BUSINESS UNDERSTANDING

SyriaTel is a Telecommucations company facing a customer churn challenge. The company is interested in reducing the revenue lost in losing valuable customers.

Data analysis will help to describe customer's behavior, understand their habits, develop appropriate marketing plans for SyriaTel to identify sales transactions and build a long-term loyalty relationship with its customerbase.

Problem Statement

Create a machine learning model to classify customers as;

```
*   likely to churn
*   not churn
```

based given dataset.

Business Objectives

```
*   Minimize churn rate by identifying at-risk customers.
*   Improve retention through targeted retention strategies.
*   Increase customer lifetime value by keeping customers longer.
*   Use cost-effective retention strategies
*   Targeted Marketing compaigns and promotions to acquire more Customers
*   Enhance the customer experience to prevent churn.
```

In [179]:

```
# importing the necessary libraries
import pandas as pd
import numpy as np

# data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# feature selection and importance
from sklearn.feature_selection import SelectKBest, chi2

# Modelling and algorithms for supervised learning
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score, roc_auc_score, confusion_matrix, classification_report
from sklearn.preprocessing import MinMaxScaler, StandardScaler, RobustScaler
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import GridSearchCV
from sklearn.tree import plot_tree
from sklearn.metrics import roc_curve, auc, roc_auc_score
from sklearn.feature_selection import RFE

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

Data Understanding

```
1.   Preview the head and tail of data
2.   Summary statistics
3.   Summary data structure
4.   Missing Values
5.   Duplicated values
6.   Summary number of columns and
```

In [111]:

```python
# import dataset
df=pd.read_csv('bigml.csv')
```

In [112]:

```python
df.head()
```

Out[112]:

	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	total night minutes	total night calls	ch
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16.78	244.7	91	
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16.62	254.4	103	
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10.30	162.6	104	
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.26	196.9	89	
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12.61	186.9	121	

5 rows × 21 columns

In [113]:

```python
df.tail()
```

Out[113]:

	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	total night minutes	total night calls
3328	AZ	192	415	414-4276	no	yes	36	156.2	77	26.55	...	126	18.32	279.1	83
3329	WV	68	415	370-3271	no	no	0	231.1	57	39.29	...	55	13.04	191.3	123
3330	RI	28	510	328-8230	no	no	0	180.8	109	30.74	...	58	24.55	191.9	91
3331	CT	184	510	364-6381	yes	no	0	213.8	105	36.35	...	84	13.57	139.2	137
3332	TN	74	415	400-4344	no	yes	25	234.4	113	39.85	...	82	22.60	241.4	77

5 rows × 21 columns

In [114]:

```python
# Overview of dataset structure
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
```

As per the dataset summary above there are no missing values in the dataset so there is no imputation

```
        *  state- state where the customer resides.
        *   area code- area code associated with the customer's phone number.
        *   phone number- customer's phone number.
        *   account length- duration of the customer's account with the telecom com
pany in months.
        *   international plan- Whether the customer has an international calling
plan (boolean values).
        *   voice mail plan- Whether the customer has a voicemail plan (boolean va
lues).
        *  number vmail messages- number of voicemail messages the customer has.
        *   total day minutes- total number of minutes the customer used during th
e daytime.
        *  total day calls- total number of calls the customer made during the day
time.
        *   total day charge- total charge for daytime usage.
        *   total eve minutes- total number of minutes the customer used during th
e evening.
        *   total eve calls- total number of calls the customer made during the ev
ening.
        *   total eve charge- total charge for evening usage.
        *   total night minutes- total number of minutes the customer used during
the nighttime
        *   total night calls- total number of calls the customer made during the
nighttime.
        *   total night charge- total charge for nighttime usage.
        *   total intl minutes- total number of international minutes used by the
customer.
        *   total intl calls- total number of international calls made by the cust
omer.
        *   total intl charge- total charge  for international usage.
        *   customer service calls- number of customer service calls made by the c
```

ustomer.

* churn- the target variable indicating whether the customer churned (boolean values).

In [115]:

```
# summary of dataset in number of rows and columns
df.shape
```

Out[115]:

```
(3333, 21)
```

In [116]:

```
# summary of statistical properties for the numerical columns
df.describe()
```

Out[116]:

	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
count	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000	3333.000000
mean	101.064806	437.182418	8.099010	179.775098	100.435644	30.562307	200.980348	100.114311	17.083540
std	39.822106	42.371290	13.688365	54.467389	20.069084	9.259435	50.713844	19.922625	4.310668
min	1.000000	408.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
25%	74.000000	408.000000	0.000000	143.700000	87.000000	24.430000	166.600000	87.000000	14.160000
50%	101.000000	415.000000	0.000000	179.400000	101.000000	30.500000	201.400000	100.000000	17.120000
75%	127.000000	510.000000	20.000000	216.400000	114.000000	36.790000	235.300000	114.000000	20.000000
max	243.000000	510.000000	51.000000	350.800000	165.000000	59.640000	363.700000	170.000000	30.910000

Data Cleaning

1. Handle missing values in this data set they do not exist
2. Handle duplicated values of which does not exist in this dataset
3. Handle outliers
4. Feature engineering

Missing Values

In [117]:

```
# missing values summary per column
df.isna().mean()*100
```

Out[117]:

	0
state	0.0
account length	0.0
area code	0.0
phone number	0.0
international plan	0.0
voice mail plan	0.0

number vmail messages	0.0
total day minutes	0.0
total day calls	0.0
total day charge	0.0
total eve minutes	0.0
total eve calls	0.0
total eve charge	0.0
total night minutes	0.0
total night calls	0.0
total night charge	0.0
total intl minutes	0.0
total intl calls	0.0
total intl charge	0.0
customer service calls	0.0
churn	0.0

dtype: float64

Duplicated values

In [118]:

```
# duplicated values summary per column
df[df.duplicated()].count()
```

Out[118]:

	0
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

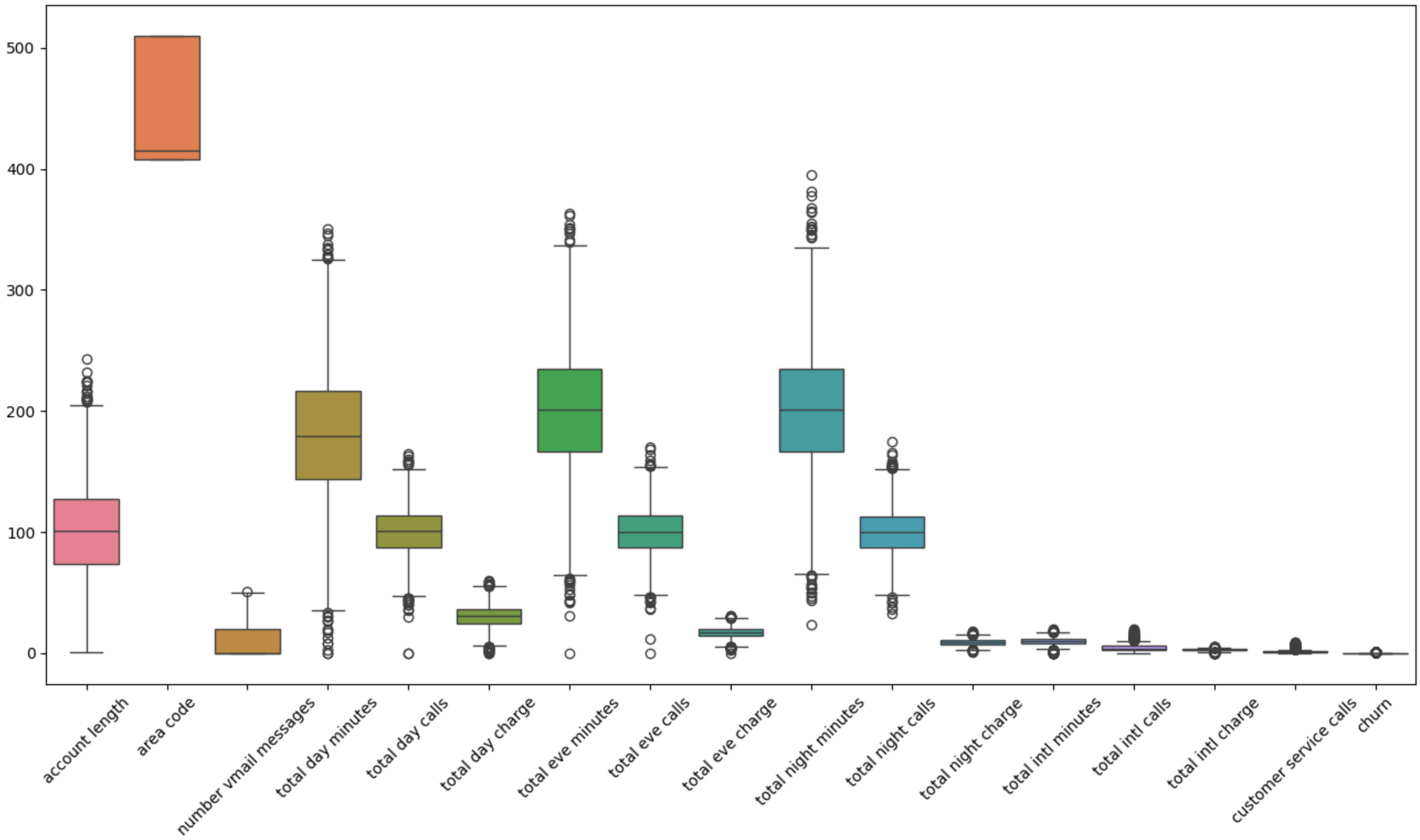
	churn	0

dtype: int64

Outliers

In [119]:

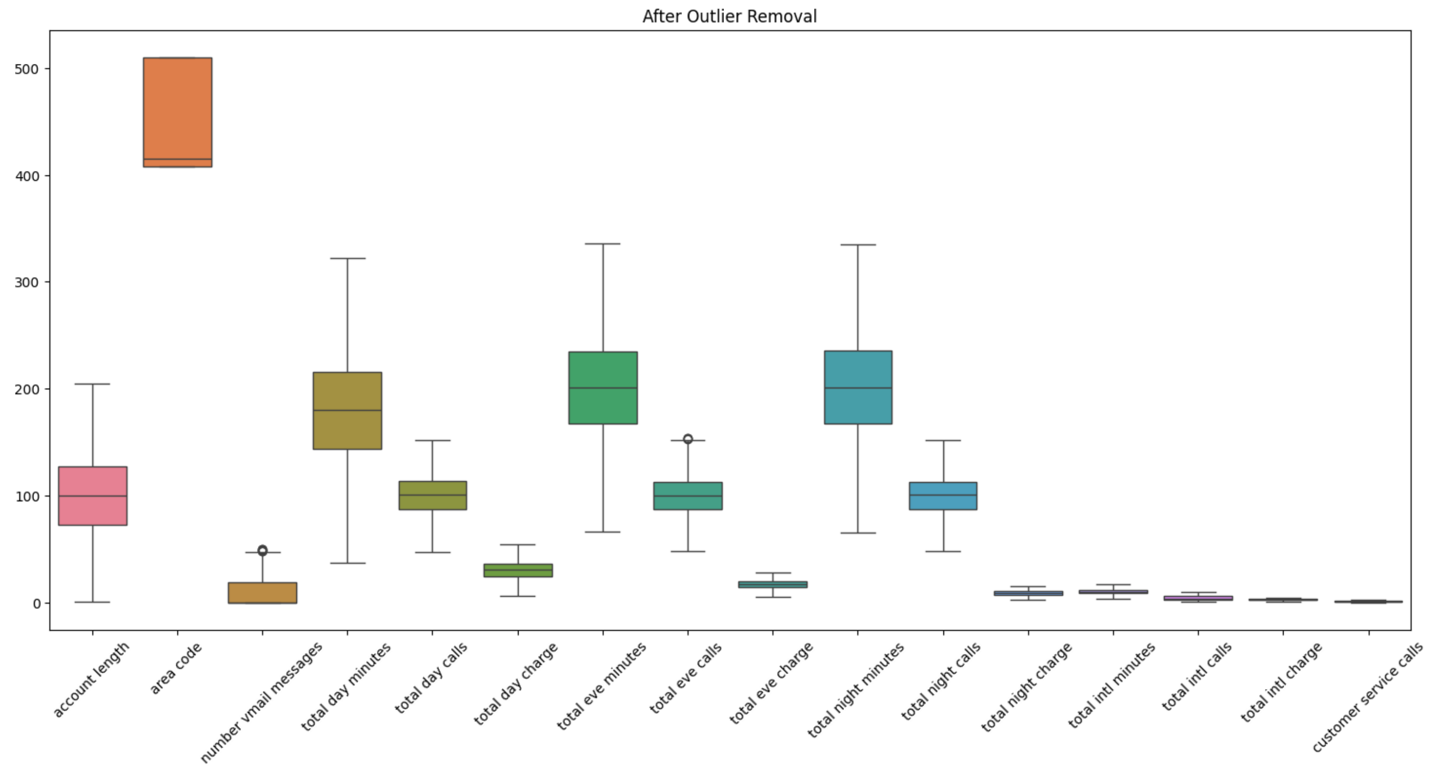
```
# visualize outliers
plt.figure(figsize=(16, 8))
sns.boxplot(df)
plt.xticks(rotation=45)
plt.show()
```



In [120]:

```
# remove Outliers
# Select numerical columns
numerical_cols = df.select_dtypes(include=['float64', 'int64']).columns

# Function to remove outliers using IQR method
def remove_outliers_iqr(data, columns):
    cleaned_df = df.copy()
    for col in columns:
        Q1 = cleaned_df[col].quantile(0.25)
        Q3 = cleaned_df[col].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        # Remove outliers
        cleaned_df = cleaned_df[(cleaned_df[col] >= lower_bound) & (cleaned_df[col] <= u
pper_bound)]
    return cleaned_df
# Apply IQR-based outlier removal
df_cleaned = remove_outliers_iqr(df, numerical_cols)

# plot figure size
plt.figure(figsize=(18, 8))
# Visualize plot after cleaning
sns.boxplot(data=df_cleaned[numerical_cols], orient="v")
```

```
plt.title("After Outlier Removal")
plt.xticks(rotation=45)
plt.show()
```



In [121]:

```
df_cleaned.shape
```

Out[121]:

```
(2797, 21)
```

The number of columns after outlier cleaning has reduced from 3333 to 2797. Close to 18 % percent of the original data set has been cleaned off

In [122]:

```
df.head()
```

Out[122]:

	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	total night minutes	total night calls	ch
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	99	16.78	244.7	91	
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	103	16.62	254.4	103	
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	110	10.30	162.6	104	
3	OH	84	408	375-9999	yes	no	0	299.4	71	50.90	...	88	5.26	196.9	89	
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	122	12.61	186.9	121	

5 rows × 21 columns

Feature engineering

Creating total_calls, total_minutes, and total_charge allows better understanding of overall customer behavior, simplifies the churn analysis and strengthens predictive model, through identification, engagement, and retention of at-risk customers. For example;

```
        1. By Identifying High-Usage Customers (Potential Upselling Opportunity)
the organization can offer personalized plans or incentives to retain them.
        2. By detecting Billing & Cost Concerns (Churn Triggers) the organizatio
n can offer better discounts, loyalty perks, or suggest better cost-efficient plan
s.
        3. By spotting Unusual Activity Patterns Proactively reach out to such cu
stomers with customized offers before they churn.
        4. By building a stronger Churn Prediction Model the organiztion can Tra
in models using  new features to improve churn prediction!
```

In [123]:

```
df_cleaned["total_minutes"] = df_cleaned["total day minutes"] + df_cleaned["total eve min
utes"] + df_cleaned["total night minutes"] + df_cleaned["total intl minutes"]
df_cleaned["total_calls"] = df_cleaned["total day calls"] +df_cleaned["total eve calls"]
+ df_cleaned["total night calls"] + df_cleaned["total intl calls"]
df_cleaned["total_charge"] = df_cleaned["total day charge"] + df_cleaned["total eve charg
e"] + df_cleaned["total night charge"] + df_cleaned["total intl charge"]
```

In [124]:

```
df_cleaned["avg_minutes_per_call"] = df_cleaned["total_minutes"] / df_cleaned["total_cal
ls"]
df_cleaned["avg_charge_per_minute"] = df_cleaned["total_charge"] / df_cleaned["total_minu
tes"]
```

In [125]:

```
df_cleaned.head()
```

Out[125]:

	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 intl minutes	total intl calls	total intl charge	customer service calls
0	KS	128	415	382-4657	no	yes	25	265.1	110	45.07	...	10.0	3	2.70	1
1	OH	107	415	371-7191	no	yes	26	161.6	123	27.47	...	13.7	3	3.70	1
2	NJ	137	415	358-1921	no	no	0	243.4	114	41.38	...	12.2	5	3.29	0
4	OK	75	415	330-6626	yes	no	0	166.7	113	28.34	...	10.1	3	2.73	3
5	AL	118	510	391-8027	yes	no	0	223.4	98	37.98	...	6.3	6	1.70	0

5 rows × 26 columns

In [126]:

```
df_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 2797 entries, 0 to 3332
Data columns (total 26 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   state                    2797 non-null   object
 1   account length           2797 non-null   int64
```

```
 2   area code               2797 non-null   int64
 3   phone number            2797 non-null   object
 4   international plan      2797 non-null   object
 5   voice mail plan         2797 non-null   object
 6   number vmail messages   2797 non-null   int64
 7   total day minutes       2797 non-null   float64
 8   total day calls         2797 non-null   int64
 9   total day charge        2797 non-null   float64
 10  total eve minutes       2797 non-null   float64
 11  total eve calls         2797 non-null   int64
 12  total eve charge        2797 non-null   float64
 13  total night minutes     2797 non-null   float64
 14  total night calls       2797 non-null   int64
 15  total night charge      2797 non-null   float64
 16  total intl minutes      2797 non-null   float64
 17  total intl calls        2797 non-null   int64
 18  total intl charge       2797 non-null   float64
 19  customer service calls  2797 non-null   int64
 20  churn                   2797 non-null   bool
 21  total_minutes           2797 non-null   float64
 22  total_calls             2797 non-null   int64
 23  total_charge            2797 non-null   float64
 24  avg_minutes_per_call    2797 non-null   float64
 25  avg_charge_per_minute   2797 non-null   float64
dtypes: bool(1), float64(12), int64(9), object(4)
memory usage: 570.9+ KB
```

Drop more columns

There are columns that are neautral to customer behaviour meaning they do not contribute crucial information to customer behavior for example state, Phone number and area code

In [127]:

```
# drop columns
df_cleaned.drop(["state", "phone number", "area code"], axis=1, inplace=True)
```

In [128]:

```
# drop more colums used in feature engineering
drop_cols = ["total day minutes", "total eve minutes", "total night minutes", "total intl
minutes",
             "total day calls", "total eve calls", "total night calls", "total intl call
s",
             "total day charge", "total eve charge", "total night charge", "total intl c
harge"]

df_cleaned.drop(columns=drop_cols, inplace=True)
```

In [129]:

```
df_cleaned["engagement_score"] = df_cleaned["voice mail plan"] * 2 + df_cleaned["interna
tional plan"] * 3 + df_cleaned["customer service calls"]
```

```
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
/usr/local/lib/python3.11/dist-packages/pandas/core/ops/array_ops.py in _na_arithmetic_op
(left, right, op, is_cmp)
    217     try:
--> 218         result = func(left, right)
    219     except TypeError:

/usr/local/lib/python3.11/dist-packages/pandas/core/computation/expressions.py in evaluat
e(op, a, b, use_numexpr)
    241             # error: "None" not callable
--> 242             return _evaluate(op, op_str, a, b)  # type: ignore[misc]
    243     return _evaluate_standard(op, op_str, a, b)

/usr/local/lib/python3.11/dist-packages/pandas/core/computation/expressions.py in  evalua
```

```
/usr/local/lib/python3.11/dist-packages/pandas/core/computation/expressions.py in _evalua
te_numexpr(op, op_str, a, b)
    130     if result is None:
--> 131         result = _evaluate_standard(op, op_str, a, b)
    132

/usr/local/lib/python3.11/dist-packages/pandas/core/computation/expressions.py in _evalua
te_standard(op, op_str, a, b)
     72         _store_test_result(False)
---> 73     return op(a, b)
     74

TypeError: can only concatenate str (not "int") to str

During handling of the above exception, another exception occurred:

TypeError                                 Traceback (most recent call last)
<ipython-input-129-2fb4f539f066> in <cell line: 0>()
----> 1 df_cleaned["engagement_score"] = df_cleaned["voice mail plan"] * 2 + df_cleaned[
"international plan"] * 3 + df_cleaned["customer service calls"]

/usr/local/lib/python3.11/dist-packages/pandas/core/ops/common.py in new_method(self, oth
er)
     74         other = item_from_zerodim(other)
     75
---> 76         return method(self, other)
     77
     78     return new_method

/usr/local/lib/python3.11/dist-packages/pandas/core/arraylike.py in __add__(self, other)
    184         moose     3.0     NaN
    185         """
--> 186         return self._arith_method(other, operator.add)
    187
    188     @unpack_zerodim_and_defer("__radd__")

/usr/local/lib/python3.11/dist-packages/pandas/core/series.py in _arith_method(self, othe
r, op)
   6133     def _arith_method(self, other, op):
   6134         self, other = self._align_for_op(other)
-> 6135         return base.IndexOpsMixin._arith_method(self, other, op)
   6136
   6137     def _align_for_op(self, right, align_asobject: bool = False):

/usr/local/lib/python3.11/dist-packages/pandas/core/base.py in _arith_method(self, other,
op)
   1380
   1381         with np.errstate(all="ignore"):
-> 1382             result = ops.arithmetic_op(lvalues, rvalues, op)
   1383
   1384         return self._construct_result(result, name=res_name)

/usr/local/lib/python3.11/dist-packages/pandas/core/ops/array_ops.py in arithmetic_op(lef
t, right, op)
    281         # error: Argument 1 to "_na_arithmetic_op" has incompatible type
    282         # "Union[ExtensionArray, ndarray[Any, Any]]"; expected "ndarray[Any, Any]
"
--> 283         res_values = _na_arithmetic_op(left, right, op)  # type: ignore[arg-type]
    284
    285     return res_values

/usr/local/lib/python3.11/dist-packages/pandas/core/ops/array_ops.py in _na_arithmetic_op
(left, right, op, is_cmp)
    225             # Don't do this for comparisons, as that will handle complex numbers
    226             #  incorrectly, see GH#32047
--> 227             result = _masked_arith_op(left, right, op)
    228         else:
    229             raise

/usr/local/lib/python3.11/dist-packages/pandas/core/ops/array_ops.py in _masked_arith_op(
x, y, op)
    161         # See GH#5284, GH#5035, GH#19448 for historical reference
    162         if mask.any():
```

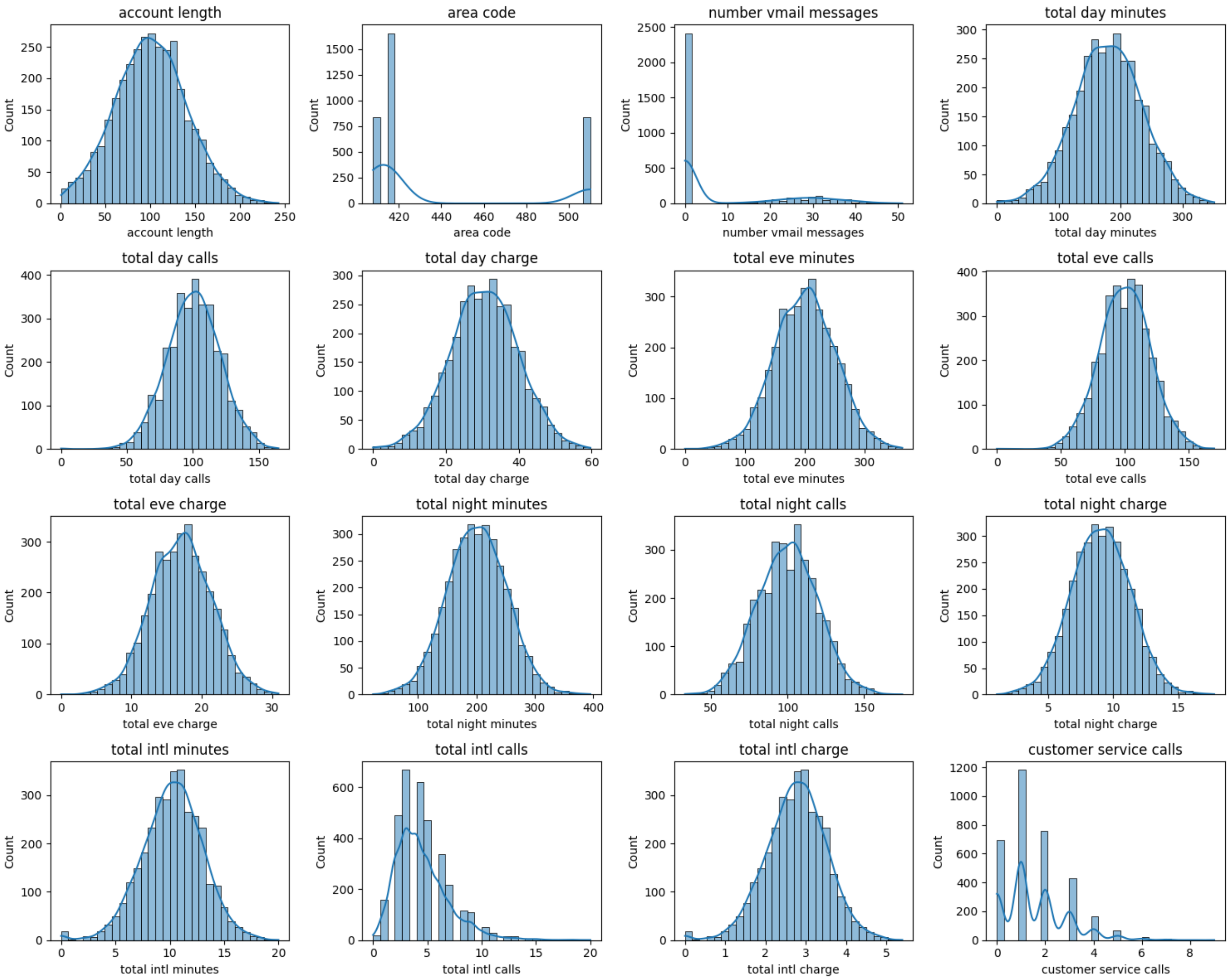
```
    162         if mask.any():
--> 163             result[mask] = op(xrav[mask], yrav[mask])
    164 
    165     else:

TypeError: can only concatenate str (not "int") to str
```

Exploratory Data Analysis (EDA)

Univariate analysis

In [130]:

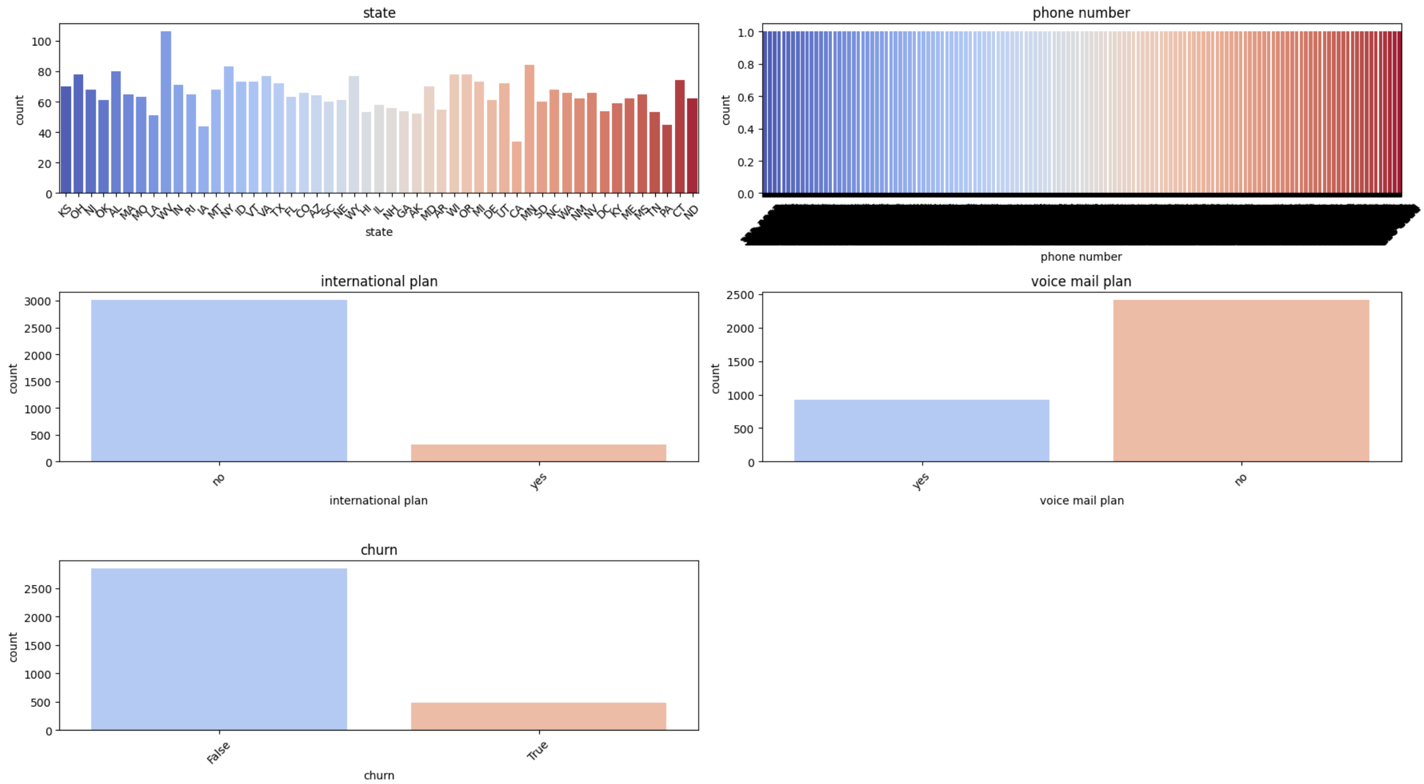
```python
# Univariate analysis of numerical columns
# select Numerical columns
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns
plt.figure(figsize=(15, 12))
for i, col in enumerate(numerical_cols, 1):
    plt.subplot(4, 4, i)
    sns.histplot(df[col], kde=True, bins=30)
    plt.title(col)
plt.tight_layout()
plt.show()
```



In [131]:

```python
# Univariate analysis for categorical columns
# define and select categorical columns
categorical_cols = df.select_dtypes(include=['object', 'bool']).columns

plt.figure(figsize=(18, 10))
```

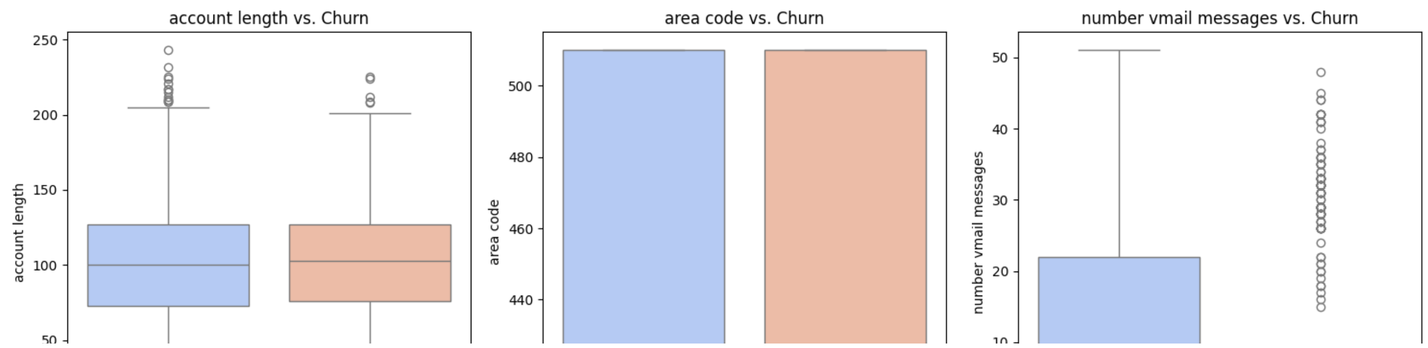
```
for i, col in enumerate(categorical_cols, 1):
    plt.subplot(3, 2, i)
    sns.countplot(x=df[col], palette="coolwarm")
    plt.title(col)
    plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```

