SYRIATEL CUSTOMER CHURN

OVERVIEW

SyriaTel continues to struggle with client retention in the dynamic world of telecommunications. Gaining a competitive edge in the face of fast market change requires an awareness of and commitment to tackling the issues that contribute to customer turnover. In order to detect trends in SyriaTel's customer data that would indicate a higher chance of churn, the main goal of this project is to create a predictive model.

INTRODUCTION

Customer retention is a major problem for businesses looking to build enduring connections and maintain income streams in the ever-changing telecoms market. This also applies to SyriaTel, a major participant in the telecommunications industry. As the telecommunications industry develops further, it is now strategically necessary to identify and manage the issues that contribute to customer attrition.

The purpose of this project is to develop a predictive model that will identify trends in SyriaTel's customer data that can point to a higher risk of customer attrition. Churn, which is the word for a customer's termination of services, affects the bottom line but also highlights areas where customer happiness and service quality might be improved.

PROBLEM STATEMENT

SyriaTel's primary concern is that factors that cause people to stop using their services might result in a loss of income and clientele. Using use patterns and historical data, the idea is to create a prediction tool that may foretell client disengagement. SyriaTel might mitigate the financial effect of customer attrition by identifying customers who are likely to leave and putting in place targeted retention initiatives to keep them onboard.

Main Objectives

The goal of the project is to anticipate customer attrition for SyriaTel by using historical data to construct a binary classification model. Through the extraction of actionable information from the model, our main goal is to customize targeted retention methods for clients that pose a risk, hence improving overall customer happiness and bolstering SyriaTel's customer retention efforts.

General Objectives

1. Develop a robust binary classification model capable of accurately predicting customer churn based on historical data.
2. Extract actionable insights from the predictive model to provide a deeper understanding of factors contributing to customer churn.
3. Tailor and optimize retention strategies by utilizing the insights derived from the model, specifically targeting at-risk customers.
4. Utilize identified patterns and factors influencing churn to enhance overall customer satisfaction and experience.
5. Document the entire process, from data preparation to model development, and effectively communicate findings and recommendations to stakeholders, ensuring transparency and understanding.

DATA UNDERSTANDING

The dataset for this project contains information related to SyriaTel's customers and their interactions with the telecommunications services. The features (columns) in the dataset capture various aspects of customer behavior and usage patterns. The process of explanatory data analysis is employed to comprehensively understand the dataset. This involves tasks such as identifying missing values, examining data types, detecting outliers, and extracting pertinent features for subsequent analysis.

Importing libraries

In [44]:

```
import numpy as np
import pandas as pd


import matplotlib.pyplot as plt
import seaborn as sns


from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, au
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.metrics import precision_recall_curve, auc
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from xgboost import XGBClassifier

%matplotlib inline
```

Loading and previewing the dataset

In [45]:

```

data = pd.read_csv("bigml_59c28831336c6604c800002a.csv")

# view the first rows of the dataframe
data.head()
```

Out[45]:

	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 calls	total eve charge
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16.78
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16.62
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10.30
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.26
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12.61

5 rows × 21 columns

In [46]:
```
# Basic statistics of the dataset
data.describe()
```

Out[46]:

	account length	area code	number vmail messages	total day minutes	total day calls	total day charge	total eve minutes	total (
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.00(
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	200.980348	100.11
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50.713844	19.92
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.00(
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166.600000	87.00(
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201.400000	100.00(
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235.300000	114.00(
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363.700000	170.00(

In [47]:
```
# Number of rows and columns
data.shape
```

Out[47]: (3333, 21)

DATA CLEANING

In [48]:
```
# Check for missing values
missing_values = data.isnull().sum()
print("Missing Values:\n", missing_values)
```

```
Missing Values:
 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
```

In [49]:
```
# Check data types
data_types = data.dtypes
print(data_types)
```

```
state                      object
account length              int64
area code                   int64
phone number               object
international plan         object
voice mail plan            object
number vmail messages       int64
total day minutes         float64
total day calls             int64
total day charge          float64
total eve minutes         float64
total eve calls             int64
total eve charge          float64
total night minutes       float64
total night calls           int64
total night charge        float64
total intl minutes        float64
total intl calls            int64
total intl charge         float64
customer service calls      int64
churn                        bool
dtype: object
```

In [50]:
```
# Converting 'international plan' and 'voice mail plan' to Numeric
data['international plan'] = data['international plan'].map({'yes': 1, 'no': 0})
data['voice mail plan'] = data['voice mail plan'].map({'yes': 1, 'no': 0})

# Converting 'churn' to Numeric
data['churn'] = data['churn'].astype(int)
```

In [51]:
```
# Check unique values in 'state'
unique_states = data['state'].unique()
print("Unique States:\n", unique_states)
```

```
Unique States:
 ['KS' 'OH' 'NJ' 'OK' 'AL' 'MA' 'MO' 'LA' 'WV' 'IN' 'RI' 'IA' 'MT' 'NY'
 'ID' 'VT' 'VA' 'TX' 'FL' 'CO' 'AZ' 'SC' 'NE' 'WY' 'HI' 'IL' 'NH' 'GA'
 'AK' 'MD' 'AR' 'WI' 'OR' 'MI' 'DE' 'UT' 'CA' 'MN' 'SD' 'NC' 'WA' 'NM'
 'NV' 'DC' 'KY' 'ME' 'MS' 'TN' 'PA' 'CT' 'ND']
```

In [52]:
```
# Dropping 'state' and 'phone number'
data = data.drop(['state', 'phone number'], axis=1)
```

In [53]:
```
# Check the cleaned dataset
print("Cleaned Dataset:\n", data.head())
```

```
Cleaned Dataset:
    account length  area code  international plan  voice mail plan  \
0             128        415                   0                1
1             107        415                   0                1
2             137        415                   0                0
3              84        408                   1                0
4              75        415                   1                0

   number vmail messages  total day minutes  total day calls  \
0                     25              265.1              110
1                     26              161.6              123
2                      0              243.4              114
3                      0              299.4               71
4                      0              166.7              113

   total day charge  total eve minutes  total eve calls  total eve charge  \
0             45.07              197.4               99             16.78
1             27.47              195.5              103             16.62
2             41.38              121.2              110             10.30
3             50.90               61.9               88              5.26
4             28.34              148.3              122             12.61

   total night minutes  total night calls  total night charge  \
0                244.7                 91               11.01
1                254.4                103               11.45
2                162.6                104                7.32
3                196.9                 89                8.86
4                186.9                121                8.41

   total intl minutes  total intl calls  total intl charge  \
0                10.0                 3               2.70
1                13.7                 3               3.70
2                12.2                 5               3.29
3                 6.6                 7               1.78
4                10.1                 3               2.73

   customer service calls  churn
0                       1      0
1                       1      0
2                       0      0
3                       2      0
4                       3      0
```

Outliers

In [54]:
```python
numerical_columns = ['account length', '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']

# Identifying outliers using IQR method
for column in numerical_columns:
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    print(f"{column}: Lower Bound = {lower_bound}, Upper Bound = {upper_bound}")
```

```
account length: Lower Bound = -5.5, Upper Bound = 206.5
total day minutes: Lower Bound = 34.64999999999996, Upper Bound = 325.45000000000005
total day calls: Lower Bound = 46.5, Upper Bound = 154.5
total day charge: Lower Bound = 5.890000000000001, Upper Bound = 55.33
total eve minutes: Lower Bound = 63.54999999999997, Upper Bound = 338.35
total eve calls: Lower Bound = 46.5, Upper Bound = 154.5
total eve charge: Lower Bound = 5.4, Upper Bound = 28.759999999999998
total night minutes: Lower Bound = 64.54999999999998, Upper Bound = 337.75
total night calls: Lower Bound = 48.0, Upper Bound = 152.0
total night charge: Lower Bound = 2.914999999999999, Upper Bound = 15.195
total intl minutes: Lower Bound = 3.1000000000000005, Upper Bound = 17.5
total intl calls: Lower Bound = -1.5, Upper Bound = 10.5
total intl charge: Lower Bound = 0.8449999999999995, Upper Bound = 4.7250000000000005
customer service calls: Lower Bound = -0.5, Upper Bound = 3.5
```

