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Business Understanding

Customer churn, the phenomenon where customers cease doing business with a company, is a critical concern for telecommunications companies like SyriaTel. Retaining customers is essential for maintaining revenue and growth in this competitive industry. Identifying factors contributing to churn, such as service dissatisfaction or competitive offers, SyriaTel can take targeted actions to mitigate churn and improve customer retention.

Introduction

This project aims to build a predictive model for SyriaTel, a telecommunications company, to identify customers at risk of churning.Accurately predicting customer churn, SyriaTel can proactively implement retention strategies, thereby reducing financial losses and enhancing customer loyalty.

Background

Syria is a country located in the Middle East, has a telecommunications sector experiencing rapid growth in mobile and internet penetration. SyriaTel, as a key player in this sector, plays a vital role in connecting people and businesses. However, increasing competition and evolving customer preferences pose challenges for customer retention. Understanding and addressing the drivers of churn are crucial for SyriaTel to sustain business success and enhance customer satisfaction

Business Problem

SyriaTel, a telecommunications company, faces the challenge of customer churn, where customers discontinue their services. This attrition impacts revenue and profitability. The business seeks to proactively identify customers at risk of churning and implement effective retention strategies to mitigate revenue loss and maintain customer loyalty.

Specifically, the project aims to address the following questions:

1.What are the primary factors driving customer churn for SyriaTel?

2.Which machine learning modelling technique to apply in accurately predicting Churn so as to take proactive measures?

3.What actionable insights can SyriaTel derive from the predictive model to improve customer retention efforts?

4.What strategies can SyriaTel put in place to reduce churn rate?

Data Understanding

Importing neccessary Libraries

In [1]:

```
import warnings
warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
import datetime as dt
from collections import Counter
import calendar
from dateutil import relativedelta
import operator
import os
import random
from functools import reduce
import matplotlib.pyplot as plt
import seaborn as sns
from itertools import combinations
import warnings
import matplotlib.ticker as ticker

pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
pd.set_option('display.float_format', lambda x: f'%.{len(str(x%1))-2}f' % x)
pd.set_option('display.max_colwidth', None)
%matplotlib inline
```

Loading the dataset

In [2]:

```
df = pd.read_csv("C:\\Users\\User\\Documents\\Phase_3_Project\\SyriaTel_df.csv")
df = df.copy()
```

Understanding the dataframe

In [3]:

```
df.head()
```

Out[3]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	total
0	KS	128	415	382-4657	no	yes	25	265.10000000000002274	110	45.07000000000000028	197.400000
1	OH	107	415	371-7191	no	yes	26	161.59999999999999943	123	27.46999999999999886	
2	NJ	137	415	358-1921	no	no	0	243.40000000000000057	114	41.38000000000000256	121.2000000
3	OH	84	408	375-9999	yes	no	0	299.39999999999997726	71	50.89999999999999986	61.899999
4	OK	75	415	330-6626	yes	no	0	166.69999999999999886	113	28.33999999999999986	148.300000

In [4]:
```
df.tail()
```

Out[4]:

	state	account length	area code	phone number	international plan	voice mail plan	number vmail messages	total day minutes	total day calls	total day charge	tot
3328	AZ	192	415	414-4276	no	yes	36	156.19999999999998863	77	26.5500000000000007	
3329	WV	68	415	370-3271	no	no	0	231.09999999999999432	57	39.28999999999999915	153.4000
3330	RI	28	510	328-8230	no	no	0	180.8000000000000114	109	30.7399999999999984	288.8000
3331	CT	184	510	364-6381	yes	no	0	213.8000000000000114	105	36.3500000000000014	159.5999
3332	TN	74	415	400-4344	no	yes	25	234.4000000000000057	113	39.8500000000000014	265.8999

In [5]:
```
df.columns
```

Out[5]:
```
Index(['state', 'account length', 'area code', 'phone number',
       'international plan', 'voice mail plan', 'number vmail messages',
       'total day minutes', 'total day calls', 'total day charge',
       'total eve minutes', 'total eve calls', 'total eve charge',
       'total night minutes', 'total night calls', 'total night charge',
       'total intl minutes', 'total intl calls', 'total intl charge',
       'customer service calls', 'churn'],
      dtype='object')
```

In [6]:
```
df.shape
```

Out[6]:
```
(3333, 21)
```

Changing Columns into Title cases

In [7]:
```
df.columns = df.columns.str.title()
df.columns
```

Out[7]:
```
Index(['State', 'Account Length', 'Area Code', 'Phone Number',
       'International Plan', 'Voice Mail Plan', 'Number Vmail Messages',
       'Total Day Minutes', 'Total Day Calls', 'Total Day Charge',
       'Total Eve Minutes', 'Total Eve Calls', 'Total Eve Charge',
       'Total Night Minutes', 'Total Night Calls', 'Total Night Charge',
       'Total Intl Minutes', 'Total Intl Calls', 'Total Intl Charge',
       'Customer Service Calls', 'Churn'],
      dtype='object')
```

In [8]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 21 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   State                   3333 non-null   object 
 1   Account Length          3333 non-null   int64  
 2   Area Code               3333 non-null   int64  
 3   Phone Number            3333 non-null   object 
 4   International Plan      3333 non-null   object 
 5   Voice Mail Plan         3333 non-null   object 
 6   Number Vmail Messages   3333 non-null   int64  
 7   Total Day Minutes       3333 non-null   float64
 8   Total Day Calls         3333 non-null   int64  
 9   Total Day Charge        3333 non-null   float64
 10  Total Eve Minutes       3333 non-null   float64
 11  Total Eve Calls         3333 non-null   int64  
 12  Total Eve Charge        3333 non-null   float64
 13  Total Night Minutes     3333 non-null   float64
 14  Total Night Calls       3333 non-null   int64  
 15  Total Night Charge      3333 non-null   float64
 16  Total Intl Minutes      3333 non-null   float64
 17  Total Intl Calls        3333 non-null   int64  
 18  Total Intl Charge       3333 non-null   float64
 19  Customer Service Calls  3333 non-null   int64  
 20  Churn                   3333 non-null   bool   
dtypes: bool(1), float64(8), int64(8), object(4)
memory usage: 524.2+ KB
```

Identifying the type of columns

In [9]:

```python
# Identifying columns
df['Churn'] = df['Churn'].astype(bool)

numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns.tolist()
categorical_cols = df.select_dtypes(include=['object', 'bool']).columns.tolist()

# Removing 'Phone Number' from categorical columns if it exists
string_cols = ['Phone Number']
for col in string_cols:
    if col in categorical_cols:
        categorical_cols.remove(col)

# Print the identified columns
print("Numerical columns:")
print(numerical_cols)

print("\nCategorical columns:")
print(categorical_cols)

print("\nString columns:")
print(string_cols)
```

```
Numerical columns:
['Account Length', 'Area Code', 'Number Vmail Messages', 'Total Day Minutes', 'Total Day Calls', 'Total
Day Charge', 'Total Eve Minutes', 'Total Eve Calls', 'Total Eve Charge', 'Total Night Minutes', 'Total N
ight Calls', 'Total Night Charge', 'Total Intl Minutes', 'Total Intl Calls', 'Total Intl Charge', 'Custo
mer Service Calls']

Categorical columns:
['State', 'International Plan', 'Voice Mail Plan', 'Churn']

String columns:
['Phone Number']
```

In [10]:
```
df.count()
```

Out[10]:
```
State                     3333
Account Length            3333
Area Code                 3333
Phone Number              3333
International Plan        3333
Voice Mail Plan           3333
Number Vmail Messages     3333
Total Day Minutes         3333
Total Day Calls           3333
Total Day Charge          3333
Total Eve Minutes         3333
Total Eve Calls           3333
Total Eve Charge          3333
Total Night Minutes       3333
Total Night Calls         3333
Total Night Charge        3333
Total Intl Minutes        3333
Total Intl Calls          3333
Total Intl Charge         3333
Customer Service Calls    3333
Churn                     3333
dtype: int64
```

Checking for null values

In [11]:
```
df.isnull().sum()
```

Out[11]:
```
State                     0
Account Length            0
Area Code                 0
Phone Number              0
International Plan        0
Voice Mail Plan           0
Number Vmail Messages     0
Total Day Minutes         0
Total Day Calls           0
Total Day Charge          0
Total Eve Minutes         0
Total Eve Calls           0
Total Eve Charge          0
Total Night Minutes       0
Total Night Calls         0
Total Night Charge        0
Total Intl Minutes        0
Total Intl Calls          0
Total Intl Charge         0
Customer Service Calls    0
Churn                     0
dtype: int64
```

Checking for duplicates

In [12]:
```
df.duplicated().sum()
```

Out[12]:
```
0
```

In [13]:
```
# function to identify unique values
for column in df.select_dtypes(include=['number']):
    unique_values = df[column].unique()
    print(f"Unique values in column '{column}': {unique_values}")

```

```
  4.94  9.02 11.22  4.97  9.15  5.45  7.27 12.91  7.75 13.46  6.32 12.13
 11.97  6.93 11.66  7.42  6.19 11.41 10.33 10.65 11.92  4.77  4.38  7.41
 12.1   7.69  8.78  9.36  9.05 12.7   6.16  6.05 10.85  8.93  3.48 10.4
  5.05 10.71  9.37  6.75  8.12 11.77 11.49 11.06 11.25 11.03 10.82  8.91
  8.57  8.09 10.05 11.7  10.17  8.74  5.51 11.11  3.29 10.13  6.8   8.49
  9.55 11.02  9.91  7.84 10.62  9.97  3.44  7.35  9.79  8.89  8.14  6.94
 10.49 10.57 10.2   6.29  8.79 10.04 12.41 15.97  9.1  11.78 12.75 11.07
 12.56  8.63  8.02 10.42  8.7   9.98  7.62  8.33  6.59 13.12 10.46  6.63
  8.32  9.04  9.28 10.76  9.64 11.44  6.48 10.81 12.66 11.34  8.75 13.05
 11.48 14.04 13.47  5.63  6.6   9.72 11.68  6.41  9.32 12.95 13.37  9.62
  6.03  8.25  8.26 11.96  9.9   9.23  5.58  7.22  6.64 12.29 12.93 11.32
  6.85  8.88  7.03  8.48  3.59  5.86  6.23  7.61  7.66 13.63  7.9  11.82
  7.47  6.08  8.4   5.74 10.94 10.35 10.68  4.34  8.73  5.14  8.24  9.99
 13.93  8.64 11.43  5.79  9.2  10.14 12.11  7.53 12.46  8.46  8.95  9.84
 10.8  11.23 10.15  9.21 14.46  6.67 12.83  9.66  9.59 10.48  8.36  4.84
 10.54  8.39  7.43  9.06  8.94 11.13  8.87  8.5   7.6  10.73  9.56 10.77
  7.73  3.47 11.86  8.11  9.78  9.42  9.65  7.    7.39  9.88  6.56  5.92
  6.95 15.71  8.06  4.86  7.8   8.58 10.06  5.21  6.92  6.15 13.49  9.38
 12.62 12.26  8.19 11.65 11.62 10.83  7.92  7.33 13.01 13.26 12.22 11.58
  5.97 10.99  8.38  9.17  8.08  5.71  3.41 12.63 11.79 12.96  7.64  6.58
```

Describing the dataframe

In [14]:
```
df.describe()
```

Out[14]:

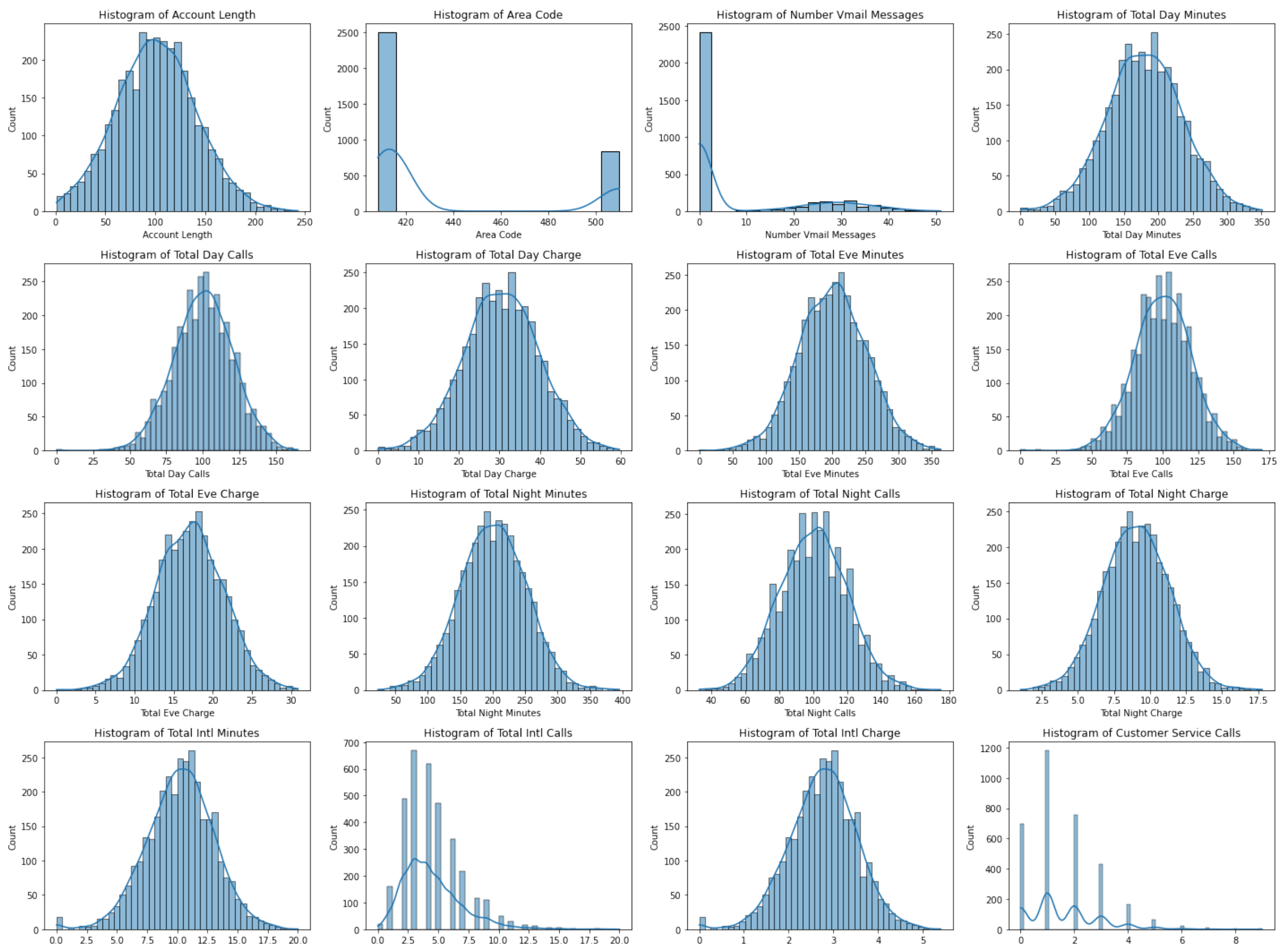
	Account Length	Area Code	Number Vmail Messages	Total Day Minutes	Total Day Calls	Tota
count	3333.0	3333.0	3333.0	3333.0	3333.0	
mean	101.06480648064805905	437.18241824182416622	8.0990099009900991	179.7750975097509354	100.4356435643564396	30.562
std	39.8221059285956045	42.3712904856066146	13.6883653720385983	54.46738920237137194	20.0690842073008966	9.2594
min	1.0	408.0	0.0	0.0	0.0	
25%	74.0	408.0	0.0	143.6999999999999886	87.0	24.4299
50%	101.0	415.0	0.0	179.4000000000000057	101.0	
75%	127.0	510.0	20.0	216.4000000000000057	114.0	36.7899
max	243.0	510.0	51.0	350.8000000000000114	165.0	59.6400

Univariant Analysis

Numerical Columns

In [15]:

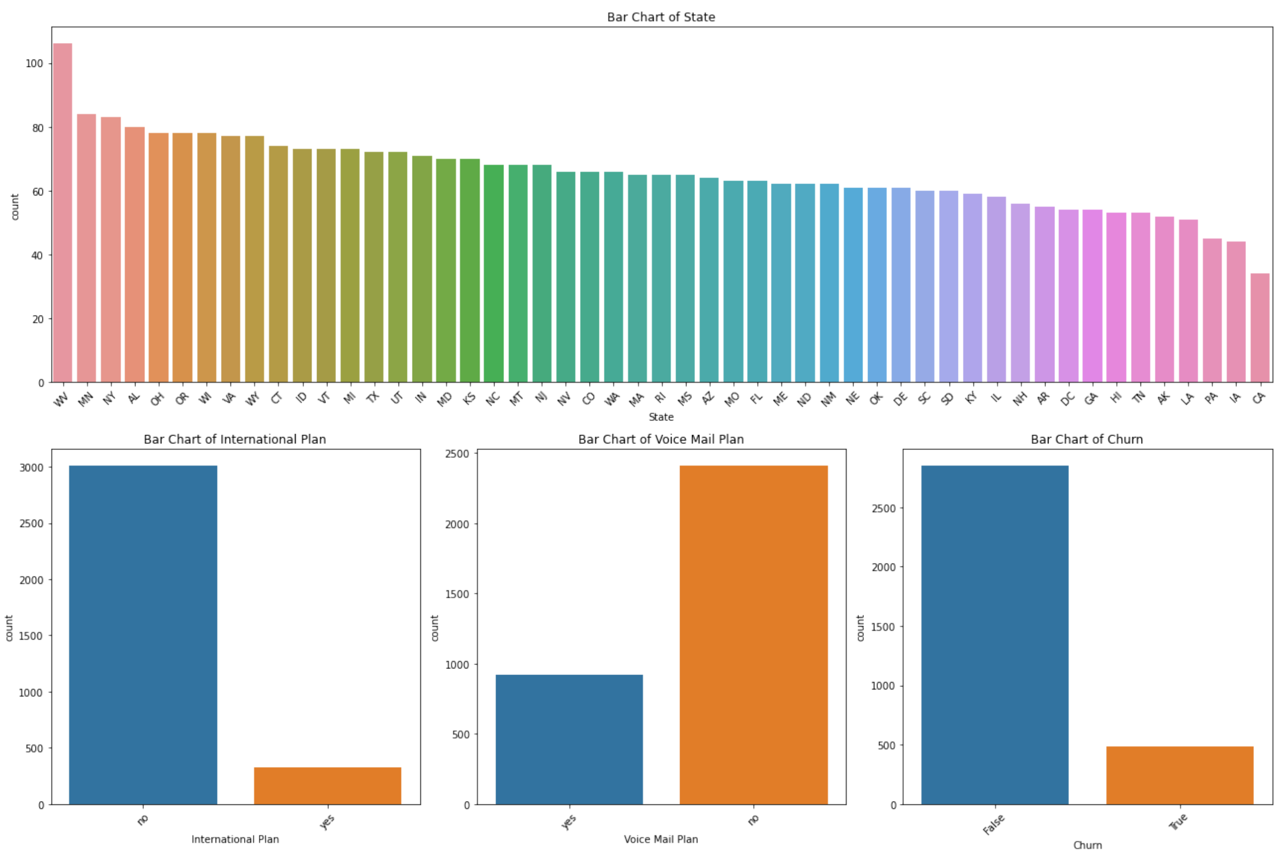
```python
# List of numerical columns
numerical_cols = ['Account Length', 'Area Code', 'Number Vmail Messages', 'Total Day Minutes', 'Total
                  'Total Day Charge', 'Total Eve Minutes', 'Total Eve Calls', 'Total Eve Charge',
                  'Total Night Minutes', 'Total Night Calls', 'Total Night Charge', 'Total Intl Minut
                  'Total Intl Calls', 'Total Intl Charge', 'Customer Service Calls']

