     18620
weighted avg       0.67      0.70      0.62     18620
```

In [73]:
```python
# ROC curve and AUC value
fpr, tpr, _ = roc_curve(y_test, predicted_probs)
roc_auc = auc(fpr, tpr)
plt.figure()
plt.plot(fpr, tpr, color='orange', lw=2, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc="lower right")
plt.show()

print(f"AUC: {roc_auc}")
```




```
AUC: 0.6609746599619529
```

In [83]:
```python
# Interpretation of metrics
accuracy = conf_matrix.diagonal().sum() / conf_matrix.sum()
precision = conf_matrix[1, 1] / (conf_matrix[0, 1] + conf_matrix[1, 1])
recall = conf_matrix[1, 1] / (conf_matrix[1, 0] + conf_matrix[1, 1])
f1_score = 2 * (precision * recall) / (precision + recall)

print(f"Accuracy: {accuracy}")
print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1 Score: {f1_score}")
```

```
Accuracy: 0.6984425349087003
Precision: 0.7040537462992484
Recall: 0.9673785496362356
F1 Score: 0.8149734734899661
```