In [55]:
```python
# Handling outliers using calculated bounds
for column in numerical_columns:
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Replacing outliers with lower/upper bounds
    data[column] = np.where(data[column] < lower_bound, lower_bound, data[column])
    data[column] = np.where(data[column] > upper_bound, upper_bound, data[column])
```

EXPLORATORY DATA ANALYSIS

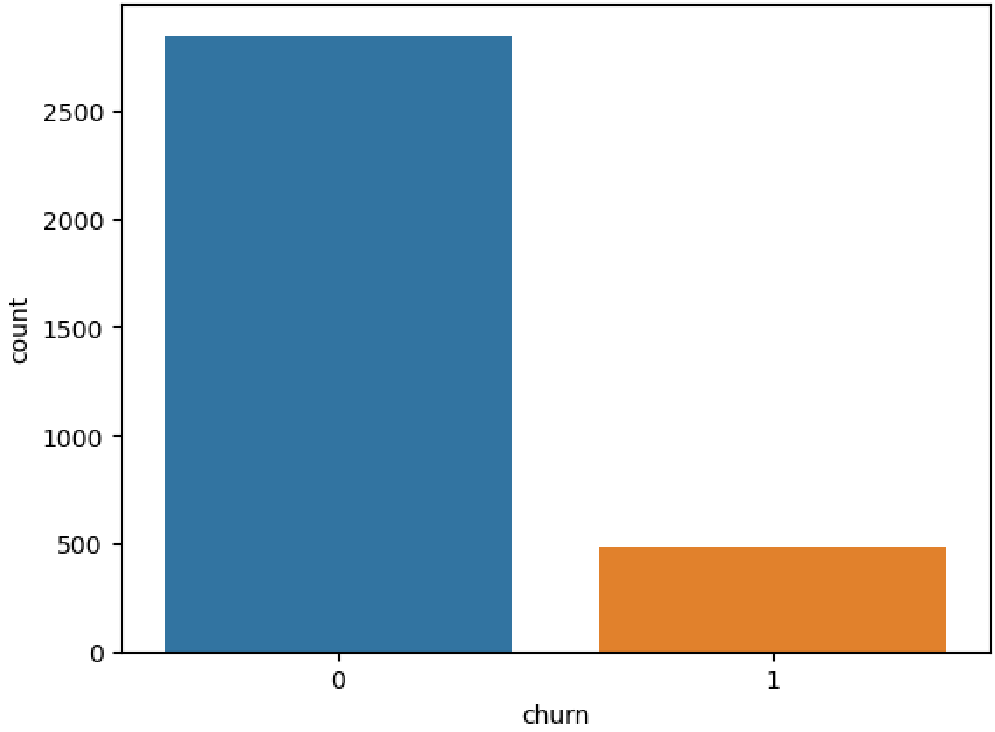
1. Univariate Analysis

i) Target Variable Distribution

In [56]:
```python
# Class distribution
data['churn'].value_counts()
```

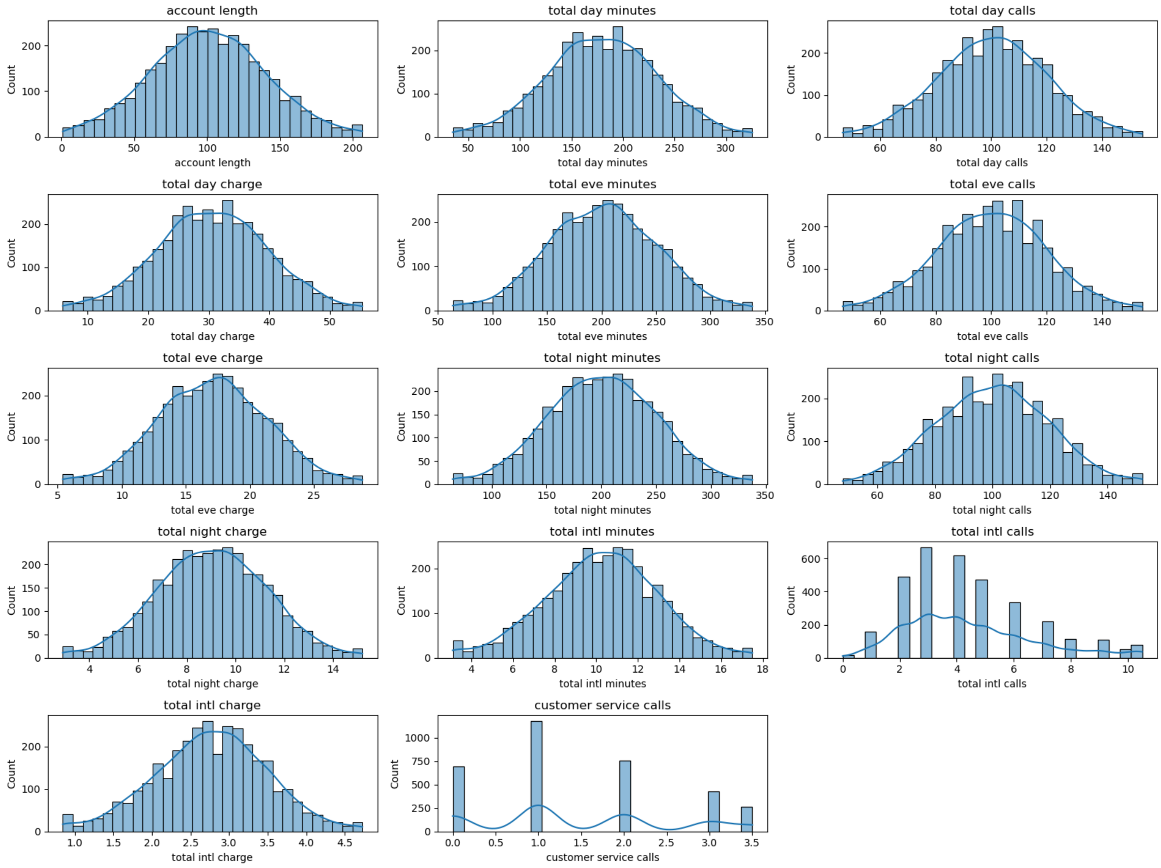
Out[56]:
```
0    2850
1     483
Name: churn, dtype: int64
```

In [57]:
```
# The distribution of the target variable ('churn')
sns.countplot(x='churn', data=data)
plt.show()
```