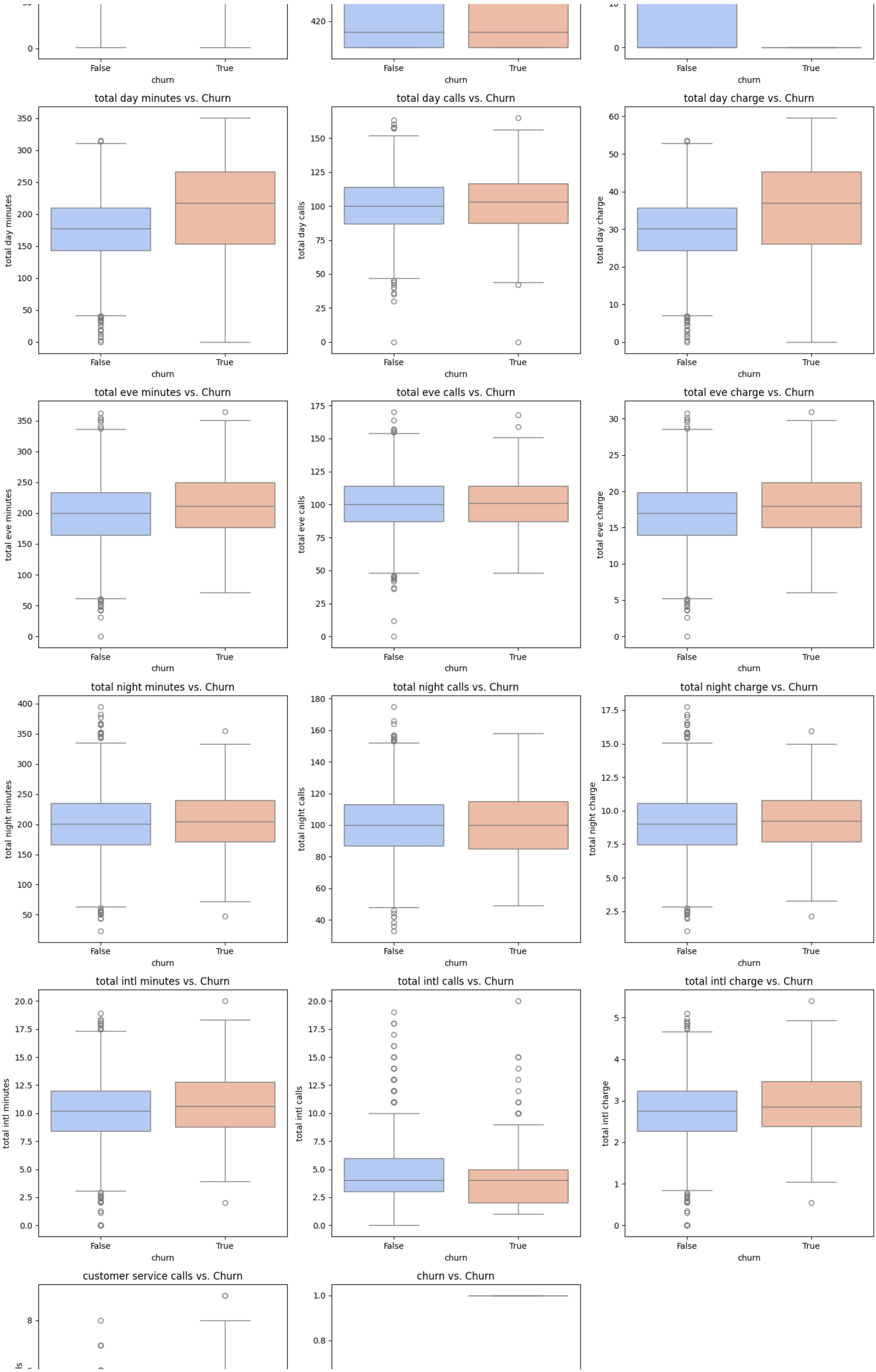


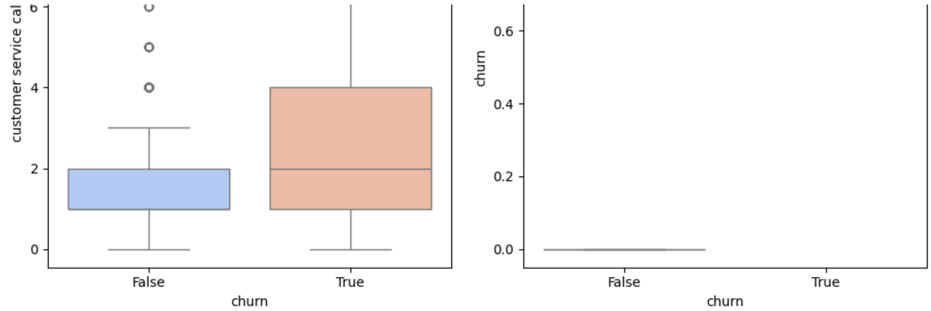
Bivariate analysis

In [132]:

```
# Define numerical columns
numerical_cols = [
    "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 charge"
,
    "total intl minutes", "total intl calls", "total intl charge", "customer service call
s", "churn"
]
# Adjust the grid size dynamically based on number of plots
rows = (len(numerical_cols) // 3) + 1  # Adjust rows automatically

plt.figure(figsize=(15, rows * 5))
for i, col in enumerate(numerical_cols, 1):
    plt.subplot(rows, 3, i)
    sns.boxplot(x=df["churn"], y=df[col], palette="coolwarm")
    plt.title(f"{col} vs. Churn")

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

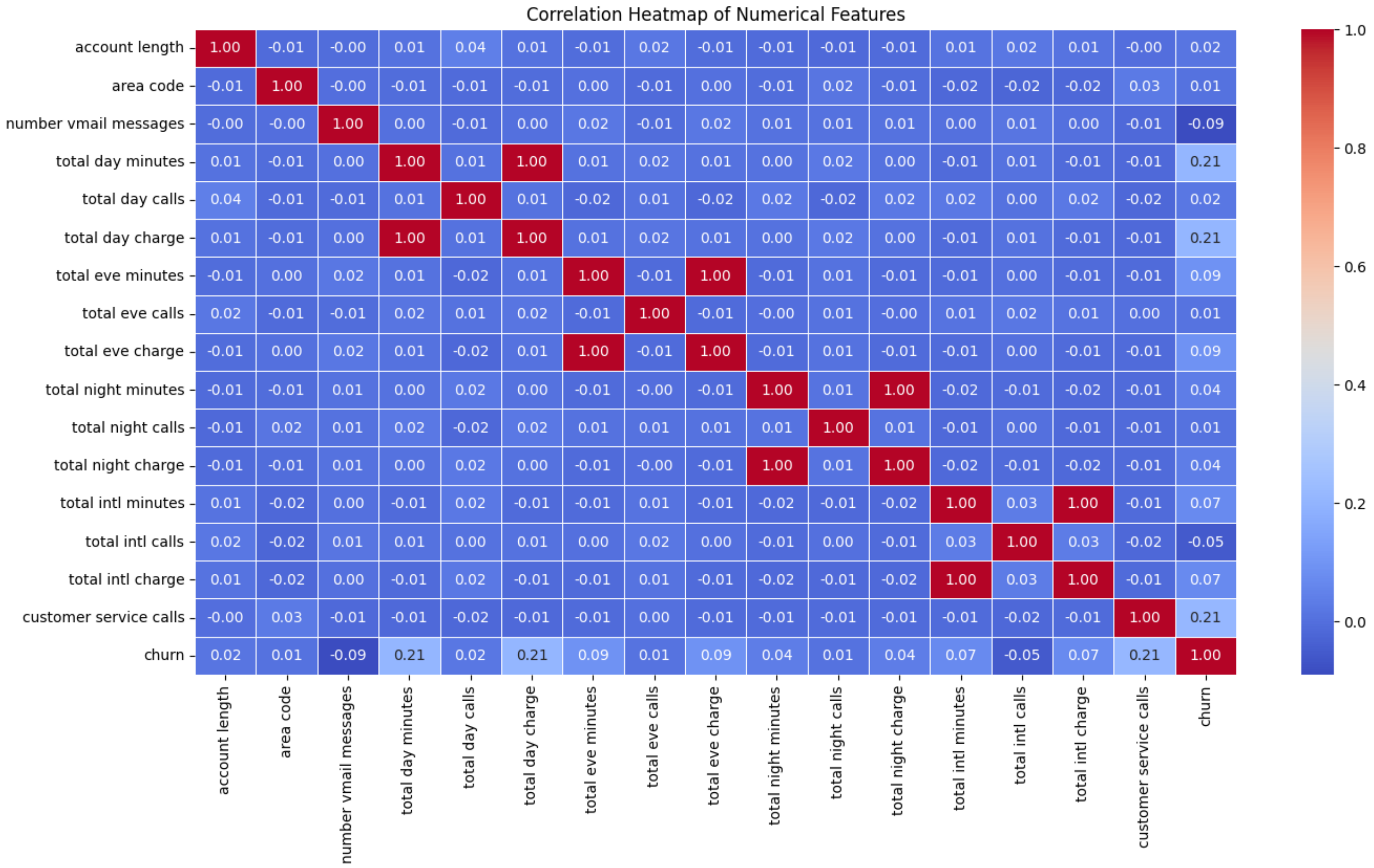



churn
False
True
total day minutes vs. Churn
total day minutes
total day calls vs. Churn
total day calls
total day charge vs. Churn
total day charge
total eve minutes vs. Churn
total eve minutes
total eve calls vs. Churn
total eve calls
total eve charge vs. Churn
total eve charge
total night minutes vs. Churn
total night minutes
total night calls vs. Churn
total night calls
total night charge vs. Churn
total night charge
total intl minutes vs. Churn
total intl minutes
total intl calls vs. Churn
total intl calls
total intl charge vs. Churn
total intl charge
customer service calls vs. Churn
churn vs. Churn



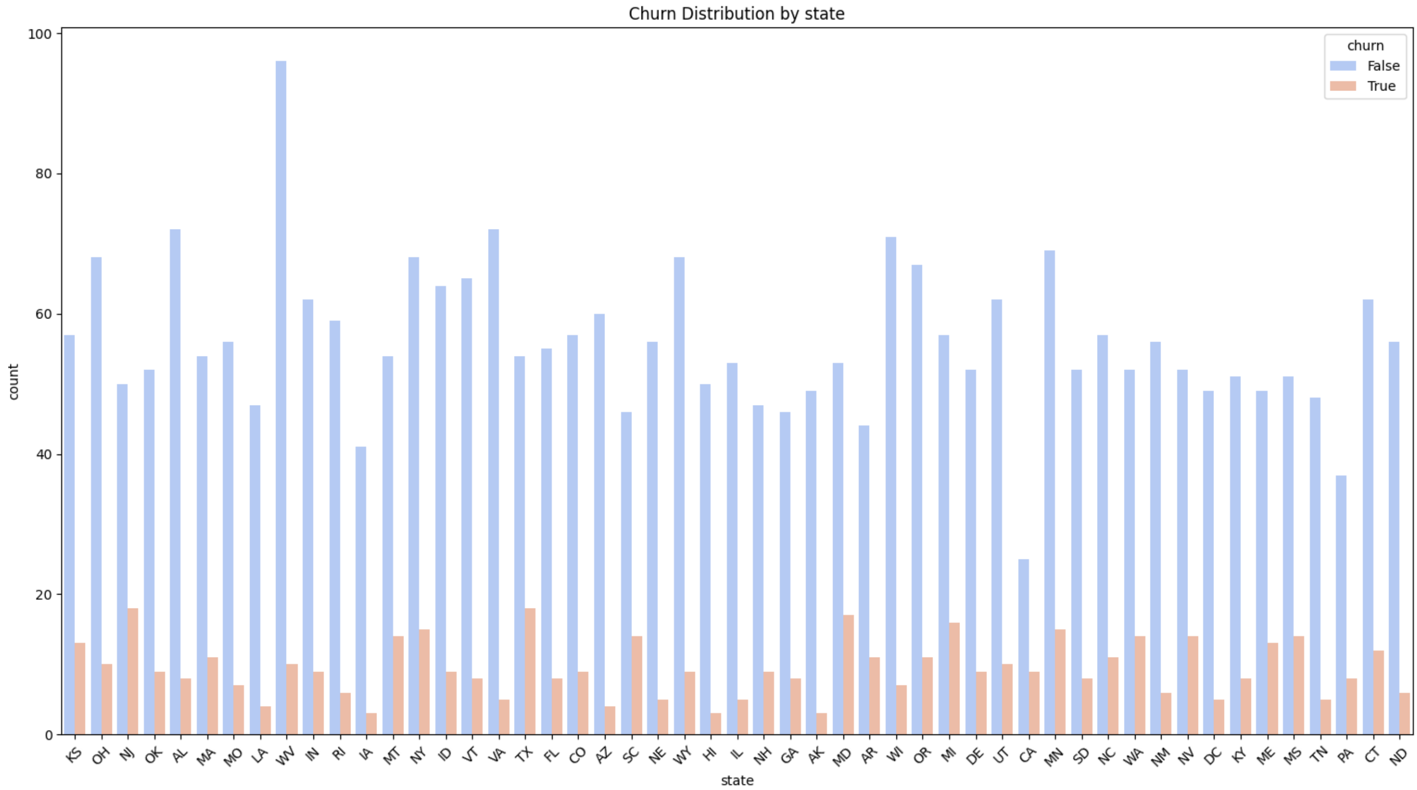
In [133]:

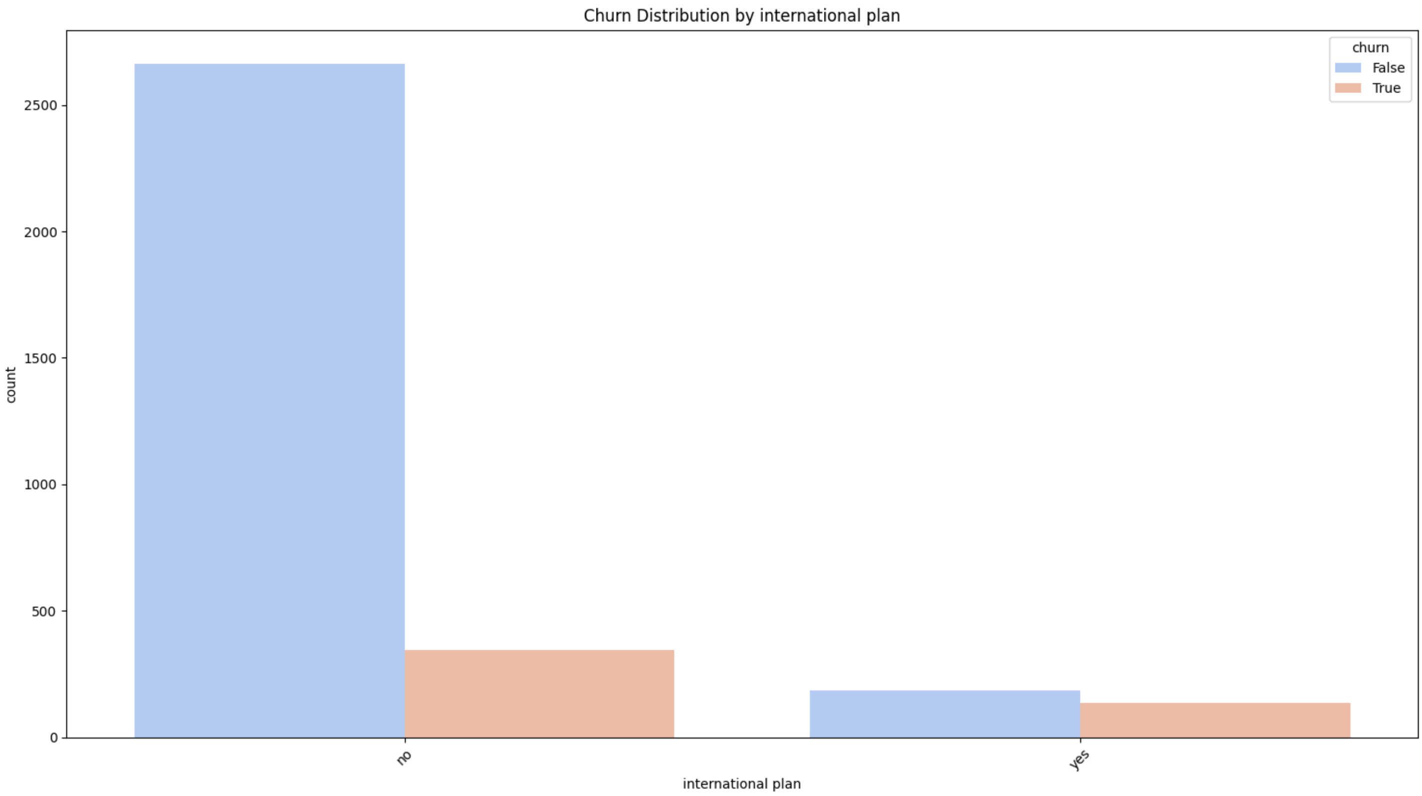
```
# figure size
plt.figure(figsize=(16, 8))