# Set the size of the plots
plt.figure(figsize=(20, 15))

# Create histograms for each numerical column
for i, col in enumerate(numerical_cols):
    plt.subplot(4, 4, i + 1)  # Adjust subplot layout as needed
    sns.histplot(df[col], kde=True)
    plt.title(f'Histogram of {col}')

# Adjust layout
plt.tight_layout()
plt.show()
```



Categorical Columns

In [16]:

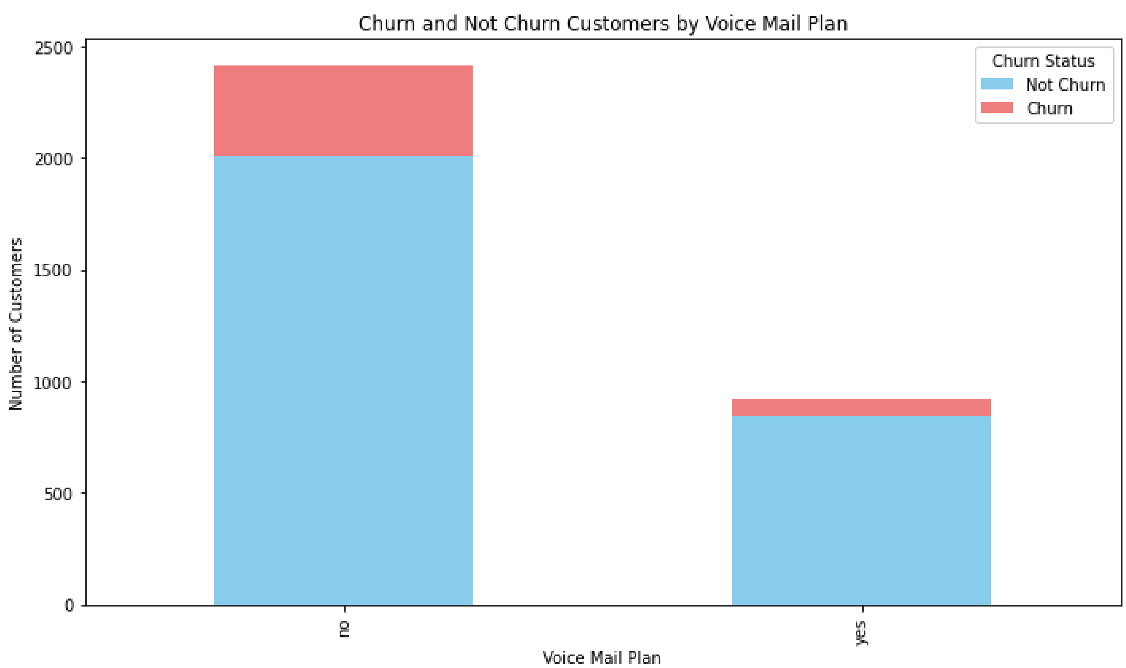
```python

# List of categorical columns, excluding 'Phone Number'
categorical_cols = ['State', 'International Plan', 'Voice Mail Plan', 'Churn']

# Set the size of the overall figure
plt.figure(figsize=(18, 12))

# Calculate the order of states by their count in descending order
state_order = df['State'].value_counts().index

# Create bar plot for 'State' with a larger size and ordered
plt.subplot(2, 1, 1)  # 2 rows, 1 column, 1st subplot
sns.countplot(data=df, x='State', order=state_order)
plt.title('Bar Chart of State')
plt.xticks(rotation=45)  # Rotate x labels if needed

# Create smaller bar plots for the other categorical columns
for i, col in enumerate(categorical_cols[1:], start=1):
    plt.subplot(2, 3, i + 3)  # 2 rows, 3 columns, starting from 4th subplot
    sns.countplot(data=df, x=col)
    plt.title(f'Bar Chart of {col}')
    plt.xticks(rotation=45)  # Rotate x labels if needed

# Adjust layout
plt.tight_layout()
plt.show()

```



Bivariant Analysis

In [17]:

```
# Group by 'Voice Mail Plan' and 'Churn' to get the counts
vmail_plan_churn_counts = df.groupby(['Voice Mail Plan', 'Churn']).size().unstack().fillna(0)

# Sort the categories by the total count of customers in descending order
vmail_plan_churn_counts['Total'] = vmail_plan_churn_counts.sum(axis=1)
vmail_plan_churn_counts = vmail_plan_churn_counts.sort_values(by='Total', ascending=False).drop(colum

# Plotting the stacked bar plot
vmail_plan_churn_counts.plot(kind='bar', stacked=True, figsize=(10, 6), color=['skyblue', 'lightcoral

# Adding title and labels
plt.title('Churn and Not Churn Customers by Voice Mail Plan')
plt.xlabel('Voice Mail Plan')
plt.ylabel('Number of Customers')
plt.legend(['Not Churn', 'Churn'], title='Churn Status')

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

```



Count of Churn Customers Per State

In [18]:

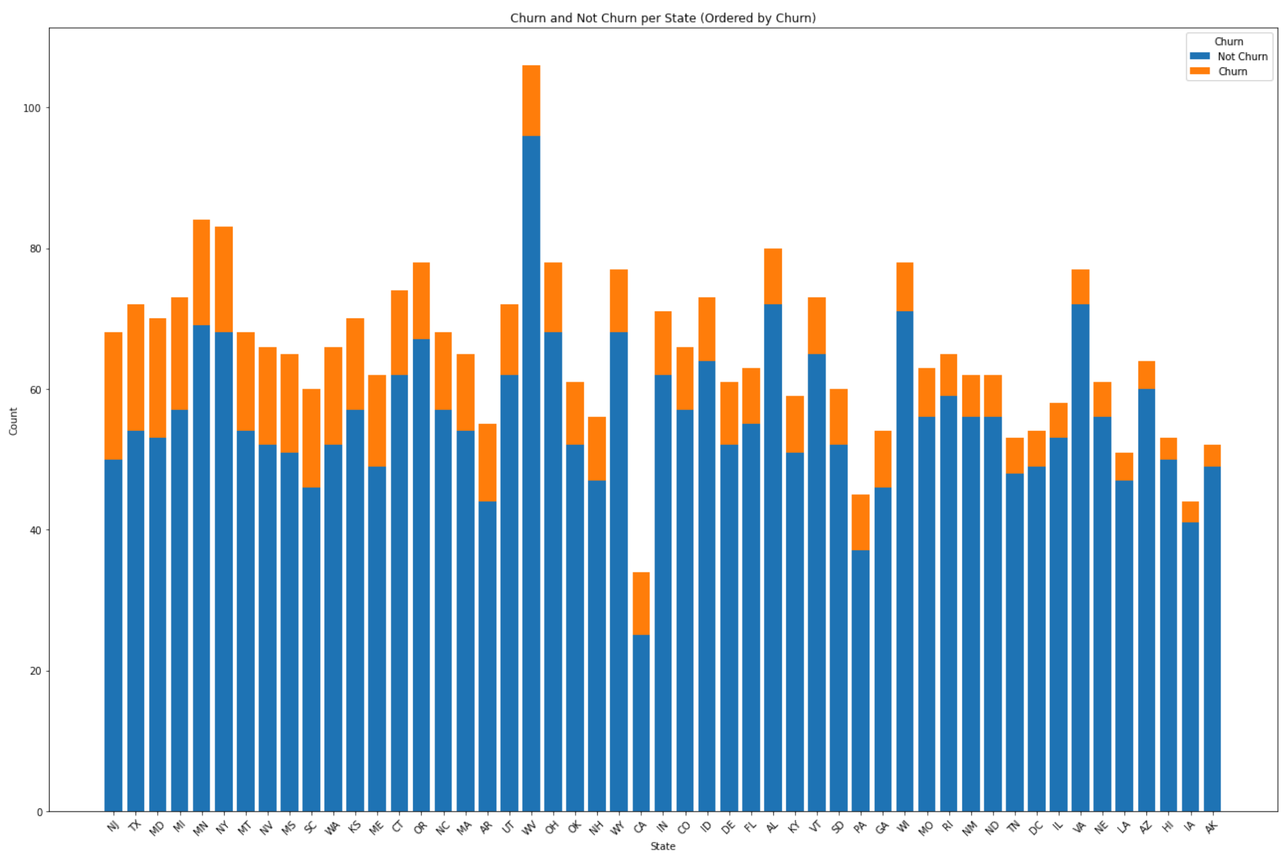
```
count_churn = df.groupby(["Churn", "State"]).agg(churn_count = ("Churn", "count")).reset_index()
count_churn.head()
```

Out[18]:

	Churn	State	churn_count
0	False	AK	49
1	False	AL	72
2	False	AR	44
3	False	AZ	60
4	False	CA	25

In [19]:

```
# Encode the "Churn" column to 0 and 1
df['Churn'] = df['Churn'].map({False: 0, True: 1})