ii) Numerical Features

In [58]:
```
# The distribution of numerical features
plt.figure(figsize=(16, 12))
for i, col in enumerate(numerical_columns, 1):
    plt.subplot(5, 3, i)
    sns.histplot(data[col], kde=True)
    plt.title(col)

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



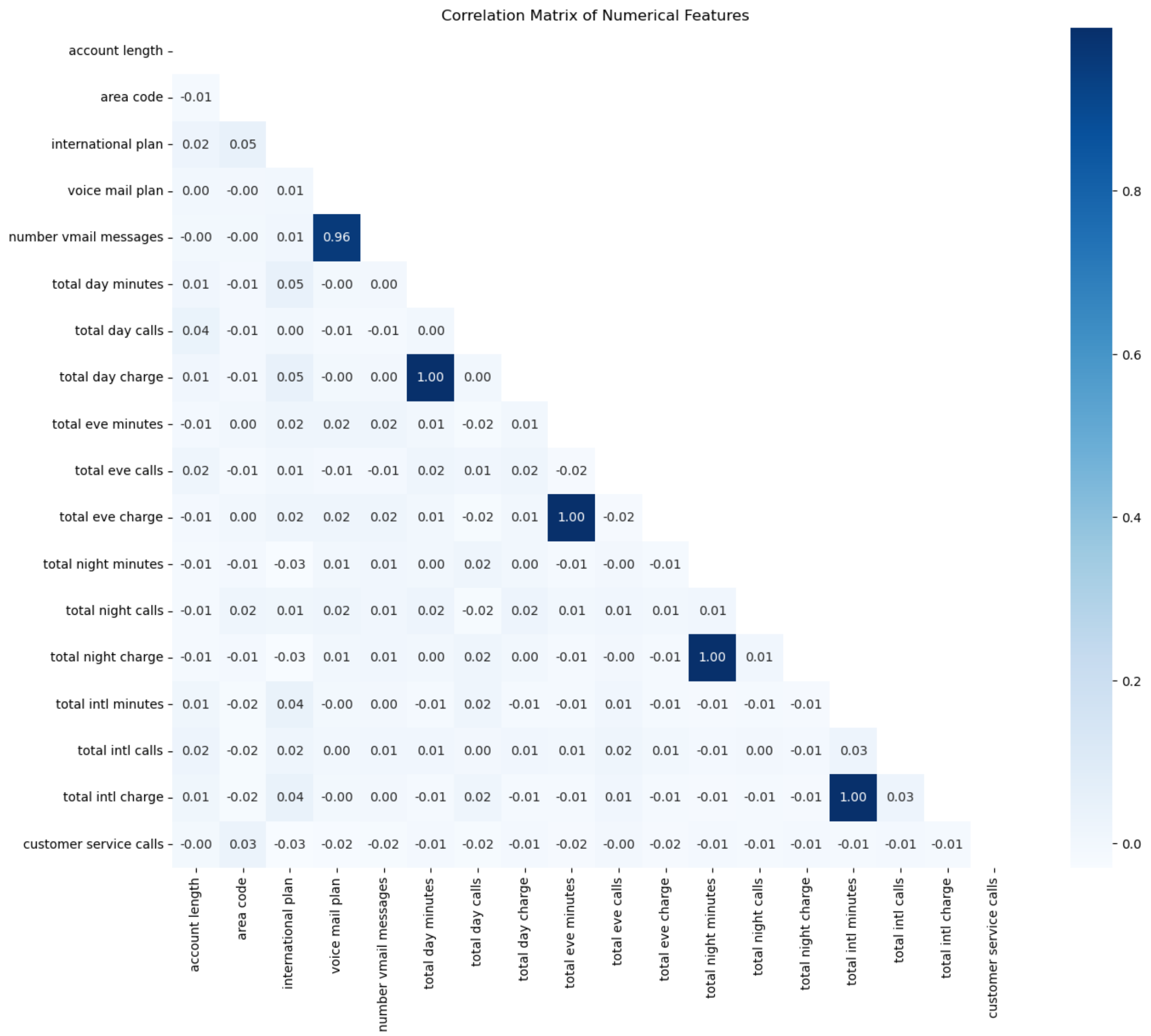
2. Multivariate Analysis

i) Correlation Matrix

A heatmap showing the correlation between numerical features.

In [59]:

```
numerical_features = data.select_dtypes(include=['float64', 'int64']).columns.tolist()


# Calculate the correlation matrix
correlation_matrix = data[numerical_features].corr()

# Create a mask for the upper triangle
mask = np.triu(np.ones_like(correlation_matrix, dtype=bool))

# Plotting the half of the correlation matrix
plt.figure(figsize=(15, 12))
sns.heatmap(correlation_matrix, mask=mask, annot=True, cmap="Blues", fmt=".2f")
plt.title("Correlation Matrix of Numerical Features")
plt.show()
```



In [60]:
```
# Updated DataFrame
print(data.head())
```

```
   account length  area code  international plan  voice mail plan  \
0           128.0        415                   0                1
1           107.0        415                   0                1
2           137.0        415                   0                0
3            84.0        408                   1                0
4            75.0        415                   1                0

   number vmail messages  total day minutes  total day calls  \
0                     25              265.1            110.0
1                     26              161.6            123.0
2                      0              243.4            114.0
3                      0              299.4             71.0
4                      0              166.7            113.0

   total day charge  total eve minutes  total eve calls  total eve charge  \
0             45.07             197.40             99.0             16.78
1             27.47             195.50            103.0             16.62
2             41.38             121.20            110.0             10.30
3             50.90              63.55             88.0              5.40
4             28.34             148.30            122.0             12.61

   total night minutes  total night calls  total night charge  \
0                244.7               91.0               11.01
1                254.4              103.0               11.45
2                162.6              104.0                7.32
3                196.9               89.0                8.86
4                186.9              121.0                8.41

   total intl minutes  total intl calls  total intl charge  \
0                10.0               3.0               2.70
1                13.7               3.0               3.70
2                12.2               5.0               3.29
3                 6.6               7.0               1.78
4                10.1               3.0               2.73

   customer service calls  churn
0                     1.0      0
1                     1.0      0
2                     0.0      0
3                     2.0      0
4                     3.0      0
```

ii) Categorical Features

In [61]:
```
# Unique values in 'international plan' column
print("Unique values in 'international plan':", data['international plan'].unique())
```

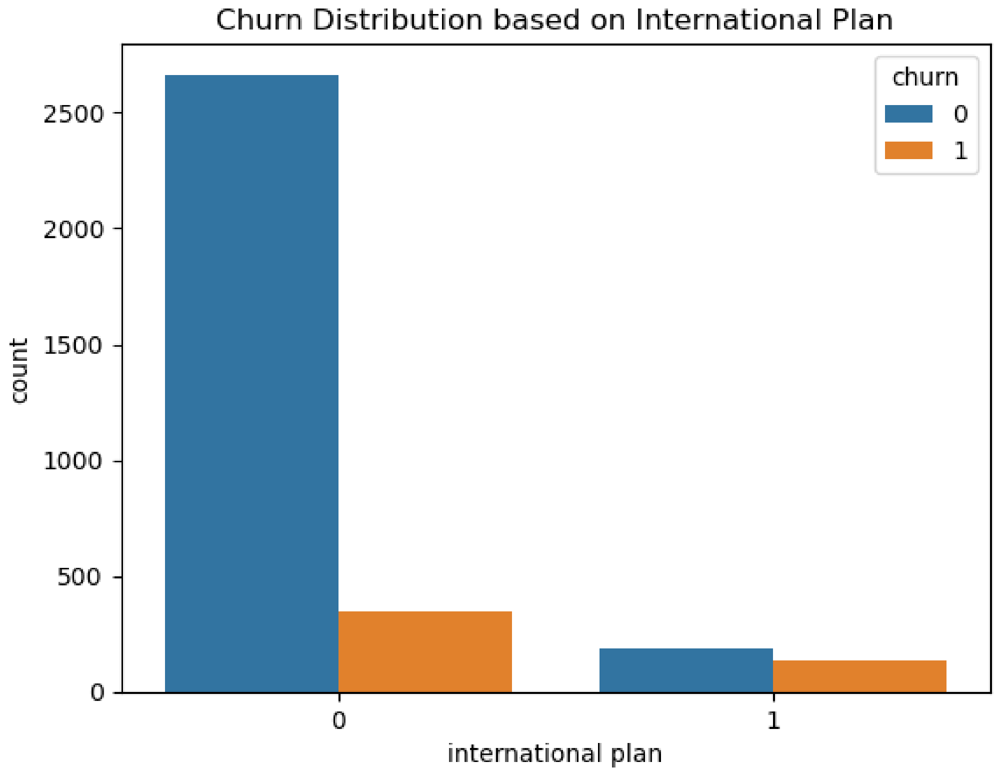
```
Unique values in 'international plan': [0 1]
```

In [62]:
```
# Replacing missing values in 'international plan' with 0
data['international plan'].fillna(0, inplace=True)

# Unique values
print("Unique values in 'international plan':", data['international plan'].unique())
```

```
Unique values in 'international plan': [0 1]
```

In [63]:

```
# The Distribution of categorical features (International Plan)
sns.countplot(x='international plan', hue='churn', data=data)
plt.title('Churn Distribution based on International Plan')
plt.show()
```



In [64]:

```
# Unique values in 'international plan' column
print("Unique values in 'international plan':", data['international plan'].unique())
```

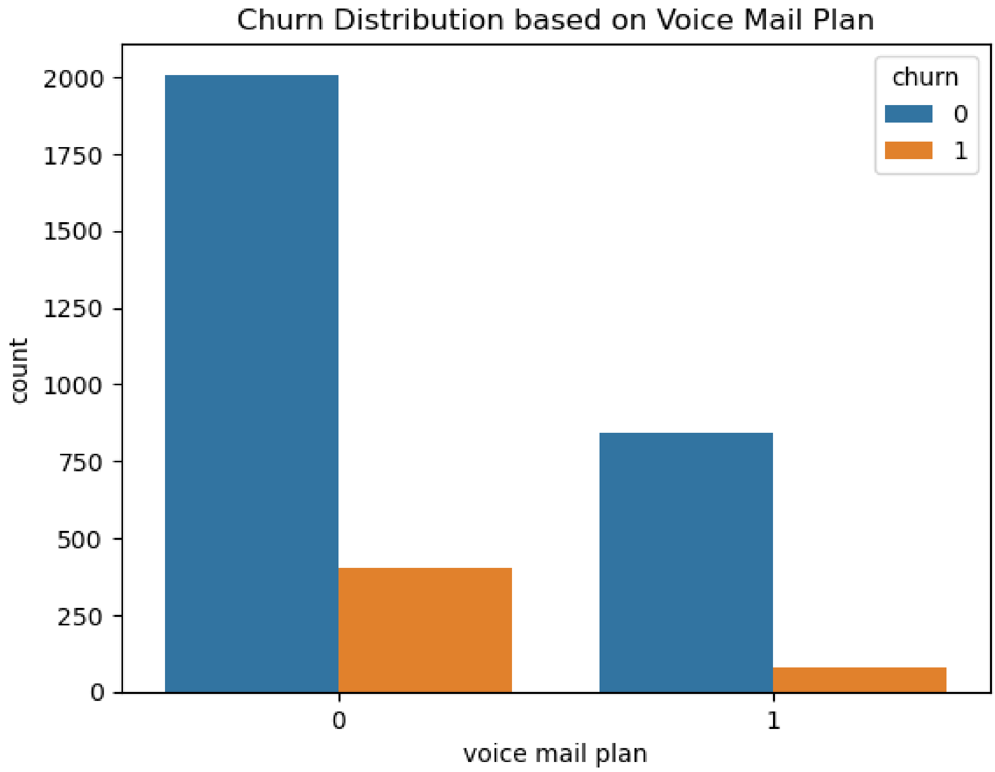
```
Unique values in 'international plan': [0 1]
```

In [65]:

```
# Replacing missing values in 'international plan' with 0
data['voice mail plan'].fillna(0, inplace=True)

# Unique values
print("Unique values in 'voice mail plan':", data['voice mail plan'].unique())
```

```
Unique values in 'voice mail plan': [1 0]
```

In [66]:
```
# The Distribution of categorical features (International Plan)
sns.countplot(x='voice mail plan', hue='churn', data=data)
plt.title('Churn Distribution based on Voice Mail Plan')
plt.show()
```



iii) Pairplot

A pairplot for selected numerical features, with differentiating points for churned and non-churned customers.

In [67]:
```
# Pairplot for selected numerical features
#selected_numerical_features = ['total day minutes', 'total eve minutes', 'total night m

#sns.pairplot(data[selected_numerical_features], hue='churn', markers=["o", "s"], diag_k
#plt.suptitle("Pairplot of Selected Numerical Features", y=1.02, fontsize=16)
#plt.show()
```

Feature Engineering

In [68]:
```
# Feature Engineering
# Usage Patterns
data['avg_day_minutes'] = data['total day minutes'] / data['total day calls']
data['day_to_evening_ratio'] = data['total day calls'] / data['total eve calls']

# Customer Engagement
data['total_engagement'] = data['customer service calls'] + data['number vmail messages

# Account Longevity
data['account_length_category'] = pd.cut(data['account length'], bins=[0, 100, 200, flo

# International Usage
data['intl_ratio'] = data['total intl minutes'] / (data['total day minutes'] + data['to

# Billing Information
data['avg_charge_per_call'] = data['total day charge'] / data['total day calls']

# Interaction Features
data['interaction_feature'] = data['avg_day_minutes'] * data['total_engagement']

# Updated dataset
print(data.head())
```

```
   account length  area code  international plan  voice mail plan  \
0           128.0        415                   0                1   
1           107.0        415                   0                1   
2           137.0        415                   0                0   
3            84.0        408                   1                0   
4            75.0        415                   1                0   

   number vmail messages  total day minutes  total day calls  \
0                     25              265.1            110.0   
1                     26              161.6            123.0   
2                      0              243.4            114.0   
3                      0              299.4             71.0   
4                      0              166.7            113.0   

   total day charge  total eve minutes  total eve calls  ...  \
0             45.07             197.40             99.0  ...   
1             27.47             195.50            103.0  ...   
2             41.38             121.20            110.0  ...   
3             50.90              63.55             88.0  ...   
4             28.34             148.30            122.0  ...   

   total intl charge  customer service calls  churn  avg_day_minutes  \
0               2.70                     1.0      0         2.410000   
1               3.70                     1.0      0         1.313821   
2               3.29                     0.0      0         2.135088   
3               1.78                     2.0      0         4.216901   
4               2.73                     3.0      0         1.475221   

   day_to_evening_ratio  total_engagement  account_length_category  \
0              1.111111              26.0                   medium   
1              1.194175              27.0                   medium   
2              1.036364               0.0                   medium   
3              0.806818               2.0                    short   
4              0.926230               3.0                    short   

   intl_ratio  avg_charge_per_call  interaction_feature  
0    0.013943             0.409727            62.660000  
1    0.021913             0.223333            35.473171  
2    0.022618             0.362982             0.000000  
3    0.011652             0.716901             8.433803  
4    0.019727             0.250796             4.425664  

[5 rows x 26 columns]
```

DATA PREPROCESSING

Encoding Categorical Variables

In [69]:

```
# Unique values in 'international plan' and 'voice mail plan' columns
print("Unique values in 'international plan':", data['international plan'].unique())
print("Unique values in 'voice mail plan':", data['voice mail plan'].unique())
```

```
Unique values in 'international plan': [0 1]
Unique values in 'voice mail plan': [1 0]
```

In [70]:

```
# Convert categorical labels to numerical labels for 'churn', 'international plan', and
label_encoder = LabelEncoder()
data['churn'] = label_encoder.fit_transform(data['churn'])
data['international plan'] = label_encoder.fit_transform(data['international plan'])
data['voice mail plan'] = label_encoder.fit_transform(data['voice mail plan'])
```

In [71]:
```
missing_values = data.isnull().sum()
print("Missing Values:\n", missing_values)
```

```
Missing Values:
 account length            0
area code                 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
avg_day_minutes           0
day_to_evening_ratio      0
total_engagement          0
account_length_category   0
intl_ratio                0
avg_charge_per_call       0
interaction_feature       0
dtype: int64
```

In [72]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3333 entries, 0 to 3332
Data columns (total 26 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   account length           3333 non-null   float64
 1   area code                3333 non-null   int64
 2   international plan       3333 non-null   int64
 3   voice mail plan          3333 non-null   int64
 4   number vmail messages    3333 non-null   int64
 5   total day minutes        3333 non-null   float64
 6   total day calls          3333 non-null   float64
 7   total day charge         3333 non-null   float64
 8   total eve minutes        3333 non-null   float64
 9   total eve calls          3333 non-null   float64
 10  total eve charge         3333 non-null   float64
 11  total night minutes      3333 non-null   float64
 12  total night calls        3333 non-null   float64
 13  total night charge       3333 non-null   float64
 14  total intl minutes       3333 non-null   float64
 15  total intl calls         3333 non-null   float64
 16  total intl charge        3333 non-null   float64
 17  customer service calls   3333 non-null   float64
 18  churn                    3333 non-null   int64
 19  avg_day_minutes          3333 non-null   float64
 20  day_to_evening_ratio     3333 non-null   float64
 21  total_engagement         3333 non-null   float64
 22  account_length_category  3333 non-null   category
 23  intl_ratio               3333 non-null   float64
 24  avg_charge_per_call      3333 non-null   float64
 25  interaction_feature      3333 non-null   float64
dtypes: category(1), float64(20), int64(5)
memory usage: 654.5 KB
```