# correlation matrix
corr_matrix = df[numerical_cols].corr()

# visualize heatmap
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", linewidths=0.5, fmt=".2f")
plt.title("Correlation Heatmap of Numerical Features")
plt.show()
```

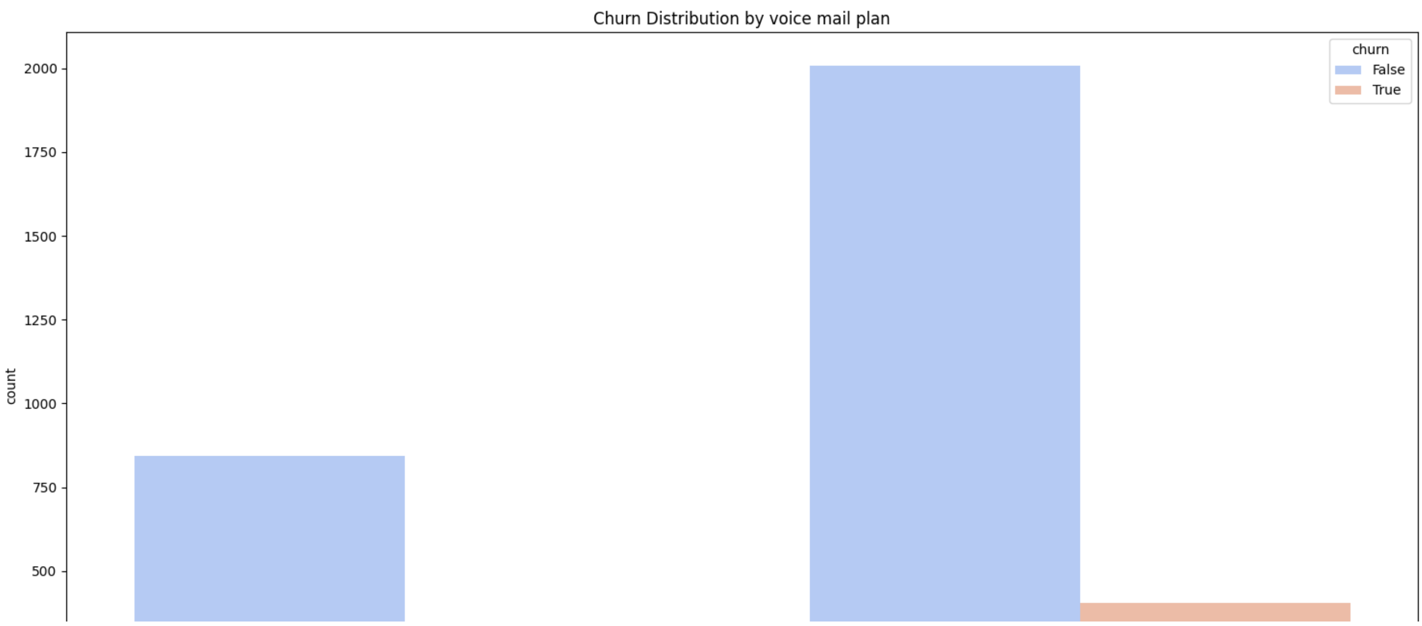


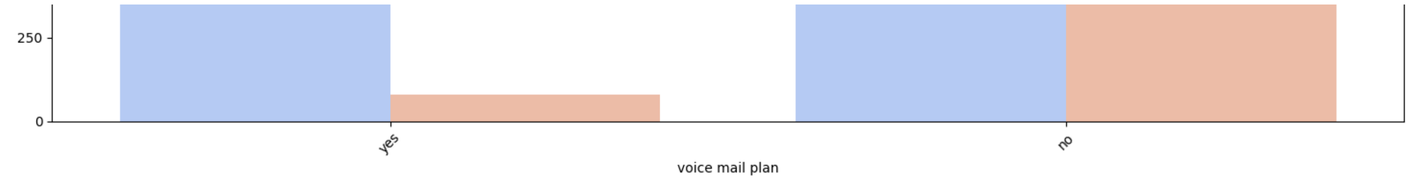
In [134]:

```
# define categorical columns
categorical_cols = ["state", "international plan", "voice mail plan"]

# figure size
plt.figure(figsize=(15, 25))
#
for i, col in enumerate(categorical_cols, 1):
    plt.subplot(3, 1, i)
    sns.countplot(x=df[col], hue=df["churn"], palette="coolwarm")
    plt.title(f"Churn Distribution by {col}")
    plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```


Churn Distribution by state
churn
False
True
count
state
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
0
20
40
60
80
100


Churn Distribution by international plan
churn
False
True
count
international plan
no
yes
0
500
1000
1500
2000
2500

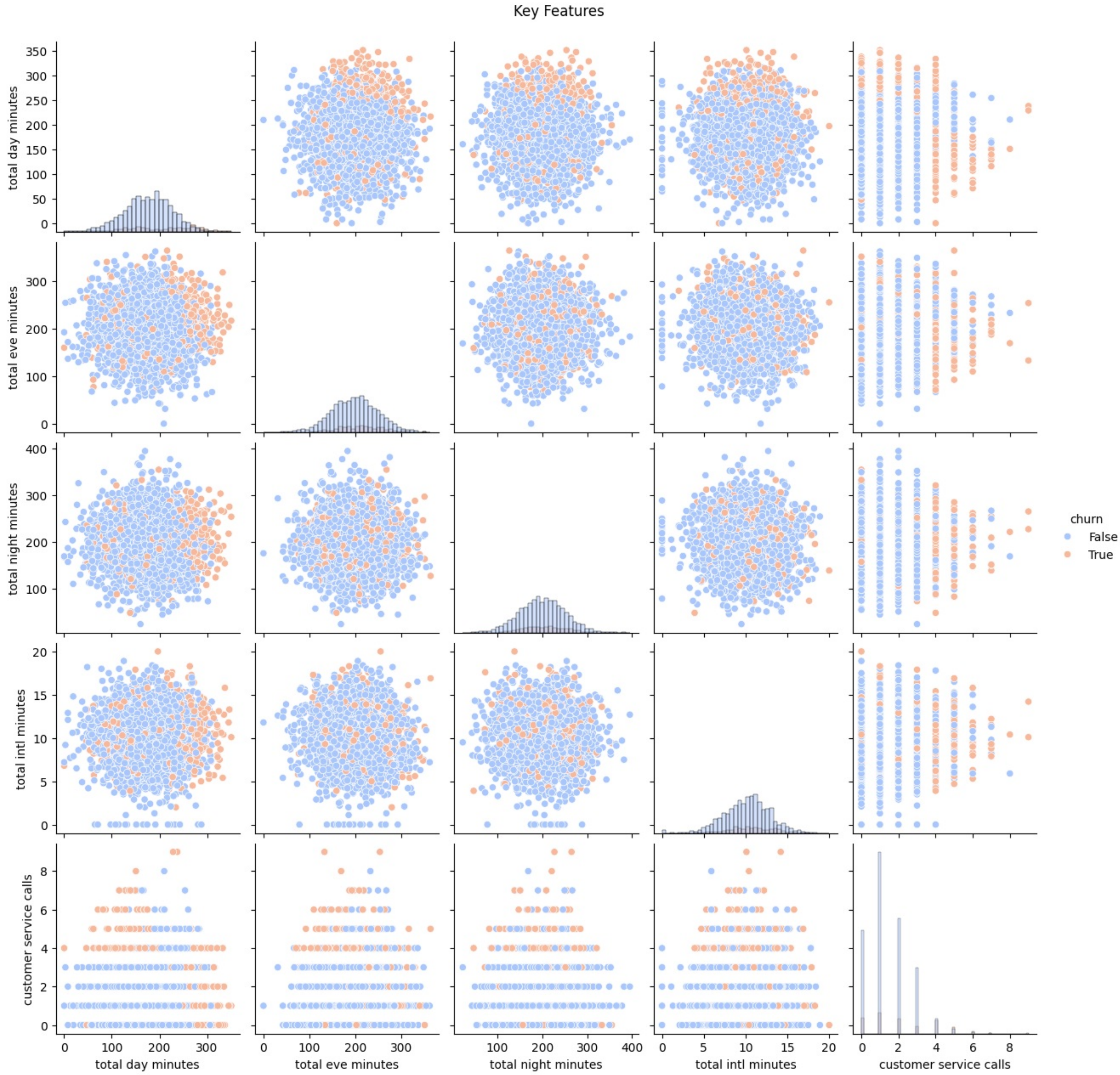

Churn Distribution by voice mail plan
churn
False
True
count
500
750
1000
1250
1500
1750
2000



Multivariate analysis

In [135]:

```
# Select relevant numerical columns
multivariate_cols = ["total day minutes", "total eve minutes", "total night minutes",
                     "total intl minutes", "customer service calls", "churn"]

# Pairplot to analyze relationships
sns.pairplot(df[multivariate_cols], hue="churn", palette="coolwarm", diag_kind="hist")
plt.suptitle("Key Features", y=1.02)
plt.show()
```



Preprocessing

Encoding

Since the state column was dropped, label encoding will be used to convert the yes /no values in voicemail plan, international plan.

The target variable will be excluded to retain its original format essential for classification.

In [136]:

```
df_cleaned["international plan"] = df_cleaned["international plan"].map({"yes": 1, "no":
0})
df_cleaned["voice mail plan"] = df_cleaned["voice mail plan"].map({"yes": 1, "no": 0})
```

In [137]:

```
df_cleaned.head()
```

Out[137]:

	account length	international plan	voice mail plan	number vmail messages	customer service calls	churn	total_minutes	total_calls	total_charge	avg_minutes_per_call	av
0	128	0	1	25	1	False	717.2	303	75.56	2.366997	
1	107	0	1	26	1	False	625.2	332	59.24	1.883133	
2	137	0	0	0	0	False	539.4	333	62.29	1.619820	
4	75	1	0	0	3	False	512.0	359	52.09	1.426184	
5	118	1	0	0	0	False	654.2	323	67.61	2.025387	

In [138]:

```
df_cleaned["engagement_score"] = df_cleaned["voice mail plan"] * 2 + df_cleaned["interna
tional plan"] * 3 + df_cleaned["customer service calls"]
```

scaling

In [139]:

```
# Define numerical columns for scaling
numerical_cols = [
    "account length", "number vmail messages", "customer service calls",
    "total_minutes", "total_calls", "total_charge",
    "avg_minutes_per_call", "avg_charge_per_minute", "engagement_score"
]

# Used Standard Scaling (Z-Score Normalization) since its more stable and widely used
standard_scaler = StandardScaler()
df_cleaned_standard_scaled = df_cleaned.copy()
df_cleaned_standard_scaled[numerical_cols] = standard_scaler.fit_transform(df_cleaned[num
erical_cols])
```

In [140]:

```
df_cleaned.head()
```

Out[140]:

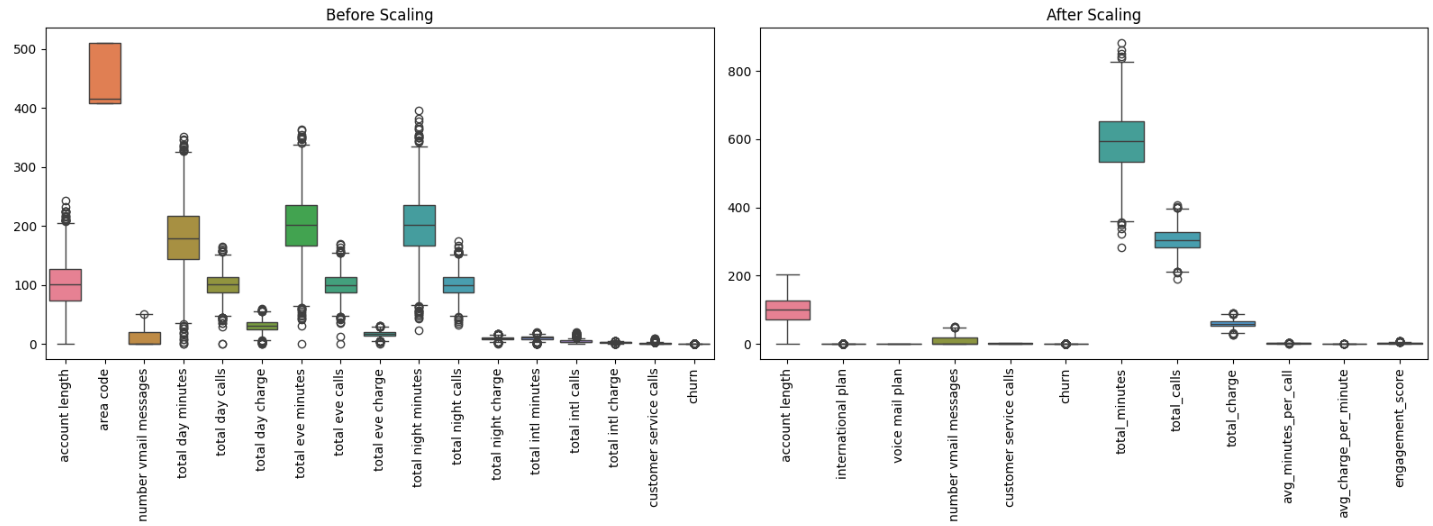
	account length	international plan	voice mail plan	number vmail messages	customer service calls	churn	total_minutes	total_calls	total_charge	avg_minutes_per_call	av
0	128	0	1	25	1	False	717.2	303	75.56	2.366997	
1	107	0	1	26	1	False	625.2	332	59.24	1.883133	

	account length	international plan	voice mail plan	number vmail messages	customer service calls	churn	total_minutes	total_calls	total_charge	avg_minutes_per_call	av
2	137	0	0	0	0	False	539.4	333	62.29	1.619820	
4	75	1	0	0	3	False	512.0	359	52.09	1.426184	
5	118	1	0	0	0	False	654.2	323	67.61	2.025387	