# Group by "State" and "Churn" and count the occurrences
count_churn = df.groupby(['State', 'Churn']).size().unstack(fill_value=0)

# Sort the DataFrame by the number of churned customers (Churn = 1) in descending order
count_churn_sorted = count_churn.sort_values(by=1, ascending=False)

# Create a new column 'State' from the index to use in seaborn
count_churn_sorted = count_churn_sorted.reset_index()

# Plotting the stacked bar plot
plt.figure(figsize=(18, 12))
bottom = count_churn_sorted[0]
top = count_churn_sorted[1]

# Plot the not churned customers
plt.bar(count_churn_sorted['State'], bottom, label='Not Churn', color='#1f77b4')

# Plot the churned customers on top of the not churned
plt.bar(count_churn_sorted['State'], top, bottom=bottom, label='Churn', color='#ff7f0e')

plt.title('Churn and Not Churn per State (Ordered by Churn)')
plt.ylabel('Count')
plt.xlabel('State')
plt.xticks(rotation=45)  # Rotate x labels if needed
plt.legend(title='Churn')

# Show plot
plt.tight_layout()
plt.show()
```



Count of Churn Customers Per Area Code

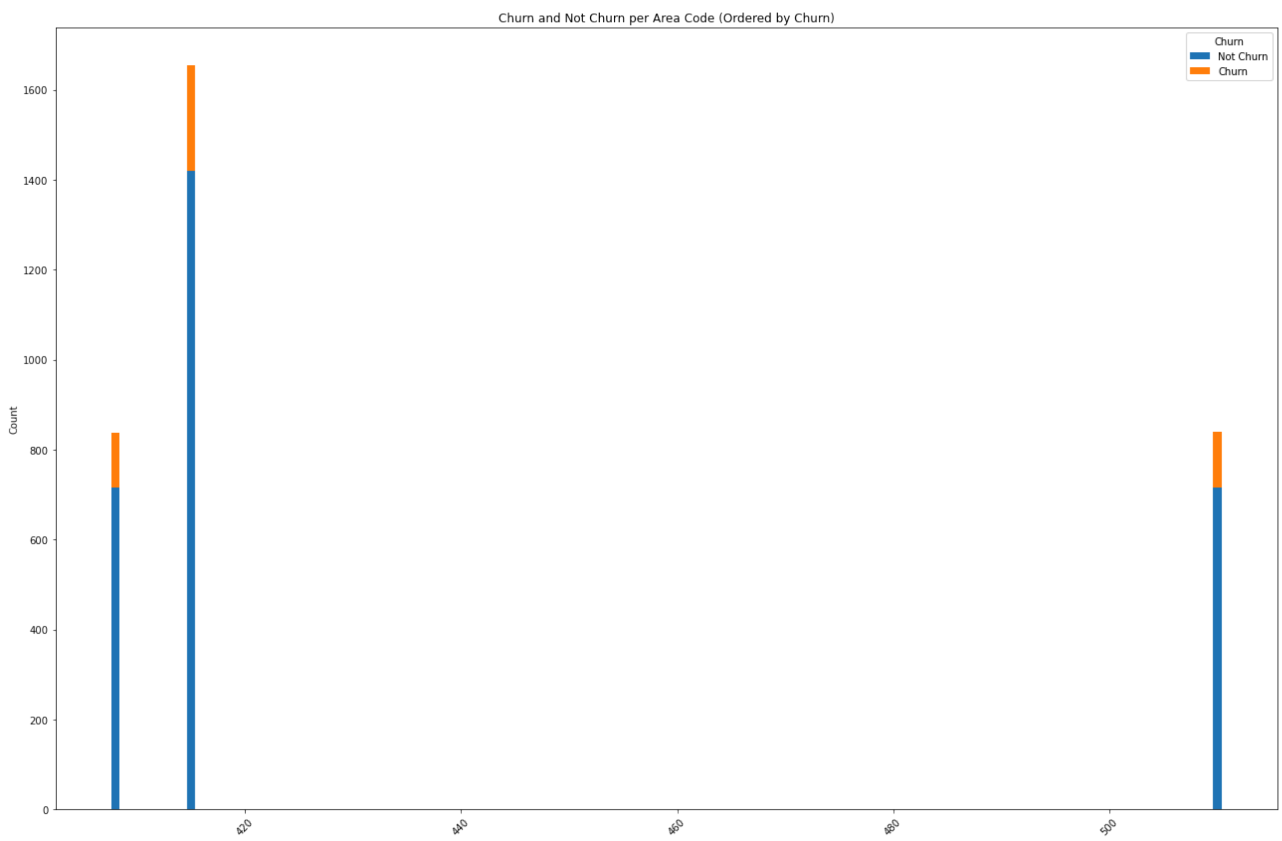
In [20]:
```
count_area_code_sorted = df.groupby(["Churn", "Area Code"]).agg(count_area_code = ("Churn", "count"))
count_area_code_sorted.head(10)
```

Out[20]:

	Churn	Area Code	count_area_code
0	0	408	716
1	0	415	1419
2	0	510	715
3	1	408	122
4	1	415	236
5	1	510	125

In [21]:

```python
# Encode the "Churn" column to 0 and 1
df['Churn'] = df['Churn'].map({False: 0, True: 1})

# Group by "Area Code" and "Churn" and count the occurrences
count_area_code_sorted = df.groupby(['Area Code', 'Churn']).size().unstack(fill_value=0)

# Sort the DataFrame by the number of churned customers (Churn = 1) in descending order
count_area_code_sorted_sorted = count_area_code_sorted.sort_values(by=1, ascending=False)

# Create a new column 'Area Code' from the index to use in seaborn
count_area_code_sorted_sorted = count_area_code_sorted_sorted.reset_index()

# Plotting the stacked bar plot
plt.figure(figsize=(18, 12))
bottom = count_area_code_sorted_sorted[0]
top = count_area_code_sorted_sorted[1]

# Plot the not churned customers
plt.bar(count_area_code_sorted_sorted['Area Code'], bottom, label='Not Churn', color='#1f77b4')

# Plot the churned customers on top of the not churned
plt.bar(count_area_code_sorted_sorted['Area Code'], top, bottom=bottom, label='Churn', color='#ff7f0e

plt.title('Churn and Not Churn per Area Code (Ordered by Churn)')
plt.ylabel('Count')
plt.xlabel('Area Code')
plt.xticks(rotation=45)  # Rotate x labels if needed
plt.legend(title='Churn')

# Show plot
plt.tight_layout()
plt.show()
```



Creating Account Category Column

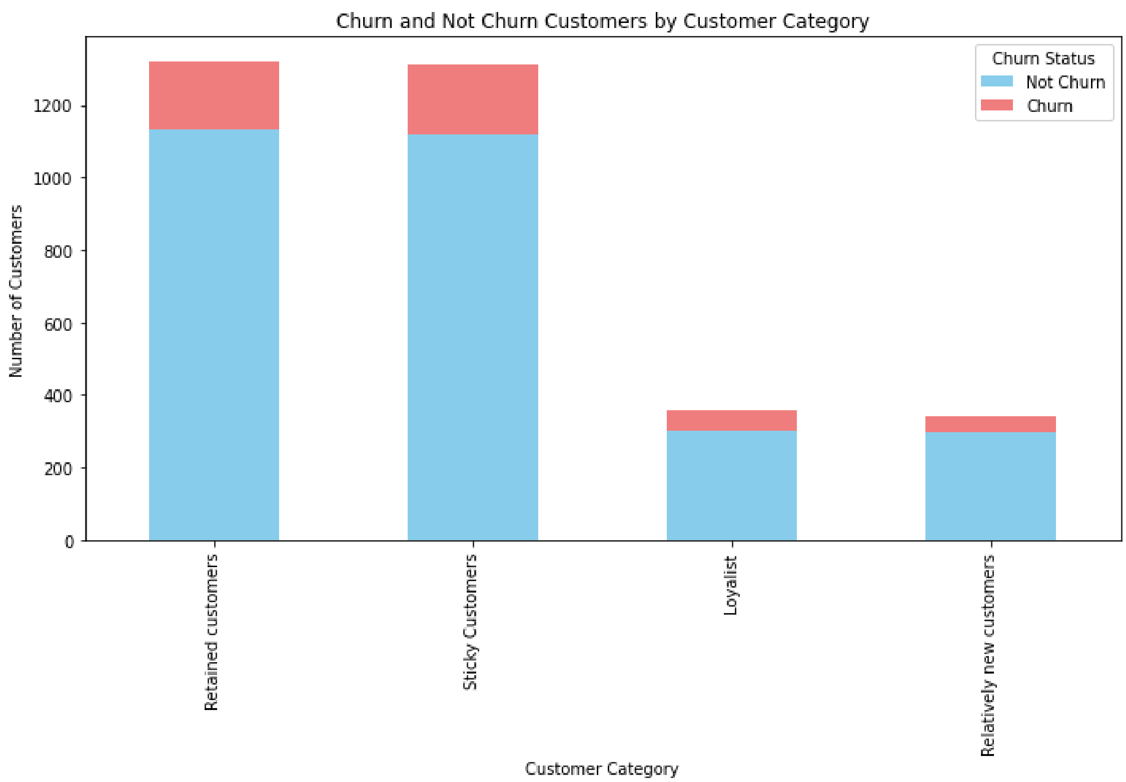
In [22]:
```
import pandas as pd

# Function to categorize customers
def categorize_customer(account_length):
    if account_length <= 50:
        return 'Relatively new customers'
    elif 50 < account_length <= 100:
        return 'Retained customers'
    elif 100 < account_length <= 150:
        return 'Sticky Customers'
    else:
        return 'Loyalist'

# Create the Customer Category column in df
df['Customer Category'] = df['Account Length'].apply(categorize_customer)

# Display the first few rows to verify
print(df[['Account Length', 'Customer Category']].head())

```

```
   Account Length   Customer Category
0             128    Sticky Customers
1             107    Sticky Customers
2             137    Sticky Customers
3              84  Retained customers
4              75  Retained customers
```

Distribution of Customer Category vs Churn

In [23]:

```
# Group by 'Customer Category' and 'Churn' to get the counts
category_churn_counts = df.groupby(['Customer Category', 'Churn']).size().unstack().fillna(0)

# Sort the categories by the total count of customers in descending order
category_churn_counts['Total'] = category_churn_counts.sum(axis=1)
category_churn_counts = category_churn_counts.sort_values(by='Total', ascending=False).drop(columns='

# Plotting the stacked bar plot
category_churn_counts.plot(kind='bar', stacked=True, figsize=(10, 7), color=['skyblue', 'lightcoral']

# Adding title and labels
plt.title('Churn and Not Churn Customers by Customer Category')
plt.xlabel('Customer Category')
plt.ylabel('Number of Customers')
plt.legend(['Not Churn', 'Churn'], title='Churn Status')

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



Plot of Syria using the Area_Code

In [24]:

```
# Extract unique area codes
unique_area_codes = df['Area Code'].unique()

# Print all unique area codes
print("Unique Area Codes:")
for area_code in unique_area_codes:
    print(area_code)
```

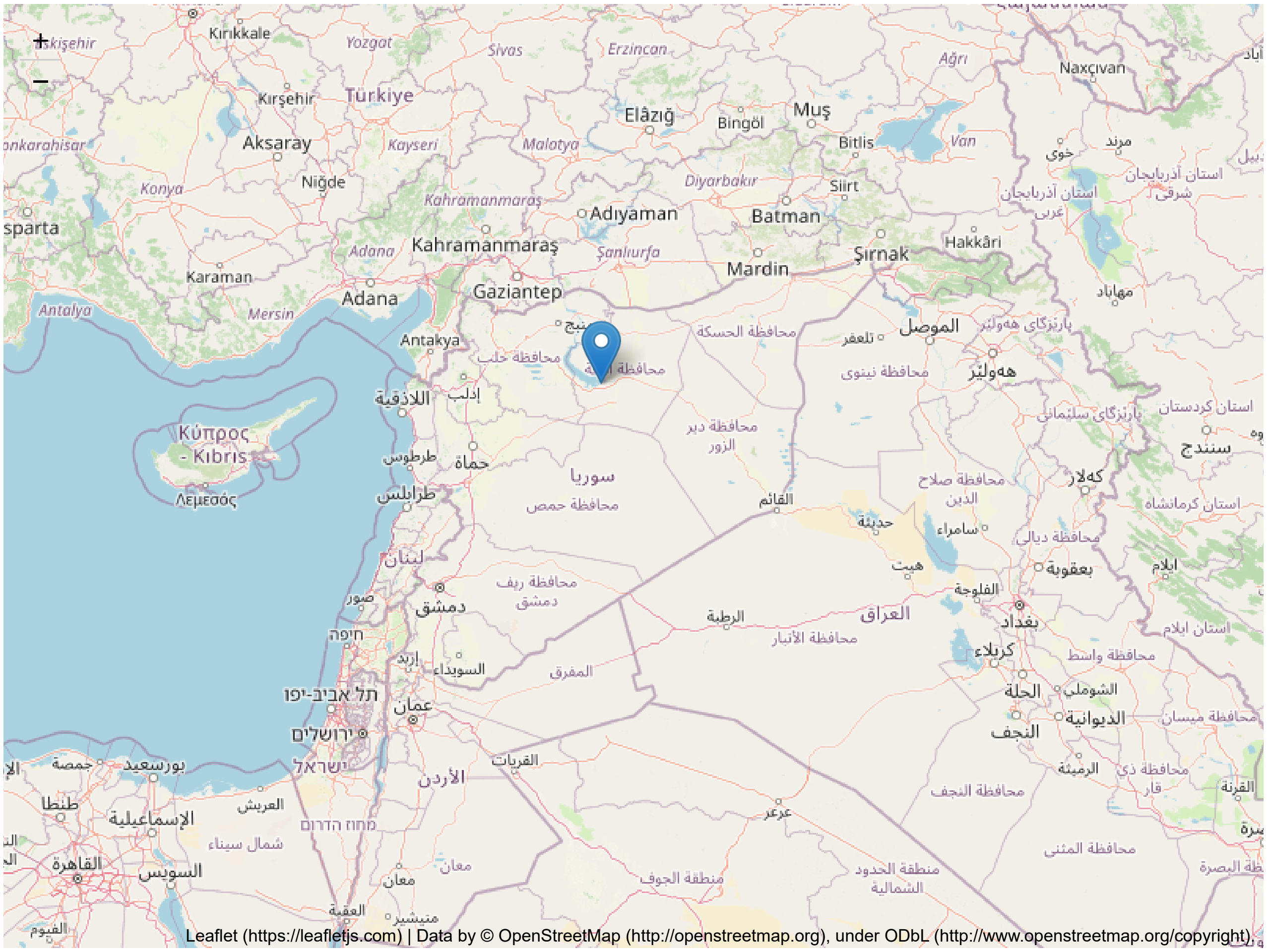
```
Unique Area Codes:
415
408
510
```

In [25]:

```python
!pip install geopy folium
from geopy.geocoders import Nominatim
import folium

# Extract unique area codes
unique_area_codes = df['Area Code'].unique()

# Initialize geocoder with a longer timeout
geolocator = Nominatim(user_agent="area_locator", timeout=10)

# Create a map centered on Syria
map_syria = folium.Map(location=[34.802075, 38.996815], zoom_start=6)

# Loop through unique area codes and get coordinates
for area_code in unique_area_codes:
    try:
        location = geolocator.geocode(f"{area_code}, Syria")
        if location:
            # Add marker to the map
            folium.Marker([location.latitude, location.longitude], popup=f"Area Code: {area_code}").a
    except Exception as e:
        print(f"Error fetching location for area code {area_code}: {e}")

# Save the map as an HTML file
map_syria.save("area_codes_map.html")

# Display the map in a Jupyter notebook
from IPython.display import IFrame
IFrame("area_codes_map.html", width=800, height=600)