Feature Scaling

In [73]:
```
scaler = StandardScaler()
numerical_features = ['account length', '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']
data[numerical_features] = scaler.fit_transform(data[numerical_features])
```

Train-Test Split

In [74]:
```
# Features (X) and target variable (y)
X = data.drop('churn', axis=1)
y = data['churn']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=4
```

MODELING

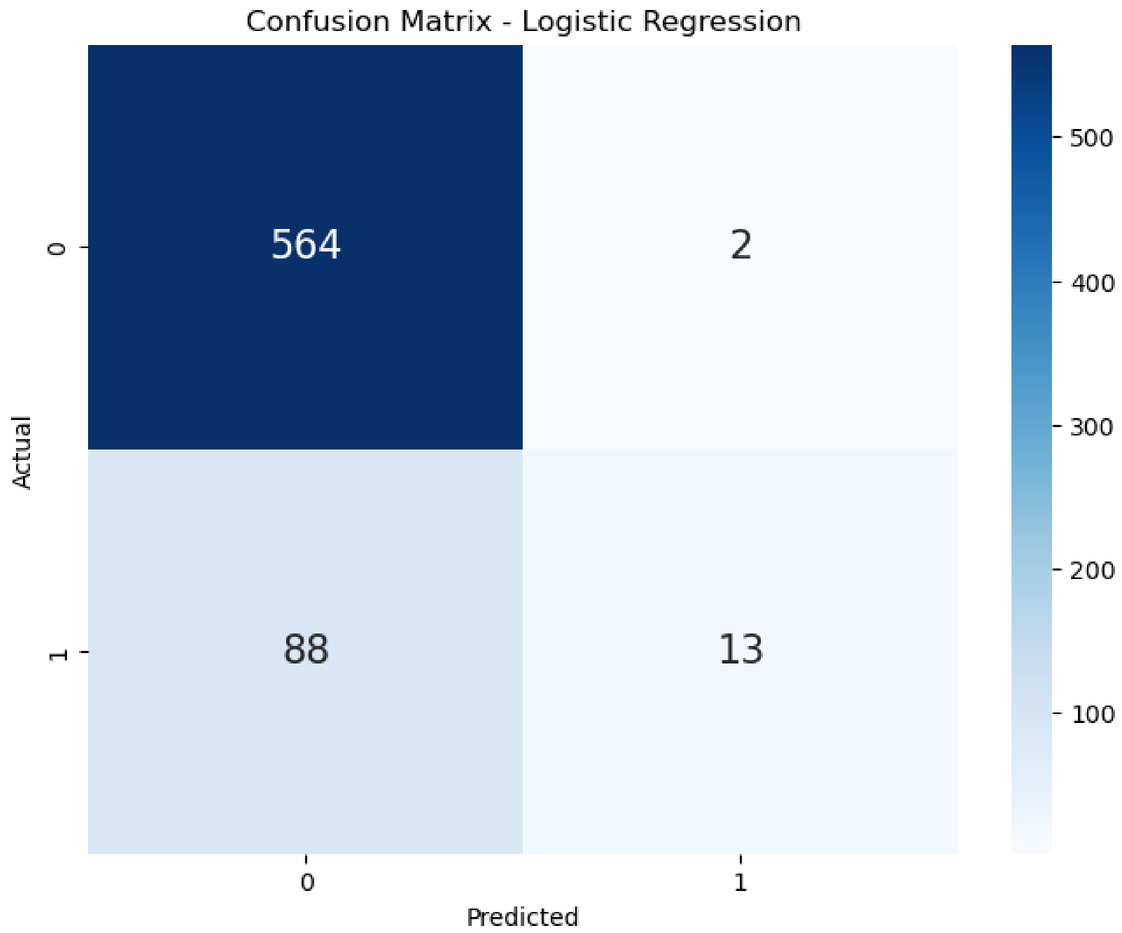
Logistic Regression (Baseline Model)

In [75]:

```
# Separating numerical and categorical features
numerical_features = X_train.select_dtypes(include=['float64']).columns
categorical_features = X_train.select_dtypes(include=['category']).columns

# Transformers for numerical and categorical features
numeric_transformer = Pipeline(steps=[
    ('scaler', StandardScaler())
])

categorical_transformer = Pipeline(steps=[
    ('onehot', OneHotEncoder())
])

# Column transformer
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numerical_features),
        ('cat', categorical_transformer, categorical_features)
    ])

# Pipeline with preprocessing and logistic regression
logreg_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', LogisticRegression(random_state=42))
])

# Fitting the model on the training data
logreg_model.fit(X_train, y_train)

# Making predictions on the test data
y_pred_logreg = logreg_model.predict(X_test)

# Evaluating the model
accuracy = accuracy_score(y_test, y_pred_logreg)
conf_matrix = confusion_matrix(y_test, y_pred_logreg)
class_report = classification_report(y_test, y_pred_logreg)

# Results
print("Accuracy:", accuracy)
print("Confusion Matrix:\n", conf_matrix)
print("Classification Report:\n", class_report)
```

```
Accuracy: 0.8650674662668666
Confusion Matrix:
 [[564   2]
 [ 88  13]]
Classification Report:
               precision    recall  f1-score   support

           0       0.87      1.00      0.93       566
           1       0.87      0.13      0.22       101

    accuracy                           0.87       667
   macro avg       0.87      0.56      0.58       667
weighted avg       0.87      0.87      0.82       667
```

In [76]:
```
# Confusion Matrix Heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap="Blues", annot_kws={"size": 16})
plt.title('Confusion Matrix - Logistic Regression')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



The model has a high accuracy due to the dominance of the negative class in the dataset. However, the low recall suggests that the model struggles to identify instances of the positive class. Further model improvement may be needed, especially since identifying positive instances is crucial for the business problem.

Hyperparameter Tuning for Logistic Regression

In [77]:

```
# Hyperparameter grid for Logistic Regression
param_grid = {
    'classifier__C': [0.001, 0.01, 0.1, 1, 10, 100],
    'classifier__penalty': ['l2'],
    'classifier__max_iter': [100, 200, 300],
}

# Preprocessing pipeline
preprocessor = ColumnTransformer(
    transformers=[
        ('numerical', Pipeline([('scaler', StandardScaler())]), numerical_features),
        ('categorical', Pipeline([('onehot', OneHotEncoder())]), categorical_features)
    ]
)

# Full pipeline with preprocessing and logistic regression
pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', LogisticRegression(random_state=42))
])

# GridSearchCV object
grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring='accuracy')

# Fitting the grid search to the data
grid_search.fit(X_train, y_train)

# Print the best hyperparameters
print("Best Hyperparameters for Logistic Regression:", grid_search.best_params_)

# The best model
best_logreg_model = grid_search.best_estimator_

# Evaluating the best model on the test set
y_pred_logreg = best_logreg_model.predict(X_test)

# Results
print("Accuracy (Logistic Regression - Tuned):", accuracy_score(y_test, y_pred_logreg))
print("Confusion Matrix (Logistic Regression - Tuned):\n", confusion_matrix(y_test, y_p
print("Classification Report (Logistic Regression - Tuned):\n", classification_report(y
```