Handle class imbalance

In [141]:

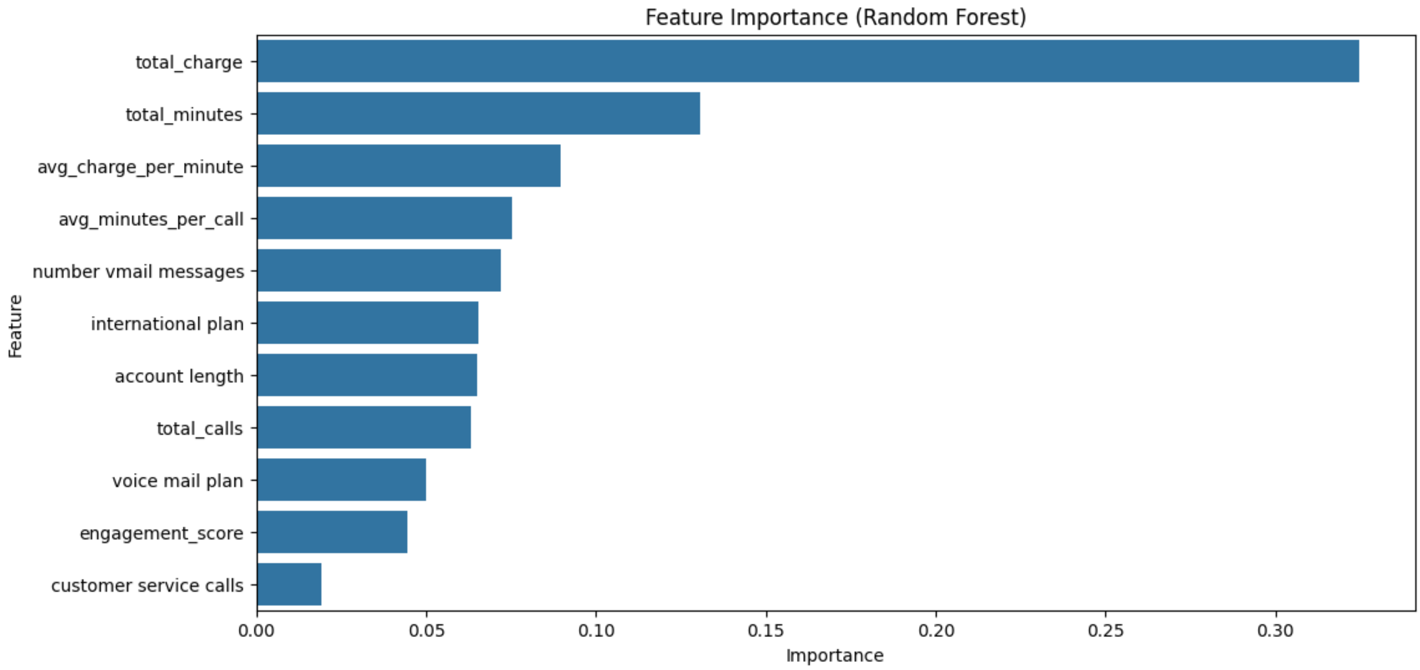
```
# Plot the dataset before and after scaling
plt.figure(figsize=(16, 6))

# Before scaling
plt.subplot(1, 2, 1)
sns.boxplot(data=df)
plt.title("Before Scaling")
plt.xticks(rotation=90)

# After scaling
plt.subplot(1, 2, 2)
sns.boxplot(data=df_cleaned)
plt.title("After Scaling")
plt.xticks(rotation=90)

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



Modelling

In [156]:

```
X = df_cleaned.drop(columns=["churn"])  # Features
y = df_cleaned["churn"]  # Target

# Train Random Forest Model
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X, y)

# Get Feature Importance
feature_importances = pd.DataFrame({"Feature": X.columns, "Importance": rf.feature_impor
tances_})
feature_importances = feature_importances.sort_values(by="Importance", ascending=False)

# Plot Feature Importance
plt.figure(figsize=(12, 6))
sns.barplot(x="Importance", y="Feature", data=feature_importances)
plt.title("Feature Importance (Random Forest)")
plt.show()
```



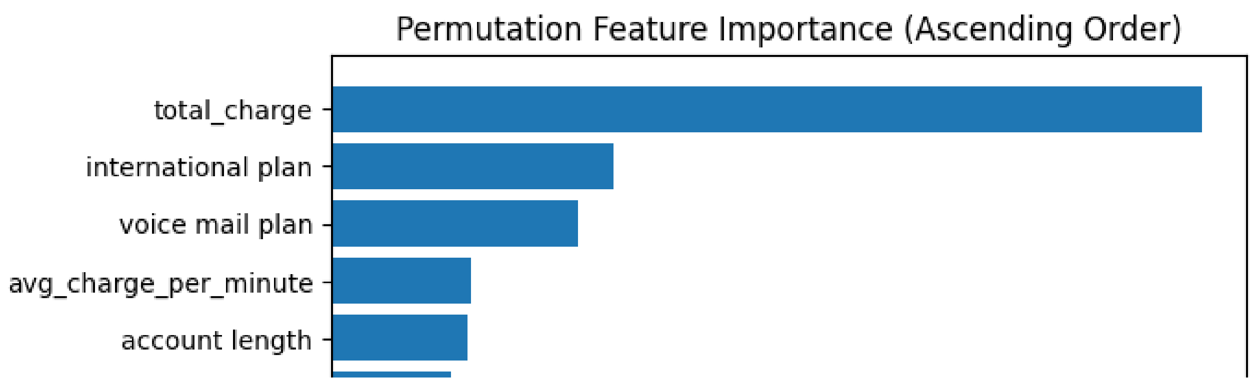
In [159]:

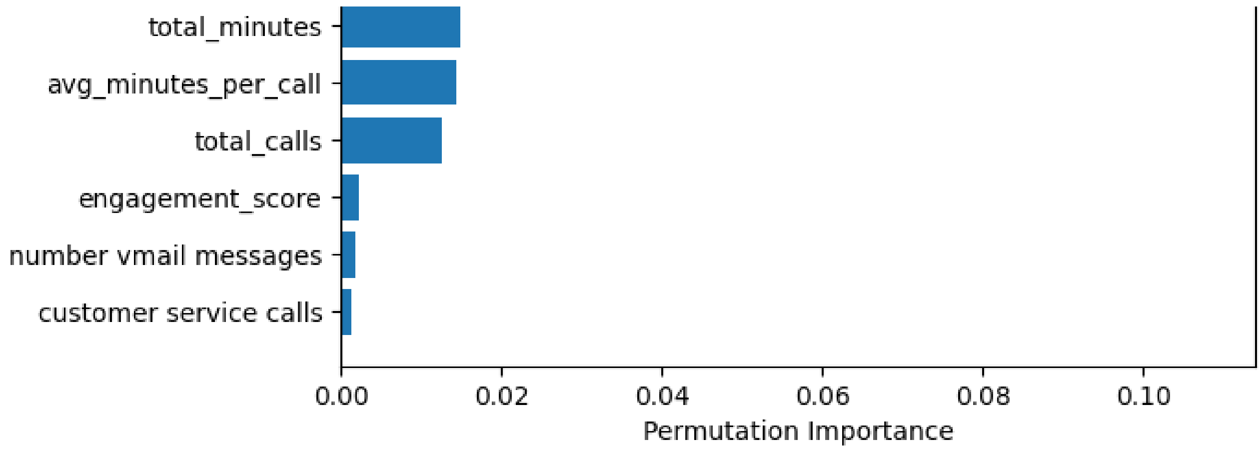
```
# Use Logistic Regression for Feature Selection
model = LogisticRegression(max_iter=1000)
rfe = RFE(model, n_features_to_select=10)  # Keep the top 10 important features
rfe.fit(X, y)

# Get selected features
selected_features = X.columns[rfe.support_]
print("Selected Features:", selected_features)
```

```
Selected Features: Index(['account length', 'international plan', 'voice mail plan',
       'number vmail messages', 'customer service calls', 'total_calls',
       'total_charge', 'avg_minutes_per_call', 'avg_charge_per_minute',
       'engagement_score'],
      dtype='object')
```

In [183]:

```
from sklearn.inspection import permutation_importance

# The model is already trained
result = permutation_importance(model, X, y, n_repeats=10, random_state=42)

# Get feature importance
importance = result.importances_mean

# Sort features based on importance in ascending order
sorted_idx = importance.argsort()

# Plotting in ascending order
plt.barh(X.columns[sorted_idx], importance[sorted_idx])
plt.xlabel('Permutation Importance')
plt.title('Permutation Feature Importance (Ascending Order)')
plt.show()
```





Logistic regression

In [161]:

```
# select independent variables/features
selected_features = [
    'account length', 'international plan', 'voice mail plan',
       'number vmail messages', 'customer service calls', 'total_calls',
       'total_charge', 'avg_minutes_per_call', 'avg_charge_per_minute',
       'engagement_score'
]

# Define X (features) and y (target)
X = df_cleaned[selected_features]  # theses are Scaled features
y = df_cleaned["churn"]  # Target/Dependent variable

# Split into dataset into (80%) training  and (20%)testing  sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
)

print("Training Set Shape:", X_train.shape)
print("Testing Set Shape:", X_test.shape)
```

```
Training Set Shape: (2237, 10)
Testing Set Shape: (560, 10)
```

In [162]:

```
# define model
model = LogisticRegression()

# Train on scaled features
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Accuracy
accuracy_lr = accuracy_score(y_test, y_pred)
print(f"Model Accuracy_lr: {accuracy_lr:.2f}")  # Fixed f-string

# Detailed Classification Report
print("\nClassification Report:\n", classification_report(y_test, y_pred))

# Confusion Matrix
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
Model Accuracy_lr: 0.89

Classification Report:
               precision    recall  f1-score   support

       False       0.90      0.99      0.94       490
        True       0.71      0.21      0.33        70
```

```
    accuracy                           0.89       560
   macro avg       0.81      0.60      0.64       560
weighted avg       0.88      0.89      0.86       560


Confusion Matrix:
 [[484   6]
 [ 55  15]]
```

The Model accuracy The model is great at identifying customers who won't churn but our interest is in the churners which the model fails to detect.

The model is struggling to correctly detect churners. The confusion matrix actually indicates that out of 70 actual churners, only 9 were correctly identified and 61 churners were incorrectly classified as non-churners.

The model is missing most churners it only finds 13% meaning that when the model predicts a churn, it’s often wrong.

This can lead to a high customer loss risk

In [163]:

```
# apply smote to the training data
X_resampled, y_resampled = SMOTE().fit_resample(X_train, y_train)
```

In [164]:

```
# Initialize the classifier
logreg = LogisticRegression()

# Train on SMOTE-resampled data
logreg.fit(X_resampled, y_resampled)

# Predict on the test set
y_pred = logreg.predict(X_test)

# Evaluate model performance
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
```

```
Accuracy: 0.8196428571428571
Confusion Matrix:
 [[411  79]
 [ 22  48]]
Classification Report:
               precision    recall  f1-score   support

       False       0.95      0.84      0.89       490
        True       0.38      0.69      0.49        70

    accuracy                           0.82       560
   macro avg       0.66      0.76      0.69       560
weighted avg       0.88      0.82      0.84       560
```

Recall for churners significantly improved from approximately 13% to 73% before SMOTE.The model now correctly identifies more churners, but at the cost of lower precision where there are more false positives.

Overall accuracy dropped slightly (79% vs. 88%), but balanced performance matters more in imbalanced datasets.

The model is correct 90% of the time, which is good. However the model had a has a churn problem. No churn predictions range from Precison of 91% to recall of 98% . While the churn predictionsare ranging from 31%, 44% and 73% which are very low despite tuning

The confusion matrix misclassified 10 as Churn and missclassified 48 as no church when in essence are churn.

Decision Tree

In [165]:

```
# decision tree
# Initialize Decision Tree Classifier
dt_model = DecisionTreeClassifier(random_state=42, max_depth=5, class_weight='balanced')