```

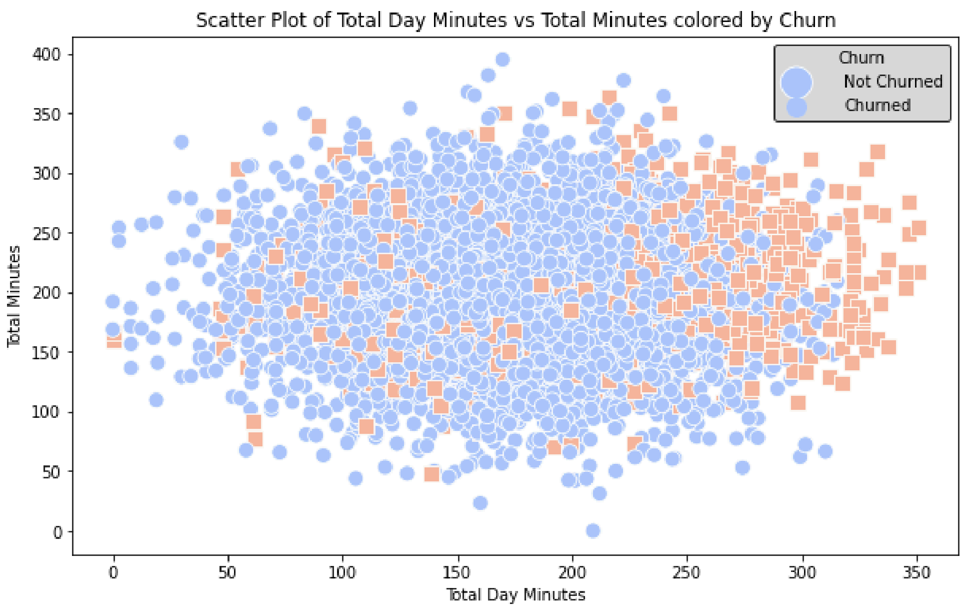
```
Requirement already satisfied: geopy in c:\users\user\anaconda3\envs\learn-env\lib\site-packages (2.4.1)
Requirement already satisfied: folium in c:\users\user\anaconda3\envs\learn-env\lib\site-packages (0.11.
0)
Requirement already satisfied: geographiclib<3,>=1.52 in c:\users\user\anaconda3\envs\learn-env\lib\site
-packages (from geopy) (2.0)
Requirement already satisfied: numpy in c:\users\user\anaconda3\envs\learn-env\lib\site-packages (from f
olium) (1.18.5)
Requirement already satisfied: branca>=0.3.0 in c:\users\user\anaconda3\envs\learn-env\lib\site-packages
(from folium) (0.4.1)
Requirement already satisfied: jinja2>=2.9 in c:\users\user\anaconda3\envs\learn-env\lib\site-packages
(from folium) (2.11.2)
Requirement already satisfied: requests in c:\users\user\anaconda3\envs\learn-env\lib\site-packages (fro
m folium) (2.24.0)
Requirement already satisfied: MarkupSafe>=0.23 in c:\users\user\anaconda3\envs\learn-env\lib\site-packa
ges (from jinja2>=2.9->folium) (1.1.1)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in c:\users\user\anaconda3\envs\l
earn-env\lib\site-packages (from requests->folium) (1.25.10)
Requirement already satisfied: chardet<4,>=3.0.2 in c:\users\user\anaconda3\envs\learn-env\lib\site-pack
ages (from requests->folium) (3.0.4)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\user\anaconda3\envs\learn-env\lib\site-pac
kages (from requests->folium) (2020.6.20)
Requirement already satisfied: idna<3,>=2.5 in c:\users\user\anaconda3\envs\learn-env\lib\site-packages
(from requests->folium) (2.10)
```

Out[25]:


Kırıkkale
Yozgat
Sivas
Erzincan
Ağrı
Naxçıvan
Kırşehir
Türkiye
Elâzığ
Bingöl
Muş
Aksaray
Kayseri
Malatya
Bitlis
Van
Niğde
Diyarbakır
Siirt
Konya
Kahramanmaraş
Adıyaman
Batman
Hakkâri
Karaman
Adana
Kahramanmaraş
Şanlıurfa
Mardin
Şırnak
Antalya
Mersin
Adana
Gaziantep
Antakya
الموصل
اللاذقية
إدلب
Κύπρος - Kıbrıs
طرطوس
حماة
سوريا
Λεμεσός
طرابلس
لبنان
دمشق
بغداد
العراق
كربلاء
النجف
עמאן
תל אביב-יפו
ירושלים
ישראל
الأردن
القاهرة
السويس
Leaflet (https://leafletjs.com) | Data by © OpenStreetMap (http://openstreetmap.org), under ODbL (http://www.openstreetmap.org/copyright).

Multivariant Analysis

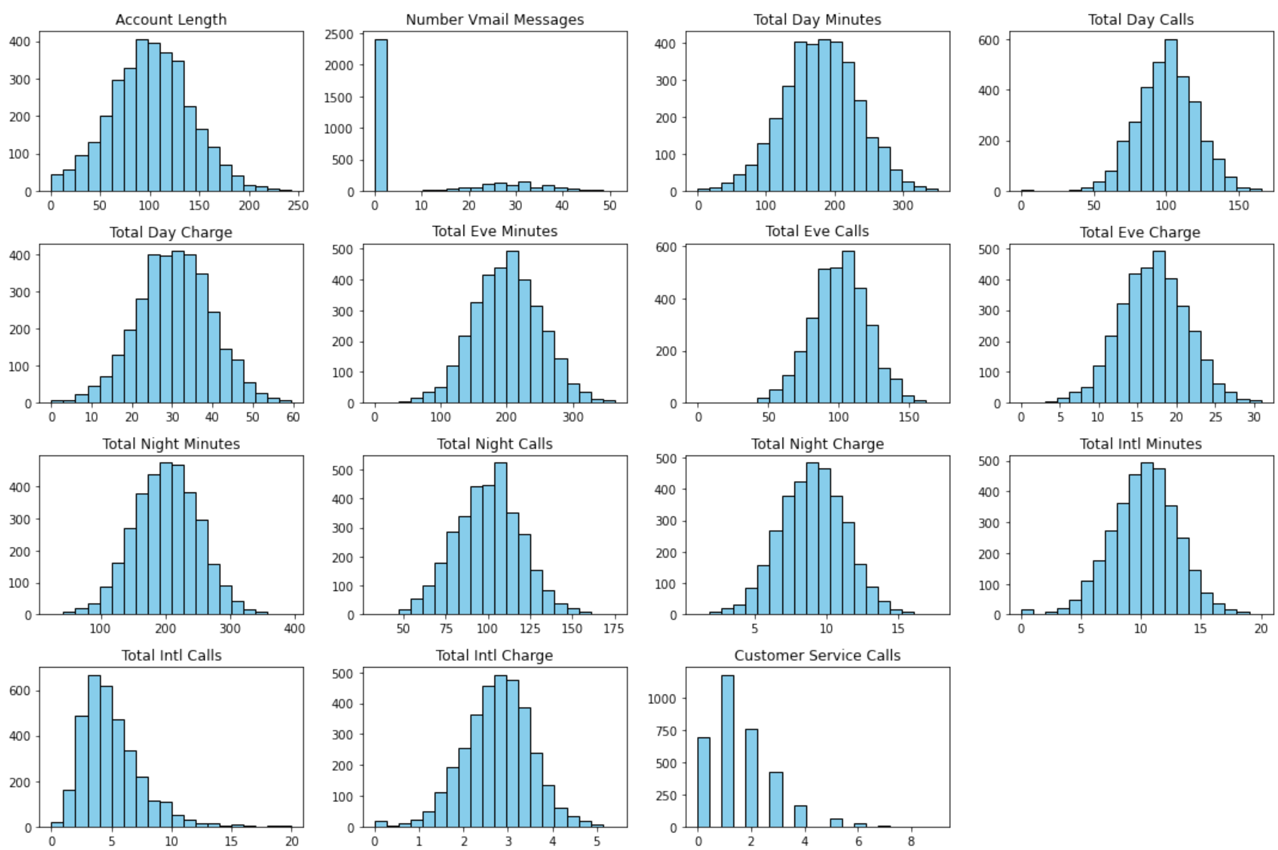
In [26]:
```
# Scatter plot of Total Day Minutes vs Total Eve Minutes vs Total Night Minutes colored by Churn
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Total Day Minutes', y='Total Eve Minutes', data=df, hue='Churn', style='Churn', pa
sns.scatterplot(x='Total Day Minutes', y='Total Night Minutes', data=df, hue='Churn', style='Churn', 
plt.xlabel('Total Day Minutes')
plt.ylabel('Total Minutes')
plt.title('Scatter Plot of Total Day Minutes vs Total Minutes colored by Churn')
legend_colors = {'Churned': sns.color_palette('coolwarm')[1], 'Not Churned': sns.color_palette('coolwa
plt.legend(title='Churn', loc='upper right', labels=['Not Churned', 'Churned'], facecolor='lightgrey'
plt.show()
```



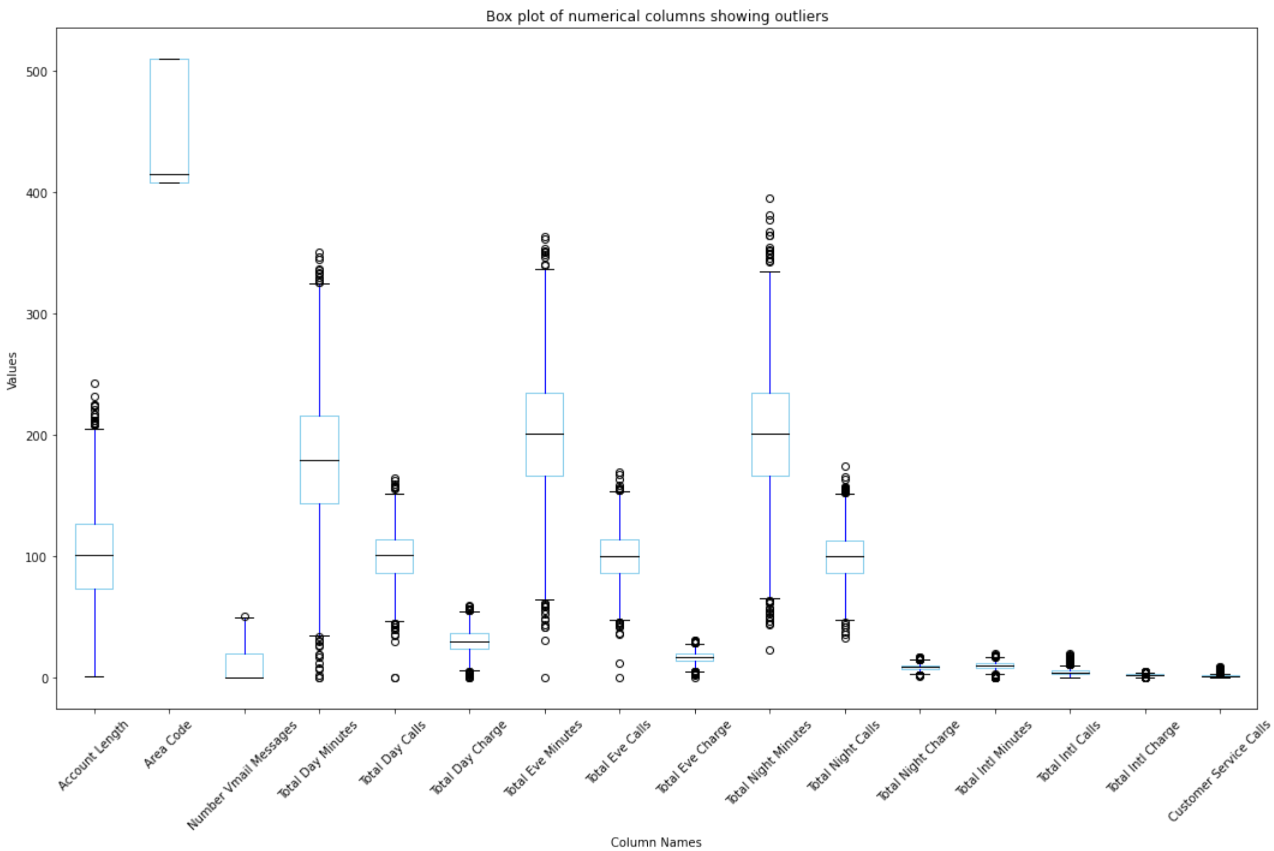
Data Preparation

In [27]:

```
# Select numerical columns excluding 'Area Code'
numerical_cols = ['Account Length', 'Number Vmail Messages', 'Total Day Minutes',
                  'Total Day Calls', 'Total Day Charge', 'Total Eve Minutes', 'Total Eve Calls',
                  'Total Eve Charge', 'Total Night Minutes', 'Total Night Calls',
                  'Total Night Charge', 'Total Intl Minutes', 'Total Intl Calls',
                  'Total Intl Charge', 'Customer Service Calls']

# Plot histograms before handling outliers
plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_cols, 1):
    plt.subplot(4, 4, i)
    plt.hist(df[col], bins=20, color='skyblue', edgecolor='black')
    plt.title(col)
plt.tight_layout()
plt.show()
```