```
C:\Users\USER\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:460: Conve
rgenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.o
rg/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (htt
ps://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
C:\Users\USER\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:460: Conve
rgenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.o
rg/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (htt
ps://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(
C:\Users\USER\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:460: Conve
rgenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.o
rg/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression (htt
ps://scikit-learn.org/stable/modules/linear_model.html#logistic-regression)
  n_iter_i = _check_optimize_result(

Best Hyperparameters for Logistic Regression: {'classifier__C': 1, 'classifier__max_it
er': 100, 'classifier__penalty': 'l2'}
Accuracy (Logistic Regression - Tuned): 0.8650674662668666
Confusion Matrix (Logistic Regression - Tuned):
 [[564   2]
 [ 88  13]]
Classification Report (Logistic Regression - Tuned):
              precision    recall  f1-score   support

           0       0.87      1.00      0.93       566
           1       0.87      0.13      0.22       101

    accuracy                           0.87       667
   macro avg       0.87      0.56      0.58       667
weighted avg       0.87      0.87      0.82       667
```

The model's accuracy remains unchanged, despite its difficulties in accurately predicting the positive class (class 1), as seen by the poor recall for this class. This indicates a low sensitivity of the model because it is failing to detect a significant proportion of the positive indications.

Decision Tree

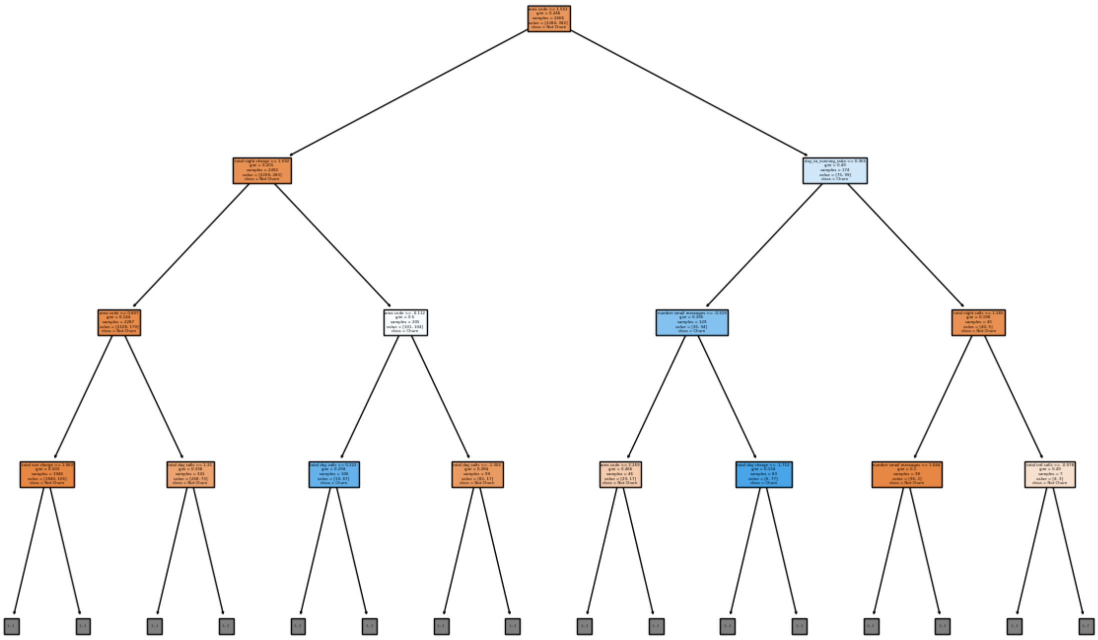
In [78]:

```
# Pipeline with preprocessing and decision tree classifier
dtc_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', DecisionTreeClassifier(random_state=42))
])

# Fiting the model on the training data
dtc_model.fit(X_train, y_train)

# Making predictions on the test data
y_pred_dtc = dtc_model.predict(X_test)

# Evaluating the model
accuracy_dtc = accuracy_score(y_test, y_pred_dtc)
conf_matrix_dtc = confusion_matrix(y_test, y_pred_dtc)
class_report_dtc = classification_report(y_test, y_pred_dtc)

# Results
print("Accuracy (Decision Tree):", accuracy_dtc)
print("Confusion Matrix (Decision Tree):\n", conf_matrix_dtc)
print("Classification Report (Decision Tree):\n", class_report_dtc)
```

```
Accuracy (Decision Tree): 0.8515742128935532
Confusion Matrix (Decision Tree):
 [[510  56]
 [ 43  58]]
Classification Report (Decision Tree):
               precision    recall  f1-score   support

           0       0.92      0.90      0.91       566
           1       0.51      0.57      0.54       101

    accuracy                           0.85       667
   macro avg       0.72      0.74      0.73       667
weighted avg       0.86      0.85      0.86       667
```

In [79]:

```
from sklearn.tree import plot_tree

# The decision tree from the pipeline
dtc_classifier = dtc_model.named_steps['classifier']

# Plot the decision tree
plt.figure(figsize=(15, 10))
plot_tree(dtc_classifier, filled=True, feature_names=X_train.columns.tolist(), class_na
plt.show()
```



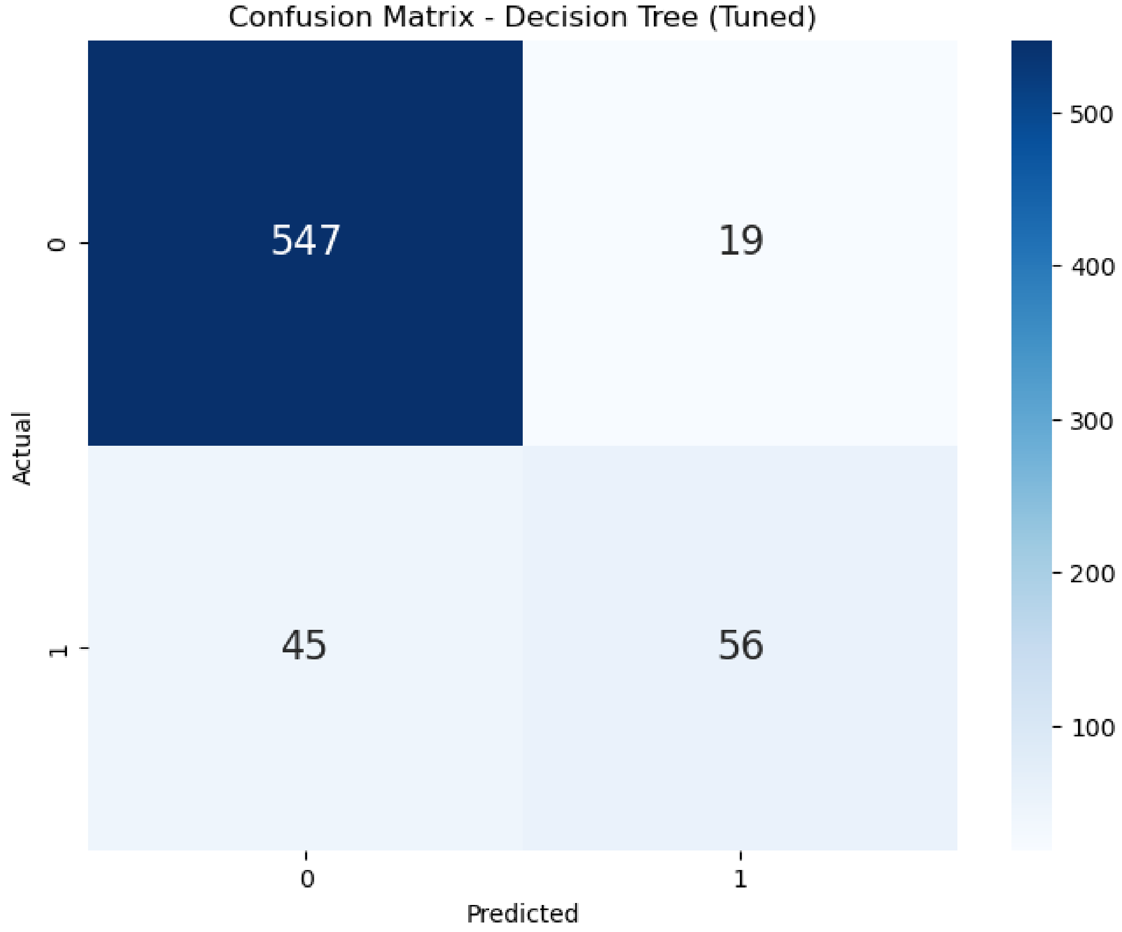
Hyperparameter Tuning for Decision Tree

In [80]:

```
# Hyperparameter grid for Decision Tree
param_grid_dtc = {
    'classifier__criterion': ['gini', 'entropy'],
    'classifier__max_depth': [None, 10, 20, 30, 40, 50],
    'classifier__min_samples_split': [2, 5, 10],
    'classifier__min_samples_leaf': [1, 2, 4],
}

# The full pipeline with preprocessing and Decision Tree
pipeline_dtc = Pipeline([
    ('preprocessor', preprocessor),
    ('classifier', DecisionTreeClassifier(random_state=42))
])

# The GridSearchCV object for Decision Tree
grid_search_dtc = GridSearchCV(pipeline_dtc, param_grid_dtc, cv=5, scoring='accuracy')

# Fitting the grid search to the data for Decision Tree
grid_search_dtc.fit(X_train, y_train)

# Print the best hyperparameters for Decision Tree
print("Best Hyperparameters for Decision Tree:", grid_search_dtc.best_params_)

# The best Decision Tree model
best_dtc_model = grid_search_dtc.best_estimator_

# Evaluating the best Decision Tree model on the test set
y_pred_dtc = best_dtc_model.predict(X_test)

# Results
print("Accuracy (Decision Tree - Tuned):", accuracy_score(y_test, y_pred_dtc))
print("Confusion Matrix (Decision Tree - Tuned):\n", confusion_matrix(y_test, y_pred_dt
print("Classification Report (Decision Tree - Tuned):\n", classification_report(y_test,
```

```
Best Hyperparameters for Decision Tree: {'classifier__criterion': 'entropy', 'classifi
er__max_depth': 10, 'classifier__min_samples_leaf': 2, 'classifier__min_samples_spli
t': 5}
Accuracy (Decision Tree - Tuned): 0.904047976011994
Confusion Matrix (Decision Tree - Tuned):
 [[547  19]
 [ 45  56]]
Classification Report (Decision Tree - Tuned):
              precision    recall  f1-score   support

           0       0.92      0.97      0.94       566
           1       0.75      0.55      0.64       101

    accuracy                           0.90       667
   macro avg       0.84      0.76      0.79       667
weighted avg       0.90      0.90      0.90       667
```

In [81]:
```
# Confusion Matrix Heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(confusion_matrix(y_test, y_pred_dtc), annot=True, fmt='d', cmap="Blues", an
plt.title('Confusion Matrix - Decision Tree (Tuned)')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```



The model showed a discernible improvement. With a 90.40% accuracy rate, the overall performance was excellent. The hyperparameters were adjusted to enhance the model's ability to spot complex patterns in the data. As a result, the f1-score, accuracy, and recall for class 1 (Churn) all improved, suggesting that the improved model is better at identifying churn cases.

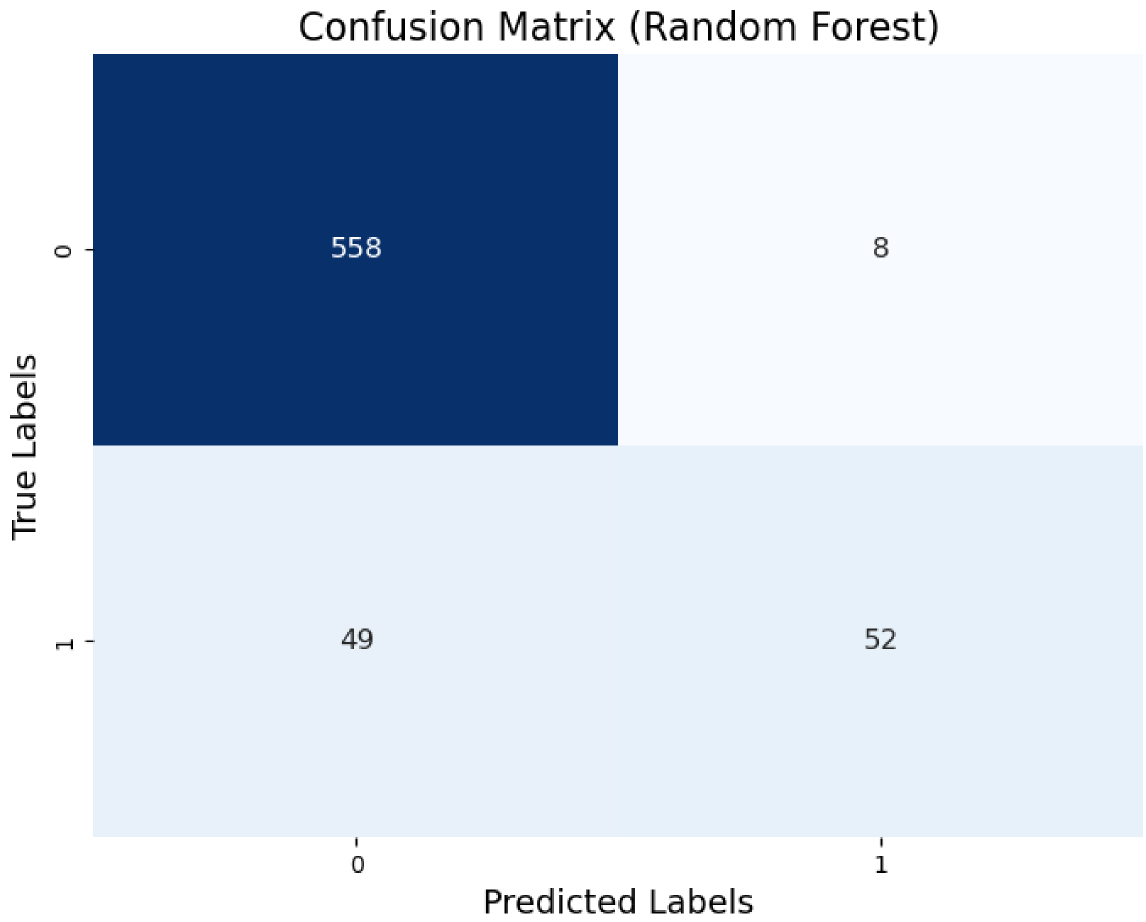
Random Forest

In [82]:

```
# Pipeline with preprocessing and Random Forest classifier
ranfor_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', RandomForestClassifier(random_state=42))
])

# Fitting the model on the training data
ranfor_model.fit(X_train, y_train)

# Predictions on the test data
y_pred_ranfor = ranfor_model.predict(X_test)

# Evaluating the model
accuracy_ranfor = accuracy_score(y_test, y_pred_ranfor)
conf_matrix_ranfor = confusion_matrix(y_test, y_pred_ranfor)
class_report_ranfor = classification_report(y_test, y_pred_ranfor)

# Results
print("Accuracy (Random Forest):", accuracy_ranfor)
print("Confusion Matrix (Random Forest):\n", conf_matrix_ranfor)
print("Classification Report (Random Forest):\n", class_report_ranfor)
```

```
Accuracy (Random Forest): 0.9145427286356822
Confusion Matrix (Random Forest):
 [[558   8]
 [ 49  52]]
Classification Report (Random Forest):
               precision    recall  f1-score   support

           0       0.92      0.99      0.95       566
           1       0.87      0.51      0.65       101

    accuracy                           0.91       667
   macro avg       0.89      0.75      0.80       667
weighted avg       0.91      0.91      0.91       667
```

In [83]:
```
# Plotting the confusion matrix heatmap for Random Forest
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix_ranfor, annot=True, cmap="Blues", fmt="d", cbar=False, annot_kw
plt.title("Confusion Matrix (Random Forest)", fontsize=16)
plt.xlabel("Predicted Labels", fontsize=14)
plt.ylabel("True Labels", fontsize=14)
plt.show()
```



The model demonstrates a high accuracy rate and decent precision. However, the recall is relatively lower, suggesting that the model may not be as effective in capturing all instances of the positive class. Further analysis and fine-tuning might be required to improve the model's performance, particularly in identifying instances of "Churn" (class 1).