# Train on scaled features
dt_model.fit(X_train, y_train)

# Make predictions
y_pred_dt = dt_model.predict(X_test)
```

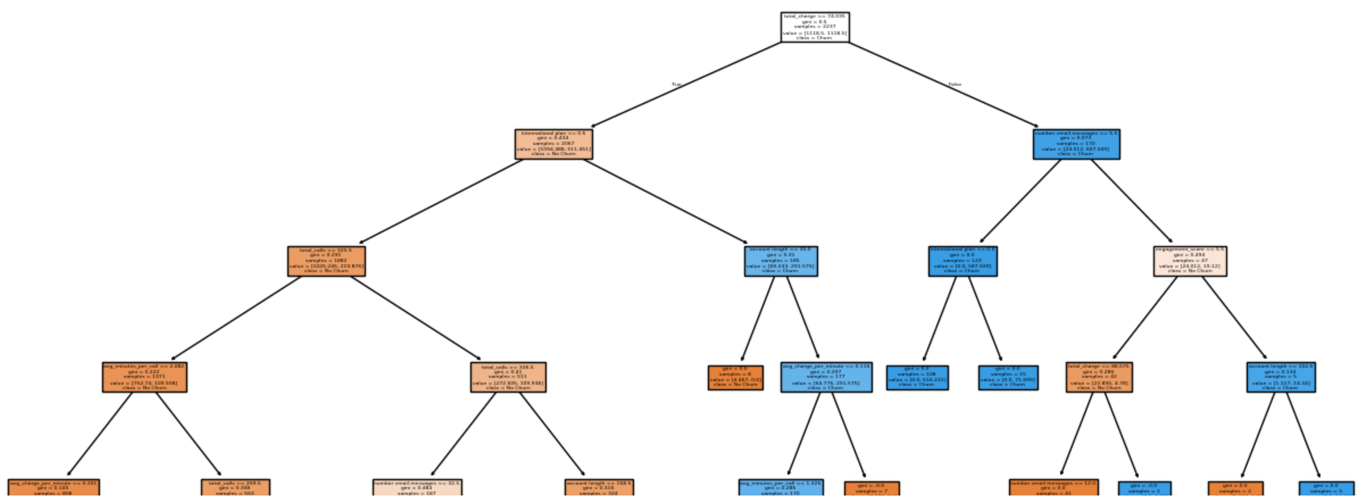
In [166]:

```
# Accuracy Score
accuracy_dt = accuracy_score(y_test, y_pred_dt)
print(f"Decision Tree Accuracy: {accuracy_dt:.2f}")

# Classification Report
print("\nClassification Report:\n", classification_report(y_test, y_pred_dt))

# Confusion Matrix
print("\nConfusion Matrix:\n", confusion_matrix(y_test, y_pred_dt))
```

```
Decision Tree Accuracy: 0.90

Classification Report:
               precision    recall  f1-score   support

       False       0.96      0.92      0.94       490
        True       0.57      0.71      0.63        70

    accuracy                           0.90       560
   macro avg       0.76      0.82      0.79       560
weighted avg       0.91      0.90      0.90       560


Confusion Matrix:
 [[452  38]
 [ 20  50]]
```

In [167]:

```
plt.figure(figsize=(16, 8))
plot_tree(dt_model, feature_names=X_train.columns, class_names=["No Churn", "Churn"], fi
lled=True)
plt.show()
```



In [168]:

```
param_grid = {
    'max_depth': [3, 5, 10],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 5]
}

grid_search = GridSearchCV(DecisionTreeClassifier(random_state=42, class_weight='balance
d'), param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Best parameters
print("Best Parameters:", grid_search.best_params_)

# Evaluate best model
best_dt_model = grid_search.best_estimator_
y_pred_best = best_dt_model.predict(X_test)
print("\nBest Decision Tree Classification Report:\n", classification_report(y_test, y_pr
ed_best))
print("Best Decision Tree Confusion Matrix:\n",confusion_matrix (y_test, y_pred_best))
```

```
Best Parameters: {'max_depth': 3, 'min_samples_leaf': 1, 'min_samples_split': 2}

Best Decision Tree Classification Report:
               precision    recall  f1-score   support

       False       0.97      0.93      0.95       490
        True       0.61      0.77      0.68        70

    accuracy                           0.91       560
   macro avg       0.79      0.85      0.82       560
weighted avg       0.92      0.91      0.91       560

Best Decision Tree Confusion Matrix:
 [[456  34]
 [ 16  54]]
```

In [169]:

```
# Initialize Random Forest with optimized parameters
rf_model = RandomForestClassifier(n_estimators=100, max_depth=10, random_state=42)
rf_model.fit(X_train, y_train)

# Prediction
y_pred_rf = rf_model.predict(X_test)

# Evaluation scores
print("Random Forest Accuracy:", accuracy_score(y_test, y_pred_rf))
print("\n Random Forest Classification Report:\n", classification_report(y_test, y_pred_
rf))
print("\n Random Forest Confusion Matrix:\n", confusion_matrix(y_test, y_pred_rf))
```

```
Random Forest Accuracy: 0.925

 Random Forest Classification Report:
               precision    recall  f1-score   support

       False       0.93      0.99      0.96       490
        True       0.85      0.49      0.62        70

    accuracy                           0.93       560
   macro avg       0.89      0.74      0.79       560
weighted avg       0.92      0.93      0.92       560
```

```
 Random Forest Confusion Matrix:
 [[484   6]
 [ 36  34]]
```

In [170]:

```python
# Initialize XGBoost with default parameters (or tune later)
xgb_model = XGBClassifier(n_estimators=100, max_depth=5, learning_rate=0.1, random_state=
42)
xgb_model.fit(X_train, y_train)

# Predictions
y_pred_xgb = xgb_model.predict(X_test)

# Evaluation
print("n XGBoost Accuracy:", accuracy_score(y_test, y_pred_xgb))
print("\n XGBoost Classification Report:\n", classification_report(y_test, y_pred_xgb))
print("\nXGBoost Confusion Matrix:\n", confusion_matrix(y_test, y_pred_xgb))
```

```
n XGBoost Accuracy: 0.9303571428571429

 XGBoost Classification Report:
               precision    recall  f1-score   support

       False       0.93      0.99      0.96       490
        True       0.88      0.51      0.65        70

    accuracy                           0.93       560
   macro avg       0.91      0.75      0.80       560
weighted avg       0.93      0.93      0.92       560


XGBoost Confusion Matrix:
 [[485   5]
 [ 34  36]]
```

Hyperparameter Tuning

In [171]:

```python
# Hyperparameter tuning for logistic regression
# Define hyperparameter grid
param_grid = {
    'C': [0.001, 0.01, 0.1, 1, 10, 100],
    'penalty': ['l1', 'l2'],  # Type of regularization
    'solver': ['liblinear', 'saga'],  # Solvers that support l1 and l2
    'max_iter': [100, 200, 500]  # Number of iterations
}

# Apply GridSearchCV
grid_search = GridSearchCV(logreg, param_grid, cv=5, scoring='accuracy', n_jobs=-1, verb
ose=2)

# Fit on training data
grid_search.fit(X_train, y_train)

# Best parameters
print("Best Parameters:", grid_search.best_params_)

# Best model
best_model = grid_search.best_estimator_

# Evaluate the tuned model
y_pred = best_model.predict(X_test)
print("Classification_report:\n", classification_report(y_test, y_pred))

# Generate Confusion Matrix
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
Fitting 5 folds for each of 72 candidates, totalling 360 fits
```

```
Fitting 5 folds for each of 72 candidates, totalling 360 fits
Best Parameters: {'C': 100, 'max_iter': 200, 'penalty': 'l1', 'solver': 'liblinear'}
Classification_report:
               precision    recall  f1-score   support

       False       0.90      0.98      0.94       490
        True       0.70      0.27      0.39        70

    accuracy                           0.89       560
   macro avg       0.80      0.63      0.67       560
weighted avg       0.88      0.89      0.87       560

Confusion Matrix:
 [[482   8]
 [ 51  19]]
```

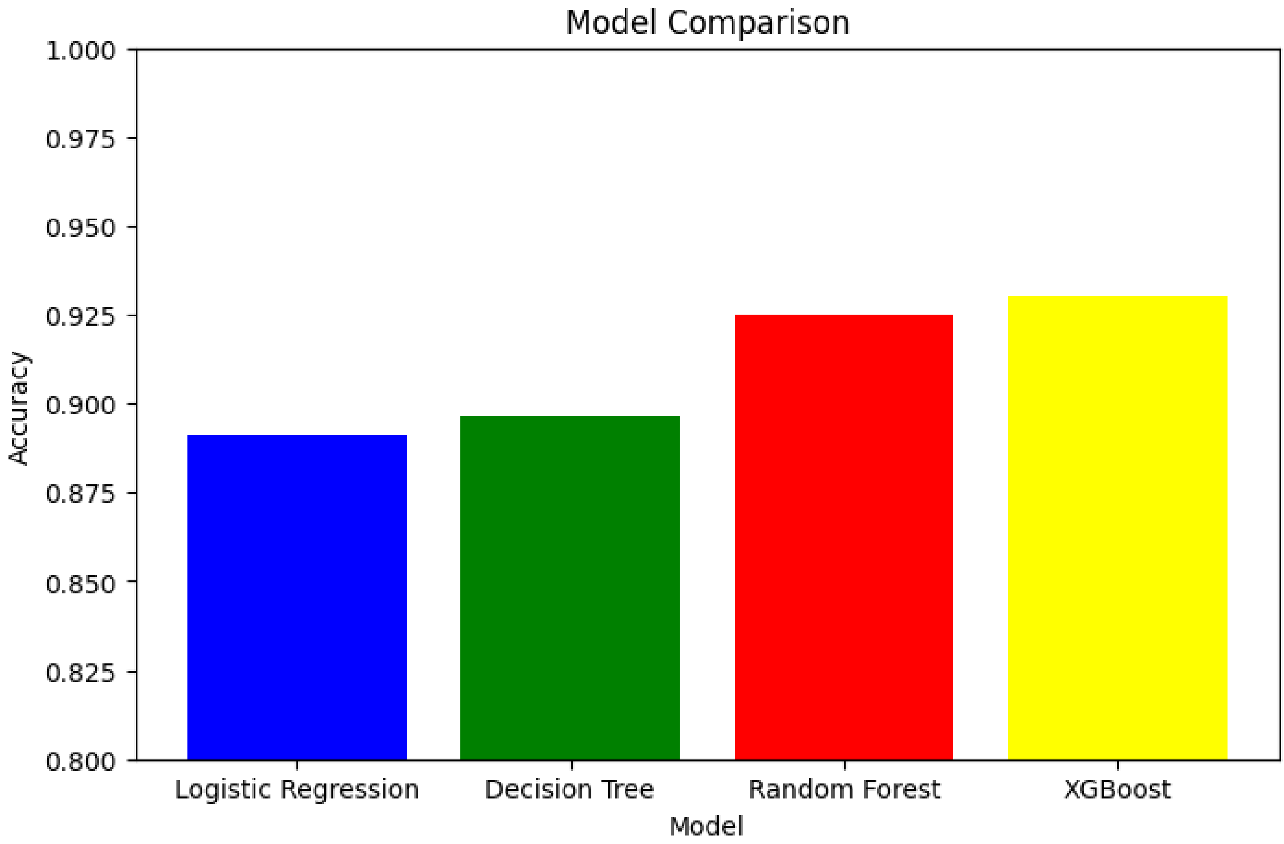
In [172]:

```
# Define parameter grid
param_grid = {
    'n_estimators': [50, 100, 200],        # Number of trees
    'max_depth': [None, 10, 20],           # Tree depth
    'min_samples_split': [2, 5, 10],       # Minimum samples to split a node
    'min_samples_leaf': [1, 2, 4],         # Minimum samples per leaf
    'criterion': ['gini', 'entropy']       # Splitting method
}

# Initialize the random forest model
rf = RandomForestClassifier(random_state=42)

# Perform Hyperparameter tuning with GridSearchCV
grid_search = GridSearchCV(rf, param_grid, cv=5, scoring='recall', n_jobs=-1, verbose=1)
grid_search.fit(X_train, y_train)

# Best parameters
print("Best Parameters:", grid_search.best_params_)

# Train final model with best parameters
best_rf = RandomForestClassifier(**grid_search.best_params_, random_state=42)
best_rf.fit(X_train, y_train)

# Predictions
y_pred = best_rf.predict(X_test)

# Evaluate model
print("Best Random Forest Accuracy:", accuracy_score(y_test, y_pred))
print("\nBest Random Forest Classification Report:\n", classification_report(y_test, y_p
red))
print("\nBest Random Forest Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

```
Fitting 5 folds for each of 162 candidates, totalling 810 fits
Best Parameters: {'criterion': 'gini', 'max_depth': 10, 'min_samples_leaf': 1, 'min_sampl
es_split': 2, 'n_estimators': 50}
Best Random Forest Accuracy: 0.9285714285714286

Best Random Forest Classification Report:
               precision    recall  f1-score   support

       False       0.93      0.99      0.96       490
        True       0.89      0.49      0.63        70

    accuracy                           0.93       560
   macro avg       0.91      0.74      0.80       560
weighted avg       0.93      0.93      0.92       560


Best Random Forest Confusion Matrix:
 [[486   4]
 [ 36  34]]
```