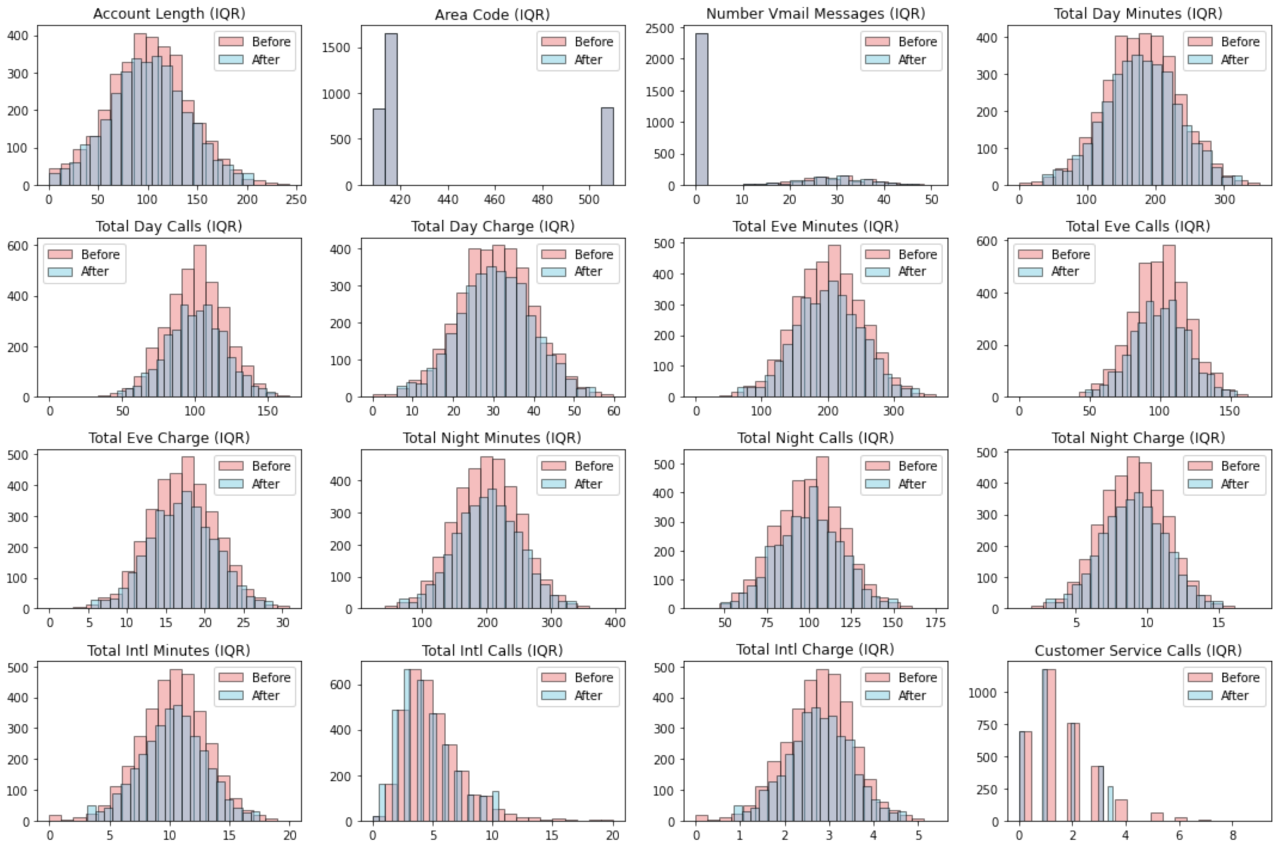
In [28]:
```
# List of numerical columns excluding 'Churn'
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns.drop('Churn')

# Create box plots for numerical columns showing outliers
plt.figure(figsize=(15, 10))
df[numerical_cols].boxplot(grid=False, color=dict(boxes='skyblue', whiskers='blue', medians='black', 
plt.title('Box plot of numerical columns showing outliers')
plt.xlabel('Column Names')
plt.ylabel('Values')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

```



Handling Outliers

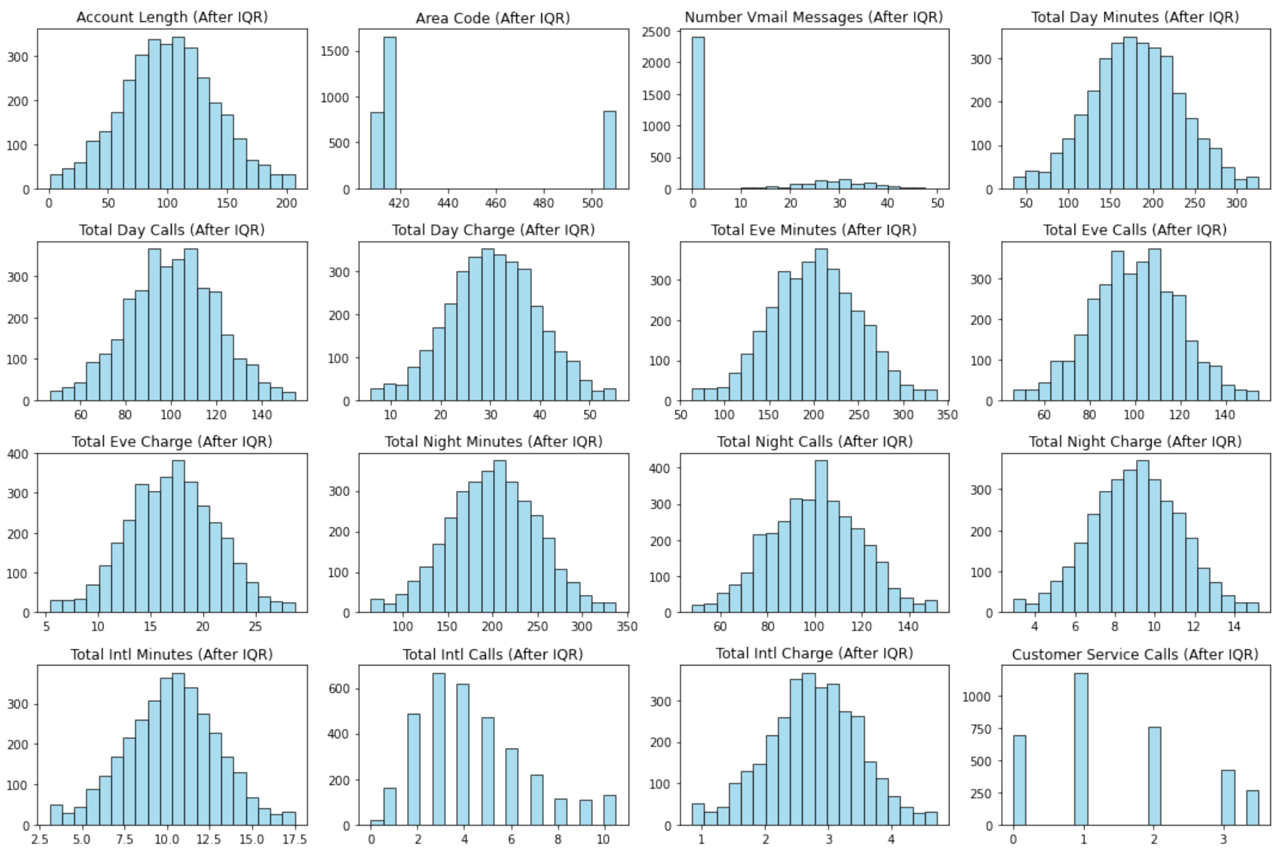
In [29]:

```
# Handling outliers using IQR
df_no_outliers = df.copy()
for col in numerical_cols:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    df_no_outliers[col] = df_no_outliers[col].clip(lower=lower_bound, upper=upper_bound)

# Plot histograms after handling outliers with different colors
plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_cols, 1):
    plt.subplot(4, 4, i)
    plt.hist(df[col], bins=20, color='lightcoral', edgecolor='black', alpha=0.5, label='Before')
    plt.hist(df_no_outliers[col], bins=20, color='skyblue', edgecolor='black', alpha=0.5, label='Afte
    plt.title(col + ' (IQR)')
    plt.legend()
plt.tight_layout()
plt.show()
```

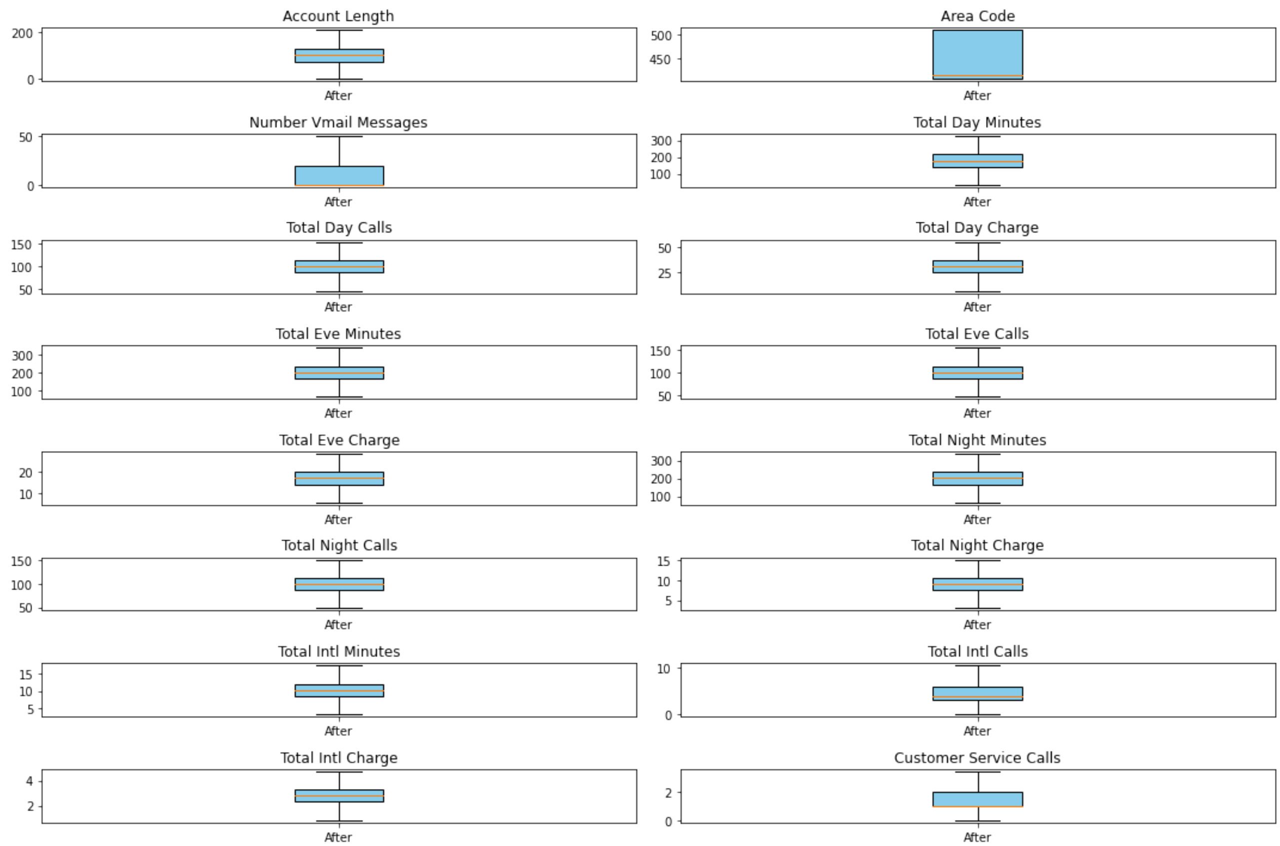


Plot After Handling Outliers

In [30]:
```
# List of numerical columns excluding 'Churn'
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns.drop('Churn')

# Handling outliers using IQR
df_no_outliers = df.copy()
for col in numerical_cols:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    df_no_outliers[col] = df_no_outliers[col].clip(lower=lower_bound, upper=upper_bound)

# Plot histograms for numerical columns after handling outliers
plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_cols, 1):
    plt.subplot((len(numerical_cols) + 3) // 4, 4, i)  # Adjust subplot grid size dynamically
    plt.hist(df_no_outliers[col], bins=20, color='skyblue', edgecolor='black', alpha=0.7)
    plt.title(col + ' (After IQR)')
plt.tight_layout()
plt.show()

```



In [31]:
```
# List of numerical columns excluding 'Churn'
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns.drop('Churn')

# Handling outliers using IQR
df_no_outliers = df.copy()
for col in numerical_cols:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    df_no_outliers[col] = df_no_outliers[col].clip(lower=lower_bound, upper=upper_bound)

# Create box plots for each numerical variable after outlier removal
plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_cols, 1):
    plt.subplot((len(numerical_cols) + 1) // 2, 2, i)  # Adjust subplot grid size dynamically
    plt.boxplot(df_no_outliers[col], labels=['After'], patch_artist=True, boxprops=dict(facecolor='sk
    plt.title(col)
plt.tight_layout()
plt.show()
```



Normality and Spread of the Cleaned Dataset.