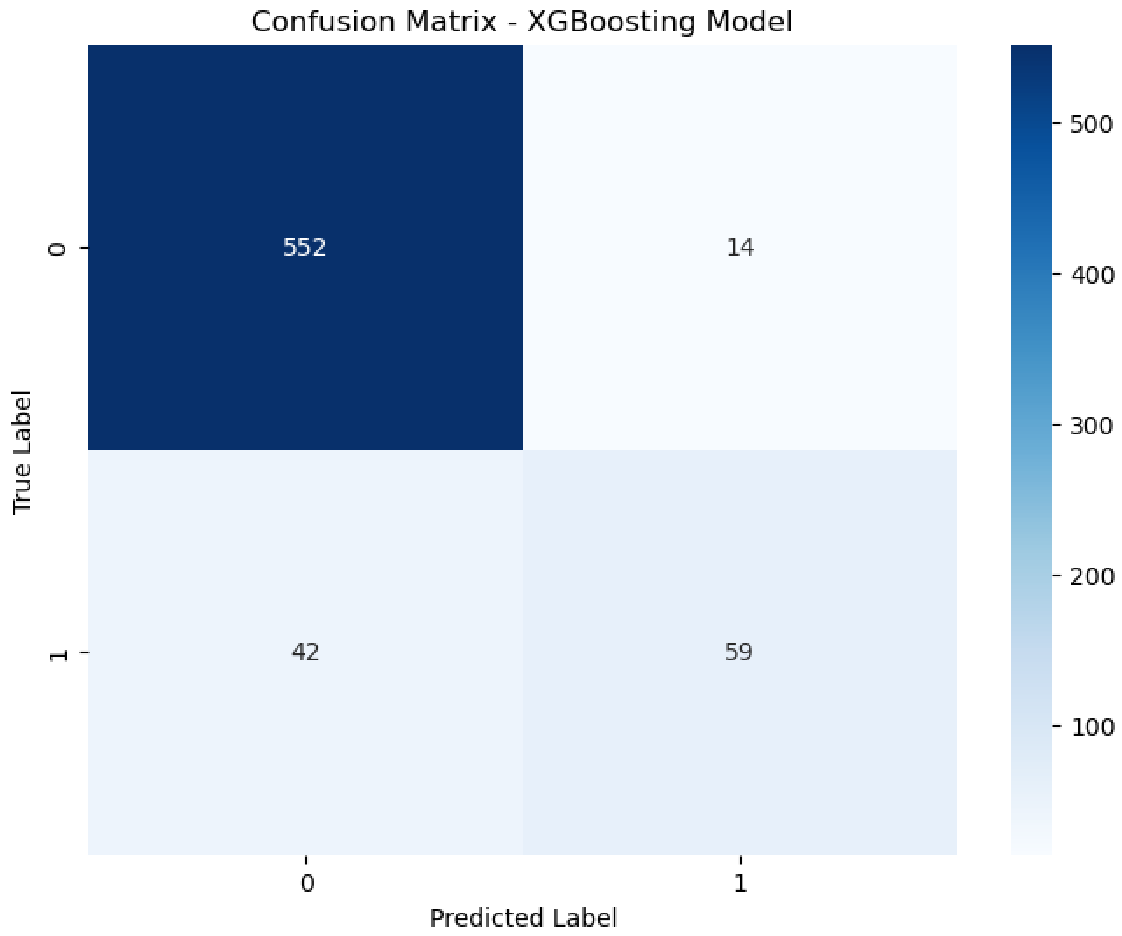
XGBoosting

In [84]:

```
# Pipeline with preprocessing and XGBoost classifier
xgb_model = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', XGBClassifier(random_state=42))
])

# Fitting the model on the training data
xgb_model.fit(X_train, y_train)

# Predictions on the test data
y_pred_xgb = xgb_model.predict(X_test)

# Evaluating the model
accuracy_xgb = accuracy_score(y_test, y_pred_xgb)
conf_matrix_xgb = confusion_matrix(y_test, y_pred_xgb)
class_report_xgb = classification_report(y_test, y_pred_xgb)

# Results
print("Accuracy (XGBoost):", accuracy_xgb)
print("Confusion Matrix (XGBoost):\n", conf_matrix_xgb)
print("Classification Report (XGBoost):\n", class_report_xgb)
```

```
Accuracy (XGBoost): 0.9160419790104948
Confusion Matrix (XGBoost):
 [[552  14]
 [ 42  59]]
Classification Report (XGBoost):
               precision    recall  f1-score   support

           0       0.93      0.98      0.95       566
           1       0.81      0.58      0.68       101

    accuracy                           0.92       667
   macro avg       0.87      0.78      0.81       667
weighted avg       0.91      0.92      0.91       667
```

In [85]:
```
# Confusion Matrix Heatmap
plt.figure(figsize=(8, 6))
conf_matrix_xgb = confusion_matrix(y_test, y_pred_xgb)
sns.heatmap(conf_matrix_xgb, annot=True, fmt="d", cmap="Blues")
plt.title('Confusion Matrix - XGBoosting Model')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```



The model demonstrates a high accuracy rate and good precision. The recall is also relatively better compared to the Random Forest model, suggesting that the XGBoost model is more effective in capturing instances of the positive class. Further analysis and fine-tuning might still be considered to enhance the model's overall performance.

Model Performance

1.The logistic regression model, despite being the baseline model, demonstrated reasonable accuracy. However, it struggled with accurately predicting the positive class (churn).

2.The decision tree model showed improvement after hyperparameter tuning, achieving a higher accuracy, especially in detecting churn cases.

3.Both the Random Forest and XGBoost models outperformed other models, with XGBoost exhibiting the highest accuracy and better performance in identifying churn cases.

RECOMMENDATIONS

1.Identify factors contributing to churn and implement strategies to address these issues, such as personalized offers, improved customer support, or service enhancements.

2.Regularly evaluate the decison tree model using new data to ensure its effectiveness in real-world scenarios.

3.Establish a feedback loop to gather information on the effectiveness of implemented strategies.

4.Adopt the Tuned Decision Tree Model since it has demonstrated better overall performance, especially in correctly identifying customers likely to churn.

5.SyriaTel should introduce flexible plans or additional services based on identified patterns to meet diverse customer needs.

NEXT STEPS

1.The company should focus on the implementation of the recommended strategies, monitoring their effectiveness, and iterating based on real-time performance.

2.Collaboration between different departments, employee training, and establishing a continuous feedback loop with customers are critical for success.

3.Conduct training sessions for customer-facing employees to equip them with the knowledge and skills needed to implement customer retention strategies effectively

4.Develop a long-term business plan that incorporates evolving market trends, technological advancements, and customer expectations.

5.Facilitate regular meetings and collaboration between different departments, including data science, marketing, sales, and customer support.

CONCLUSION

1.Regular monitoring of competitors and adjustments to strategies based on market dynamics will be crucial for maintaining a competitive edge.

2.A customer-centric approach, informed by data-driven insights, will be instrumental in building lasting relationships and loyalty.

3.SyriaTel should plan for the long term, incorporating scalability, sustainability, and adaptability to evolving market trends and customer expectations.

4.Ethical considerations and transparent communication are crucial in building trust with customers and maintaining a positive brand image.

5.Consideration of flexible service plans and continuous innovation in services can cater to diverse customer needs and preferences.