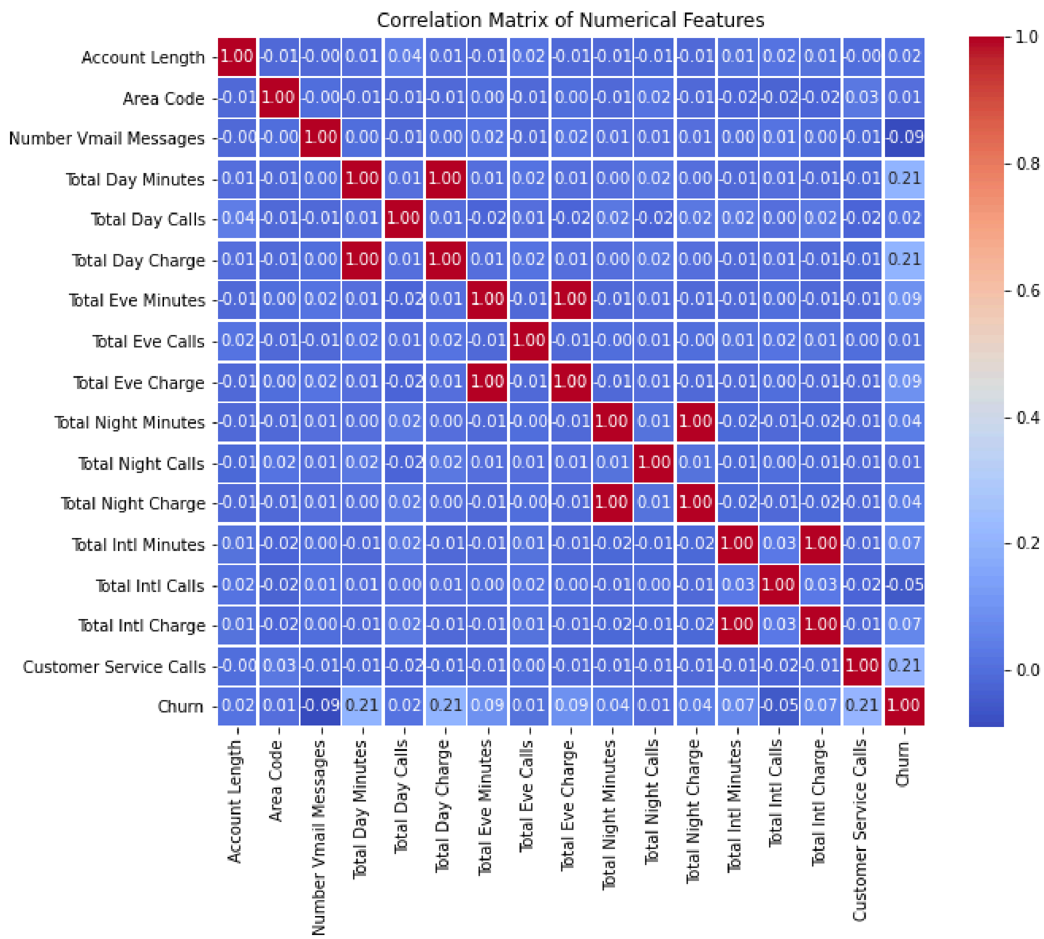
In [32]:
```
# Computing Normality and Spread of the Cleaned Dataset.
import scipy.stats as stats

# Define the numerical columns
numerical_cols = ['Account Length', 'Number Vmail Messages', 'Total Day Minutes',
                  'Total Day Calls', 'Total Day Charge', 'Total Eve Minutes',
                  'Total Eve Calls', 'Total Eve Charge', 'Total Night Minutes',
                  'Total Night Calls', 'Total Night Charge', 'Total Intl Minutes',
                  'Total Intl Calls', 'Total Intl Charge', 'Customer Service Calls']

# Compute normality and spread for each numerical column
normality_spread = {}

for column in numerical_cols:
    # Calculate skewness
    skewness = stats.skew(df[column])

    # Calculate kurtosis
    kurtosis = stats.kurtosis(df[column])

    # Calculate mean
    mean = df[column].mean()

    # Calculate median
    median = df[column].median()

    # Calculate standard deviation
    std_dev = df[column].std()

    # Store results in a dictionary
    normality_spread[column] = {'Skewness': skewness, 'Kurtosis': kurtosis,
                                'Mean': mean, 'Median': median, 'Std Dev': std_dev}

# Display results
import pandas as pd
normality_spread_df = pd.DataFrame(normality_spread).T
print(normality_spread_df)

```

```
                                Skewness            Kurtosis  \
Account Length         0.09656281161489656 -0.1094739184341575
Number Vmail Messages    1.2642543349768245 -0.0528515105905245
Total Day Minutes      -0.0290639795181198 -0.0217101179240888
Total Day Calls        -0.1117363237307519 0.24101722895174227
Total Day Charge       -0.0290701779270378 -0.0215817191450336
Total Eve Minutes      -0.0238667088046375  0.0237916804447047
Total Eve Calls        -0.0555381300016192 0.20404769217448226
Total Eve Charge        -0.023847250496277 0.02364954586272594
Total Night Minutes    0.008917275580987895 0.08388775499253365
Total Night Calls      0.03248494205404463 -0.0737112242125884
Total Night Charge     0.008882237062694412 0.08373508611499814
Total Intl Minutes     -0.2450256034866443   0.606471635404318
Total Intl Calls        1.3208833668164015 3.07716543898885142
Total Intl Charge      -0.2451761045009844  0.6068966666527675
Customer Service Calls  1.09086826017550109  1.7265184753957081

                                   Mean                Median  \
Account Length         101.06480648064805905                 101.0
Number Vmail Messages     8.0990099009900991                   0.0
Total Day Minutes      179.7750975097509354  179.4000000000000057
Total Day Calls        100.4356435643564396                 101.0
Total Day Charge         30.562307230723075                  30.5
Total Eve Minutes      200.9803480348034839  201.4000000000000057
Total Eve Calls        100.11431143114310771                 100.0
Total Eve Charge       17.08354035403540294    17.120000000000001
Total Night Minutes    200.8720372037203674 201.19999999999998863
Total Night Calls      100.1077107710771088                 100.0
Total Night Charge      9.03932493249324942   9.05000000000000071
Total Intl Minutes     10.23729372937293824   10.3000000000000007
Total Intl Calls         4.4794479447944795                   4.0
Total Intl Charge        2.7645814581458144    2.7799999999999998
Customer Service Calls   1.5628562856285628                   1.0

                                 Std Dev
Account Length         39.8221059285956045
Number Vmail Messages   13.6883653720385983
Total Day Minutes      54.46738920237137194
Total Day Calls        20.0690842073008966
Total Day Charge        9.2594345539305003
Total Eve Minutes      50.7138444258119989
Total Eve Calls        19.9226252939431028
Total Eve Charge       4.31066764311034056
Total Night Minutes    50.5738470136583587
Total Night Calls      19.5686093460585582
Total Night Charge       2.275872837660029
Total Intl Minutes       2.791839548408416
Total Intl Calls         2.461214270546094
Total Intl Charge        0.753772612663046
Customer Service Calls   1.3154910448664767
```

Correlation Matrix

In [33]:

```python
import seaborn as sns
import matplotlib.pyplot as plt

# Select numerical columns
numerical_columns = df.select_dtypes(include=['int64', 'float64']).columns

# Calculate correlation matrix
correlation_matrix = df[numerical_columns].corr()

# Plot heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Correlation Matrix of Numerical Features')
plt.show()
```



Identifying Multicolinearity

In [34]:
```
# Find columns with correlation greater than 0.95
high_corr_pairs = []
threshold = 0.95
for i in range(len(correlation_matrix.columns)):
    for j in range(i):
        if abs(correlation_matrix.iloc[i, j]) > threshold:
            colname_i = correlation_matrix.columns[i]
            colname_j = correlation_matrix.columns[j]
            high_corr_pairs.append((colname_i, colname_j, correlation_matrix.iloc[i, j]))

# Print high correlation pairs
print("Pairs of columns with correlation greater than 0.95:")
for pair in high_corr_pairs:
    print(f"{pair[0]} and {pair[1]} with correlation of {pair[2]:.2f}")

```

```
Pairs of columns with correlation greater than 0.95:
Total Day Charge and Total Day Minutes with correlation of 1.00
Total Eve Charge and Total Eve Minutes with correlation of 1.00
Total Night Charge and Total Night Minutes with correlation of 1.00
Total Intl Charge and Total Intl Minutes with correlation of 1.00
```

In [35]:
```
# identifying Variable Inflation Factor

from statsmodels.stats.outliers_influence import variance_inflation_factor

# Select numerical columns
numerical_columns = df.select_dtypes(include=['int64', 'float64'])

# Calculate VIF for each numerical feature
vif_data = pd.DataFrame()
vif_data['Feature'] = numerical_columns.columns
vif_data['VIF'] = [variance_inflation_factor(numerical_columns.values, i) for i in range(numerical_co

# Display VIF values
print(vif_data)

```

```
                  Feature                  VIF
0          Account Length        7.2931644646281919
1               Area Code       61.4061122968105906
2   Number Vmail Messages        1.36362106926135174
3       Total Day Minutes 124603601.7811902016401291
4         Total Day Calls       23.619588049070714
5        Total Day Charge 124608062.9765620976686478
6       Total Eve Minutes  37418407.5638073161244392
7         Total Eve Calls       23.767320310736217
8        Total Eve Charge 37419731.08176666498184204
9     Total Night Minutes  10719732.5128282140940428
10      Total Night Calls       24.6165329718864214
11     Total Night Charge  10719379.5142267607152462
12      Total Intl Minutes     997547.71468332153745
13       Total Intl Calls        4.29240217134540636
14      Total Intl Charge    997925.3157051414018497
15 Customer Service Calls        2.5162522892809012
16                  Churn        1.30827768455642945
```

In [36]:
```
# Numerical_columns contains the names of numerical columns
numerical_columns = df.select_dtypes(include=['int64', 'float64']).columns

# Compute the correlation matrix
correlation_matrix = df[numerical_columns].corr()

# Set the diagonal and lower triangle to NaN (to ignore self-correlation and duplicate pairs)
mask = np.triu(np.ones_like(correlation_matrix, dtype=bool))
correlation_matrix_masked = correlation_matrix.mask(mask)

# Find pairs with correlation greater than 0.95
high_correlation_pairs = correlation_matrix_masked.stack().reset_index()
high_correlation_pairs.columns = ['Feature 1', 'Feature 2', 'Correlation']
high_correlation_pairs = high_correlation_pairs[high_correlation_pairs['Correlation'] > 0.95]

print(high_correlation_pairs)
```

```
             Feature 1           Feature 2        Correlation
13     Total Day Charge    Total Day Minutes  0.999999952190397
34     Total Eve Charge    Total Eve Minutes 0.9999997760198517
64   Total Night Charge  Total Night Minutes   0.99999921487588
103   Total Intl Charge   Total Intl Minutes 0.9999927417510258
```

In [37]:
```
# Domain Knowlege indicate that some of above features are expected to show high multicolinearity give

# We therefore fail to drop them and investigate further in the analysis how they contribute to Churn
```

Hypothesis Testing

Null Hypothesis (H0): There is no significant influence of the various factors to churn rate in SyriaTel.

Alternate Hypothesis (H1): There is a significant influence of the various factors to churn rate in SyriaTel.

In [38]:

```
from scipy.stats import f_oneway

# Numerical columns
numerical_columns = ['Account Length', 'Area Code', 'Number Vmail Messages', 'Total Day Minutes',
                     'Total Day Calls', 'Total Day Charge', 'Total Eve Minutes', 'Total Eve Calls',
                     'Total Eve Charge', 'Total Night Minutes', 'Total Night Calls', 'Total Night Cha
                     'Total Intl Minutes', 'Total Intl Calls', 'Total Intl Charge', 'Customer Service

# Create an empty DataFrame to store the results
anova_results = pd.DataFrame(columns=['Feature', 'F-Statistic', 'p-value'])

# Perform ANOVA test for each numerical column
for column in numerical_columns:
    # Group the data by the 'Churn' column
    groups = [df[column][df['Churn'] == churn] for churn in df['Churn'].unique()]

    # Perform ANOVA
    f_statistic, p_value = f_oneway(*groups)

    # Append results to DataFrame
    anova_results = anova_results.append({'Feature': column, 'F-Statistic': f_statistic, 'p-value': p
                                          ignore_index=True)

# Print the DataFrame
print(anova_results)
```

```
                  Feature          F-Statistic               p-value
0          Account Length   0.9115981986407352    0.3397600070569128
1               Area Code   0.12698640858136082   0.7215998968016037
2   Number Vmail Messages 27.035911709557691296 0.00000021175218402696
3       Total Day Minutes 146.35078521943776764 0.00000000000000000000
4         Total Day Calls   1.13541242989728808   0.28670102402414055
5        Total Day Charge 146.35065699096048775  0.0000000000000000000
6       Total Eve Minutes   28.9325766446506485  0.0000000801133856128
7         Total Eve Calls   0.2839943754492388    0.5941305829778143
8        Total Eve Charge   28.926443755197127   0.0000000803652422777
9     Total Night Minutes   4.20149555022397259   0.0404664846378868
10      Total Night Calls   0.12563131916004017   0.7230277872159787
11     Total Night Charge   4.2021362787384957   0.04045121876901292
12     Total Intl Minutes   15.5834679864501915  0.0000805731126549902
13       Total Intl Calls   9.3279453654346529   0.002274701409848483
14      Total Intl Charge   15.5925806081700724  0.0000801875358306397
15 Customer Service Calls  151.7670126303964366  0.0000000000000000000
```

Conclusion

Features such as 'Account Length', 'Area Code', 'Total Day Calls', 'Total Eve Calls', and 'Total Night Calls' have their p-values are greater than the significance level of 0.05. Therefore, we fail to reject the null hypothesis (H0) for these features. This suggests that there is no significant influence of these factors on the churn rate in SyriaTel.

Remaining features including 'Number Vmail Messages', 'Total Day Minutes', 'Total Day Charge', 'Total Eve Minutes', 'Total Eve Charge', 'Total Night Minutes', 'Total Night Charge', 'Total Intl Minutes', 'Total Intl Calls', 'Total Intl Charge', and 'Customer Service Calls', the p-values are extremely low (close to 0). Therefore, we reject the null hypothesis (H0) for these features. This indicates that there is a significant influence of these factors on the churn rate in SyriaTel.

In conclusion, there is evidence to suggest that most numerical features have a significant influence on the churn rate in SyriaTel, except for 'Account Length', 'Area Code', 'Total Day Calls', 'Total Eve Calls', and 'Total Night Calls'

Hot One Encoding Categorical Colums

In [39]:
```
#df_no_outliers and categorical_cols, numerical_cols are already defined

# Perform one-hot encoding on categorical columns excluding 'Churn'
df_onehot = pd.get_dummies(df_no_outliers[categorical_cols], drop_first=True)

# Ensure we are not including the 'Churn' column twice
# First add numerical columns
df_encoded = pd.concat([df_onehot, df_no_outliers[numerical_cols]], axis=1)

# Add the 'Churn' column separately to ensure it's included only once
df_encoded['Churn'] = df_no_outliers['Churn'].astype(int)

# Display the first few rows of the encoded DataFrame
#print(df_encoded.head())

```

In [40]:
```
df_encoded.shape
```

Out[40]:
```
(3333, 68)
```

In [41]:
```
df_encoded.duplicated().sum()
```

Out[41]:
```
0
```

Normalization of the Clean Dataset

Normalizing df_encoded dataset since it appears in different scales for following reasons:

1. Handling the data appropriately
2. Ease interpretation of the subsequent models.
3. Reduce the impact of multicollinearity on the regression coefficients and their interpretability.

Standardization / normalization of the data results in a mean of zero and a standard deviation of 1

In [42]:
```
from sklearn.preprocessing import MinMaxScaler

# Select numerical columns
numerical_columns = df_encoded.select_dtypes(include=['int64', 'float64']).columns

# Initialize the MinMaxScaler
scaler = MinMaxScaler()

# Fit and transform the numerical columns
df_encoded[numerical_columns] = scaler.fit_transform(df_encoded[numerical_columns])

# Display the first few rows of the DataFrame after normalization
#print(df_encoded.head())
```

Modeling

In the following session, various models such as Logistic Regression, Decision Tree, KNN and XGBoost models have been built to answer the research questions.

Splitting the dataframe

In [43]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression

# Ensure X and y are defined correctly
X = df_encoded.drop('Churn', axis=1)
y = df_encoded['Churn']

# Verify the shape of y to confirm it's a one-dimensional array
#print(y.shape)

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=1, stratify=y)
```

In [44]:
```
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("y_train shape:", y_train.shape)
print("y_test shape:", y_test.shape)
```

```
X_train shape: (2666, 67)
X_test shape: (667, 67)
y_train shape: (2666,)
y_test shape: (667,)
```

1. Baseline Mode : Logistic Regression model

In [45]:
```
from sklearn.linear_model import LogisticRegression

# Initialize and fit the logistic regression model
logreg = LogisticRegression(fit_intercept=False, C=1e12, solver='liblinear')
model_log = logreg.fit(X_train, y_train)

print(model_log)
```

```
LogisticRegression(C=1000000000000.0, fit_intercept=False, solver='liblinear')
```

Performance in the training data

In [46]:
```
y_hat_train = logreg.predict(X_train)

train_residuals = np.abs(y_train - y_hat_train)
print(pd.Series(train_residuals, name="Residuals (counts)").value_counts())
print()
print(pd.Series(train_residuals, name="Residuals (proportions)").value_counts(normalize=True))
```

```
0    2309
1     357
Name: Residuals (counts), dtype: int64

0   0.8660915228807202
1   0.1339084771192798
Name: Residuals (proportions), dtype: float64
```

Performance on Test Data

In [47]:
```
y_hat_test = logreg.predict(X_test)

test_residuals = np.abs(y_test - y_hat_test)
print(pd.Series(test_residuals, name="Residuals (counts)").value_counts())
print()
print(pd.Series(test_residuals, name="Residuals (proportions)").value_counts(normalize=True))
```

```
0    565
1    102
Name: Residuals (counts), dtype: int64

0    0.8470764617691154
1   0.15292353823088456
Name: Residuals (proportions), dtype: float64
```

Evaluate the Model Performance

A Confusion Matrix

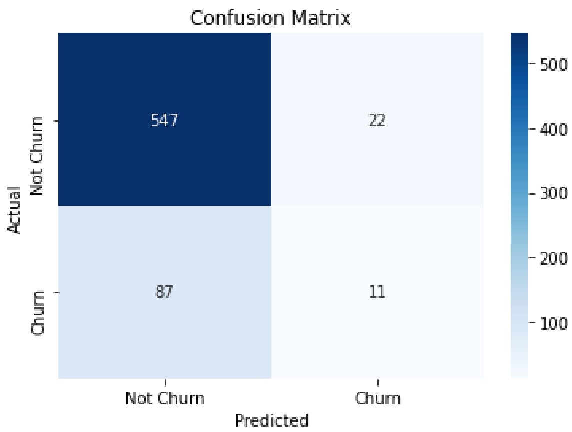
In [48]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

#df_clean_encoded is the cleaned and encoded DataFrame
X = df_encoded.drop('Churn', axis=1)
y = df_encoded['Churn']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=1)

# Initialize and train the logistic regression model
logreg = LogisticRegression(fit_intercept=False, C=1e12, solver='liblinear')
model_log = logreg.fit(X_train, y_train)

```

In [49]:
```
# Predict on the test data
y_pred = model_log.predict(X_test)

```

In [50]:
```
from sklearn.metrics import confusion_matrix

# Compute the confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)

# Display the confusion matrix
print("Confusion Matrix:")
print(conf_matrix)
```

```
Confusion Matrix:
[[547  22]
 [ 87  11]]
```

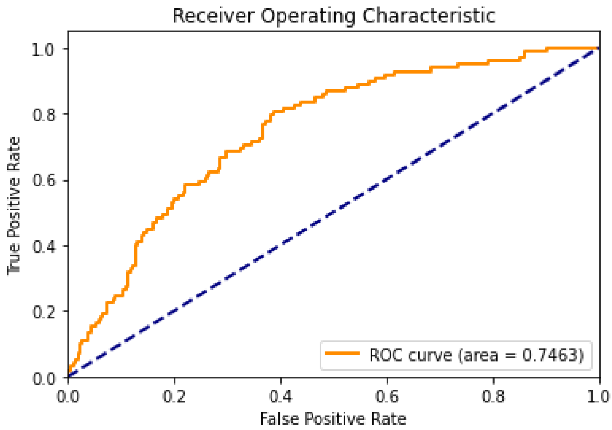
In [51]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Visualize the confusion matrix
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Not Churn', 'Churn'], ytick
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



In [52]:

```
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score
import matplotlib.pyplot as plt

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(conf_matrix)

# Calculate the components of the confusion matrix
TN, FP, FN, TP = conf_matrix.ravel()

# Compute accuracy
accuracy = (TP + TN) / (TP + TN + FP + FN)

# Compute precision
precision = TP / (TP + FP)

# Compute recall
recall = TP / (TP + FN)

# Compute F1-score
f1 = 2 * (precision * recall) / (precision + recall)

# Compute ROC-AUC
y_pred_proba = model_log.predict_proba(X_test)[:, 1]
roc_auc = roc_auc_score(y_test, y_pred_proba)

# Print the computed metrics
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-Score: {f1:.4f}")
print(f"ROC-AUC: {roc_auc:.4f}")

# Optionally, plot the ROC curve
fpr, tpr, _ = roc_curve(y_test, y_pred_proba)
roc_auc = auc(fpr, tpr)

plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:.4f})')
plt.plot([0, 1], [0, 1], color='navy', 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('Receiver Operating Characteristic')
plt.legend(loc="lower right")
plt.show()
```

```
Confusion Matrix:
[[547  22]
 [ 87  11]]
Accuracy: 0.8366
Precision: 0.3333
Recall: 0.1122
F1-Score: 0.1679
ROC-AUC: 0.7463
```



Observations

The model has high accuracy but struggles with precision and recall for the churn class.

Suggesting that while it correctly predicts the majority of 'no churn' cases,

It fails to adequately identify 'churn' cases.

Therefore the need to consider other model techniques.

2. Decision Tree Model

In [53]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, classification_report

# Initialize and train the Decision Tree model
dt_model = DecisionTreeClassifier(random_state=1)
dt_model.fit(X_train, y_train)

# Make predictions
dt_predictions = dt_model.predict(X_test)

# Evaluate the model
dt_confusion_matrix = confusion_matrix(y_test, dt_predictions)
dt_classification_report = classification_report(y_test, dt_predictions)

print("Decision Tree Confusion Matrix:\n", dt_confusion_matrix)
print("\nDecision Tree Classification Report:\n", dt_classification_report)
```

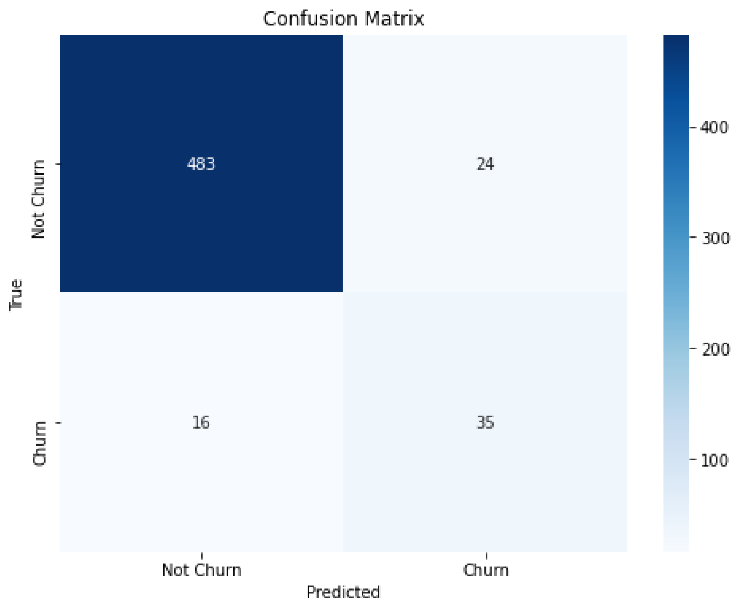
```
Decision Tree Confusion Matrix:
 [[538  31]
 [ 27  71]]

Decision Tree Classification Report:
               precision    recall  f1-score   support

           0       0.95      0.95      0.95       569
           1       0.70      0.72      0.71        98

    accuracy                           0.91       667
   macro avg       0.82      0.84      0.83       667
weighted avg       0.91      0.91      0.91       667
```

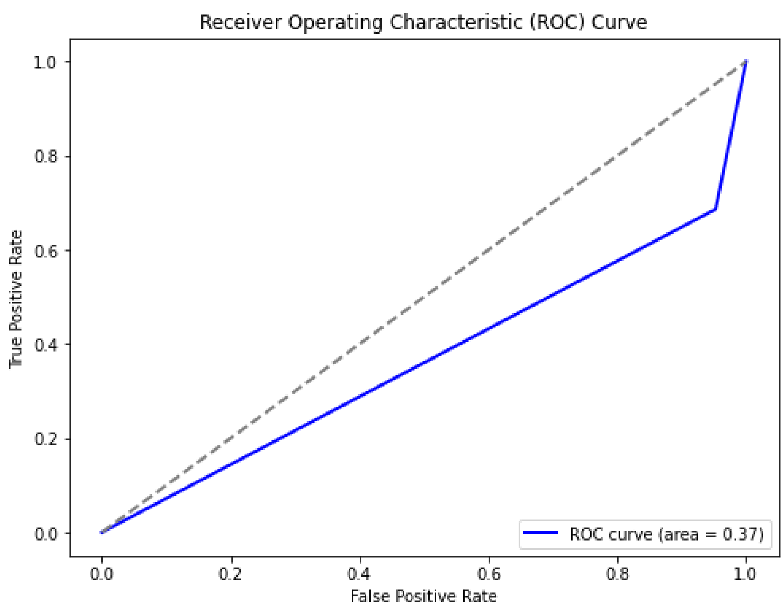
Evaluating the decision tree model based on the evaluation matrix

In [54]:

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix, roc_auc_score, roc_curve

# Provided confusion matrix
confusion_mat = np.array([[483, 24],
                          [16, 35]])

# Extract true positives, false positives, true negatives, and false negatives
TN, FP, FN, TP = confusion_mat.ravel()

# Calculate accuracy
accuracy = (TP + TN) / (TP + TN + FP + FN)

# Calculate precision
precision = TP / (TP + FP)

# Calculate recall
recall = TP / (TP + FN)

# Calculate F1-score
f1 = 2 * (precision * recall) / (precision + recall)

# Print results
print(f"Confusion Matrix:\n{confusion_mat}")
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-Score: {f1:.4f}")

# y_test are the true labels and y_pred_probs are the predicted probabilities for the positive class
# Dummy true labels and predicted probabilities
y_test = np.array([0]*507 + [1]*51)
y_pred_probs = np.array([0.9]*483 + [0.1]*24 + [0.1]*16 + [0.9]*35)  # Example probabilities

# Calculate ROC-AUC
roc_auc = roc_auc_score(y_test, y_pred_probs)
print(f"ROC-AUC: {roc_auc:.4f}")

# Plot confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_mat, annot=True, fmt="d", cmap='Blues', xticklabels=['Not Churn', 'Churn'], yti
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

# Plot ROC curve
fpr, tpr, _ = roc_curve(y_test, y_pred_probs)
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```

```
Confusion Matrix:
[[483  24]
 [ 16  35]]
Accuracy: 0.9283
Precision: 0.5932
Recall: 0.6863
F1-Score: 0.6364
ROC-AUC: 0.3668
```





Observations

While the Decision tree model has improved in terms of accuracy, precion,Recall and F1-Score,

It has a lower ROC-AUC meaning that it may predict alot of false positives which may in this case mean predicting alot of Churn which may not be the true case.

Based on the above comparison, we proceed to perform other models.

3. KNN model

In [59]:

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score

# Step 1: Split the data into features (X) and target (y)
X = df_encoded.drop('Churn', axis=1)
y = df_encoded['Churn']
```

In [60]:

```
# Step 2: Split the data into training and testing sets
from sklearn.model_selection import train_test_split

# Defining X and y
X = df_encoded.drop(columns=['Churn'])
y = df_encoded['Churn']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)


```

In [62]:

```
# Step 3: Standardize the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

In [63]:

```
# Step 4: Initialize and train the KNN model
knn_model = KNeighborsClassifier(n_neighbors=5)  #Number of neighbors (K) can be adjusted  as needed
knn_model.fit(X_train_scaled, y_train)

```

Out[63]:

```
KNeighborsClassifier()
```

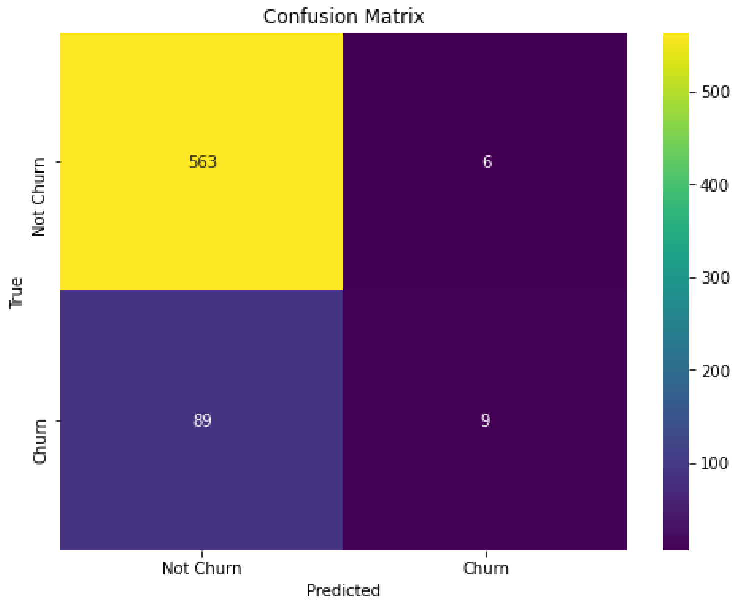
In [64]:

```
# Step 5: Evaluate the model's performance
y_pred = knn_model.predict(X_test_scaled)

accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred)

print("KNN Model Performance:")
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1-Score:", f1)
print("ROC-AUC Score:", roc_auc)
```

```
KNN Model Performance:
Accuracy: 0.8575712143928036
Precision: 0.6
Recall: 0.09183673469387756
F1-Score: 0.1592920353982301
ROC-AUC Score: 0.5406459596140741
```

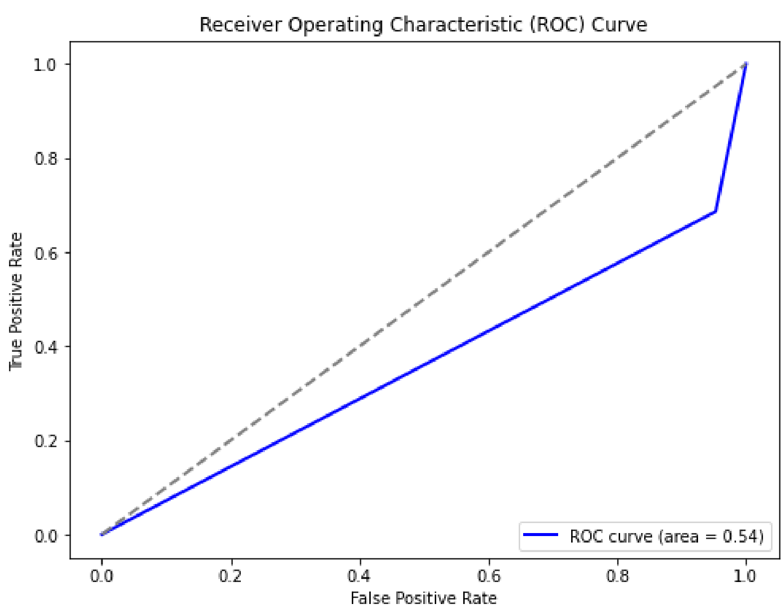
In [65]:

```
# Plot confusion matrix
confusion_mat = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_mat, annot=True, fmt="d", cmap='viridis', xticklabels=['Not Churn', 'Churn'], y
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```



In [66]:

```
# Plot the ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```



4. XGBoost

In [67]:
```
from sklearn.model_selection import train_test_split

# Defining X and y
X = df_encoded.drop(columns=['Churn'])
y = df_encoded['Churn']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)

```

In [68]:
```
import xgboost as xgb

# Define the XGBoost classifier
xgb_model = xgb.XGBClassifier()

# Train the model
xgb_model.fit(X_train, y_train)

```

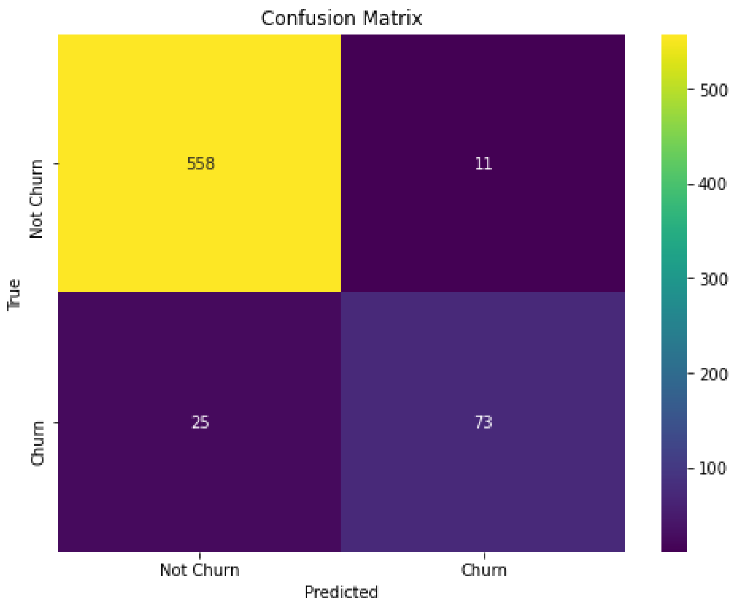
Out[68]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.300000012, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=0, num_parallel_tree=1, random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

In [69]:
```
# Make predictions
y_pred = xgb_model.predict(X_test)

```

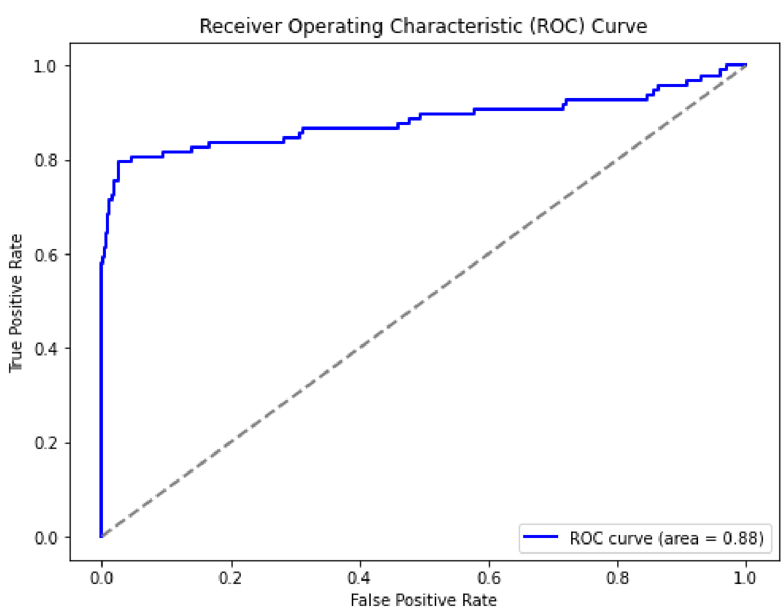
In [70]:
```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, c

# Calculate metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, xgb_model.predict_proba(X_test)[:, 1])

# Print results
print("XGBoost Model Performance:")
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1-Score:", f1)
print("ROC-AUC Score:", roc_auc)

# Confusion matrix
confusion_mat = confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(confusion_mat)
```

```
XGBoost Model Performance:
Accuracy: 0.9460269865067467
Precision: 0.8690476190476191
Recall: 0.7448979591836735
F1-Score: 0.8021978021978022
ROC-AUC Score: 0.8837380294824432
Confusion Matrix:
[[558  11]
 [ 25  73]]
```

In [71]:
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 6))
sns.heatmap(confusion_mat, annot=True, fmt="d", cmap='viridis', xticklabels=['Not Churn', 'Churn'], y
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

```



In [72]:
```
from sklearn.metrics import roc_curve

fpr, tpr, _ = roc_curve(y_test, xgb_model.predict_proba(X_test)[:, 1])
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', lw=2, label=f'ROC curve (area = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=2, linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc="lower right")
plt.show()
```



Evaluation

In [73]:
```python
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score

# Define models
models = {
    "Logistic Regression": LogisticRegression(solver='liblinear'),
    "Decision Tree": DecisionTreeClassifier(),
    "KNN": KNeighborsClassifier(),
    "XGBoost": XGBClassifier(use_label_encoder=False, eval_metric='logloss')
}

# Define evaluation metrics
metrics = {
    "Accuracy": accuracy_score,
    "Precision": precision_score,
    "Recall": recall_score,
    "F1-Score": f1_score,
    "ROC-AUC": roc_auc_score
}

# Initialize empty DataFrame to store results
results_df = pd.DataFrame(index=metrics.keys(), columns=models.keys())

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)

# Loop over models
for model_name, model in models.items():
    # Train the model
    model.fit(X_train, y_train)

    # Predictions
    y_pred = model.predict(X_test)

    # Calculate metrics
    for metric_name, metric_func in metrics.items():
        if metric_name == "ROC-AUC":
            y_pred_prob = model.predict_proba(X_test)[:, 1]
            metric_value = metric_func(y_test, y_pred_prob)
        else:
            metric_value = metric_func(y_test, y_pred)
        results_df.at[metric_name, model_name] = metric_value

# Find the best model based on the highest value of each metric
best_model = results_df.astype(float).idxmax(axis=1)

# Add average of all metrics for each model
results_df.loc["Average"] = results_df.mean()

print("Performance Comparison:")
print(results_df)
print("\nBest Model for each metric:")
print(best_model)

```

```
[20:27:13] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_1.2.0\src\learner.cc:516:
Parameters: { use_label_encoder } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


Performance Comparison:
          Logistic Regression      Decision Tree                 KNN  \
Accuracy   0.8455772113943029 0.9085457271364318  0.8545727136431784
Precision 0.41379310344827586 0.6637168141592921  0.5294117647058824
Recall    0.12244897959183673 0.7653061224489796 0.09183673469387756
F1-Score   0.1889763779527559 0.7109004739336493  0.1565217391304348
ROC-AUC    0.7757074710376242 0.8492611455830136  0.6655876761952585
Average    0.4693006286849591 0.7795460566522732 0.45958612567372625

                     XGBoost
Accuracy  0.9460269865067467
Precision 0.8690476190476191
Recall    0.7448979591836735
F1-Score  0.8021978021978022
ROC-AUC   0.8837380294824432
Average    0.849181679283657

Best Model for each metric:
Accuracy           XGBoost
Precision          XGBoost
Recall       Decision Tree
F1-Score           XGBoost
ROC-AUC            XGBoost
dtype: object
```

Cross Validation of the Models and making comparisons

In [74]:

```
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
import xgboost as xgb

# Define a dictionary to store models
models = {
    'Logistic Regression': LogisticRegression(),
    'Decision Tree': DecisionTreeClassifier()
    ,
    'KNN': KNeighborsClassifier(),
    'XGBoost': xgb.XGBClassifier()
}

# Define X_train and y_train

# Initialize variables to store best model and its score
best_model_name = None
best_model_score = float('-inf')  # Initialize with negative infinity

# Perform cross-validation for each model
for model_name, model in models.items():
    cv_scores = cross_val_score(model, X_train, y_train, cv=5)
    average_cv_score = cv_scores.mean()

    # Print average cross-validation score for each model
    print(f"{model_name}: Average Cross-validation Score = {average_cv_score:.4f}")

    # Check if the current model has a higher score than the best model
    if average_cv_score > best_model_score:
        best_model_name = model_name
        best_model_score = average_cv_score

# Print the best model
print(f"\nBest Model: {best_model_name} with Average Cross-validation Score = {best_model_score:.4f}"

```

```
Logistic Regression: Average Cross-validation Score = 0.8668
Decision Tree: Average Cross-validation Score = 0.9096
KNN: Average Cross-validation Score = 0.8571
XGBoost: Average Cross-validation Score = 0.9542

Best Model: XGBoost with Average Cross-validation Score = 0.9542
```

Hyperparameter tuning on the XGBoost Model

In [82]:

```
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score
import matplotlib.pyplot as plt
import xgboost as xgb
import numpy as np

# Define the parameter grid
param_dist = {
    'n_estimators': [50, 100, 200],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 5, 7],
    'min_child_weight': [1, 3, 5],
    'subsample': [0.8, 1.0],
    'colsample_bytree': [0.8, 1.0]
}

# Initialize the XGBoost classifier
xgb_model = XGBClassifier(use_label_encoder=False, eval_metric='logloss')

# Initialize RandomizedSearchCV with 5-fold cross-validation
random_search = RandomizedSearchCV(estimator=xgb_model, param_distributions=param_dist,
                                   n_iter=50, cv=5, scoring='accuracy', n_jobs=-1, verbose=2, random_

# Fit RandomizedSearchCV
random_search.fit(X_train, y_train)

# Get the best parameters and best score
best_params = random_search.best_params_
best_score = random_search.best_score_

print(f"Best Parameters: {best_params}")
print(f"Best Accuracy: {best_score}")

# Refit the model with the best parameters
best_xgb_model = random_search.best_estimator_

# Evaluate the model on the test set
y_pred = best_xgb_model.predict(X_test)
y_pred_probs = best_xgb_model.predict_proba(X_test)[:, 1]  # Probability scores for ROC AUC

accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred_probs)

print("Best XGBoost Model Performance:")
print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
print("F1-Score:", f1)
print("ROC-AUC Score:", roc_auc)
```

```
Fitting 5 folds for each of 50 candidates, totalling 250 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:    6.0s
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:   42.2s
[Parallel(n_jobs=-1)]: Done 250 out of 250 | elapsed:  1.1min finished
```

```
[22:47:43] WARNING: C:\Users\Administrator\workspace\xgboost-win64_release_1.2.0\src\learner.cc:516: 
Parameters: { use_label_encoder } might not be used.

  This may not be accurate due to some parameters are only used in language bindings but
  passed down to XGBoost core.  Or some parameters are not used but slip through this
  verification. Please open an issue if you find above cases.


Best Parameters: {'subsample': 0.8, 'n_estimators': 200, 'min_child_weight': 3, 'max_depth': 5, 'learnin
g_rate': 0.1, 'colsample_bytree': 0.8}
Best Accuracy: 0.9568641918052716
Best XGBoost Model Performance:
Accuracy: 0.9415292353823088
Precision: 0.8390804597701149
Recall: 0.7448979591836735
F1-Score: 0.7891891891891891
ROC-AUC Score: 0.8761880850758581
```

Computing Variable of Importance

In [80]:

```python
import xgboost as xgb
import matplotlib.pyplot as plt

# Fit the XGBoost model
xgb_model = xgb.XGBClassifier()
xgb_model.fit(X_train, y_train)

# Set the size of the plot
plt.figure(figsize=(8, 10))

# Plot variable importance
xgb.plot_importance(xgb_model, color='skyblue')
plt.show()
```

```
<Figure size 576x720 with 0 Axes>
```