In [173]:

```
#compare Model performance
models = ["Logistic Regression","Decision Tree", "Random Forest", "XGBoost"]
accuracies = [accuracy_lr, accuracy_dt, accuracy_score(y_test, y_pred_rf), accuracy_scor
e(y_test, y_pred_xgb)]

# Create a bar chart to compare accuracy
import matplotlib.pyplot as plt

plt.figure(figsize=(8, 5))
plt.bar(models, accuracies, color=['blue', 'green', 'red', 'Yellow'])
plt.xlabel("Model")
plt.ylabel("Accuracy")
plt.title("Model Comparison")
plt.ylim(0.8, 1)  # Adjust based on accuracy range
plt.show()
```



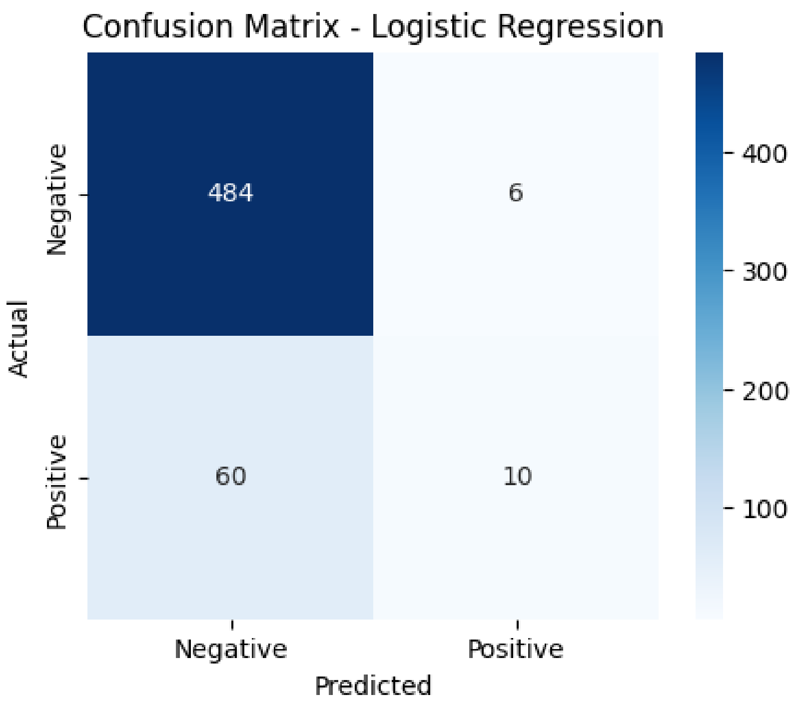
Model Evaluation

In [180]:

```
# Assume target column is 'target' and others are features
X = df_cleaned.drop(columns=['churn'])
y = df_cleaned['churn']

# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42
)
# Initialize models
models = {
    "Logistic Regression": LogisticRegression(),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(),
    "XGBoost": XGBClassifier(use_label_encoder=False, eval_metric='logloss')
}

# Store results
results = {}

# Train and evaluate models
for name, model in models.items():
    model.fit(X_train, y_train)
```

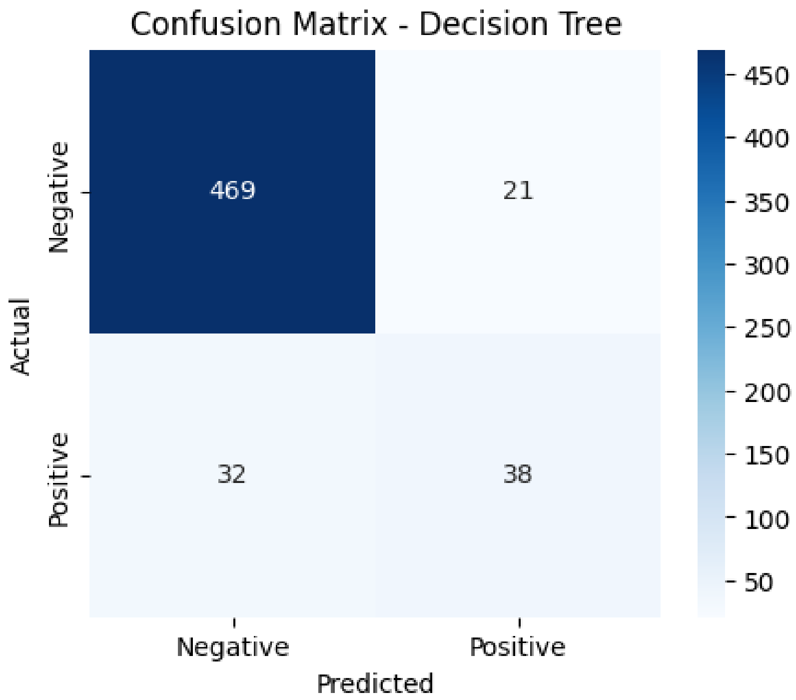
```
    y_pred = model.predict(X_test)
    y_prob = model.predict_proba(X_test)[:, 1] if hasattr(model, "predict_proba") else N
one

    # 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, y_prob) if y_prob is not None else None

    # Save results
    results[name] = {"Accuracy": accuracy, "Precision": precision, "Recall": recall, "F1
Score": f1, "ROC-AUC": roc_auc}

    # Print classification report
    print(f"\n{name} Classification Report:\n", classification_report(y_test, y_pred))

    # Confusion Matrix
    cm = confusion_matrix(y_test, y_pred)
    plt.figure(figsize=(5,4))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["Negative", "Positiv
e"], yticklabels=["Negative", "Positive"])
    plt.title(f'Confusion Matrix - {name}')
    plt.ylabel('Actual')
    plt.xlabel('Predicted')
    plt.show()

# Convert results to DataFrame
results_df = pd.DataFrame(results).T
print("\nModel Evaluation Results:\n", results_df)
```

```
Logistic Regression Classification Report:
               precision    recall  f1-score   support

       False       0.89      0.99      0.94       490
        True       0.62      0.14      0.23        70

    accuracy                           0.88       560
   macro avg       0.76      0.57      0.58       560
weighted avg       0.86      0.88      0.85       560
```

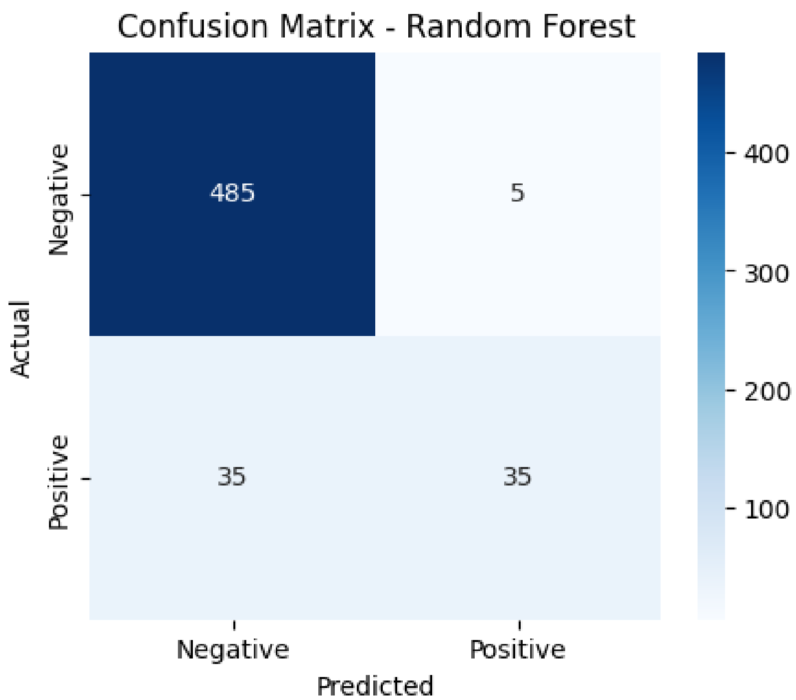



```
Decision Tree Classification Report:
               precision    recall  f1-score   support

       False       0.94      0.96      0.95       490
        True       0.64      0.54      0.59        70
```

```
    accuracy                           0.91       560
   macro avg       0.79      0.75      0.77       560
weighted avg       0.90      0.91      0.90       560
```

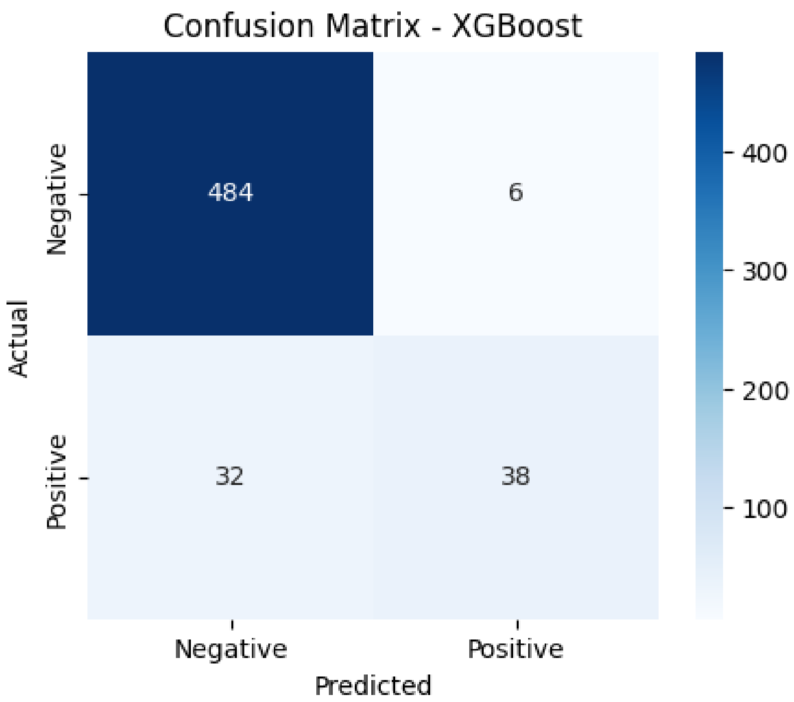



```
Random Forest Classification Report:
              precision    recall  f1-score   support

       False       0.93      0.99      0.96       490
        True       0.88      0.50      0.64        70

    accuracy                           0.93       560
   macro avg       0.90      0.74      0.80       560
weighted avg       0.93      0.93      0.92       560
```




```
XGBoost Classification Report:
              precision    recall  f1-score   support

       False       0.94      0.99      0.96       490
        True       0.86      0.54      0.67        70

    accuracy                           0.93       560
```

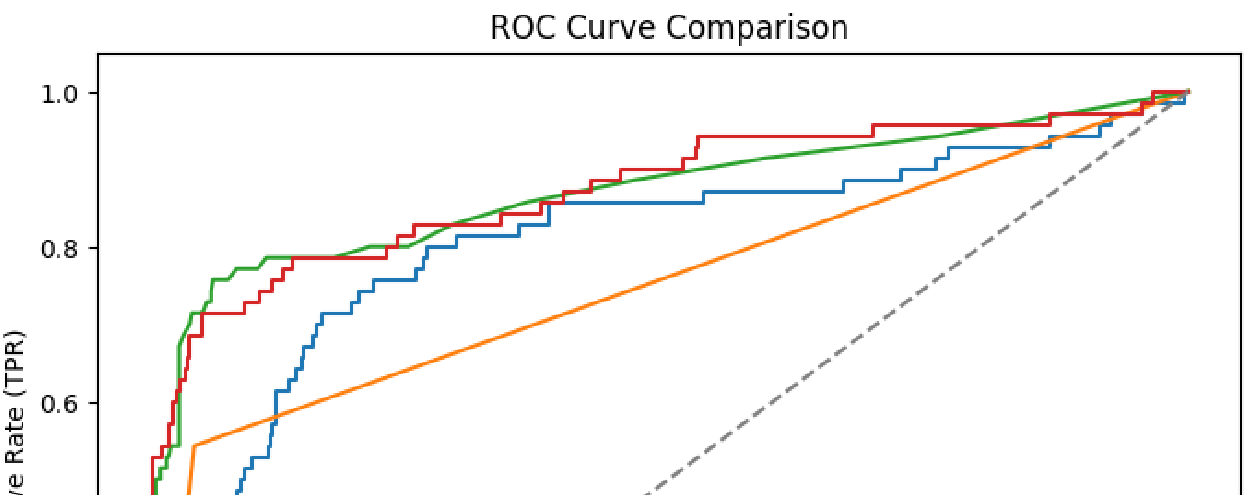
```
   macro avg       0.90      0.77      0.81       560
weighted avg       0.93      0.93      0.93       560
```

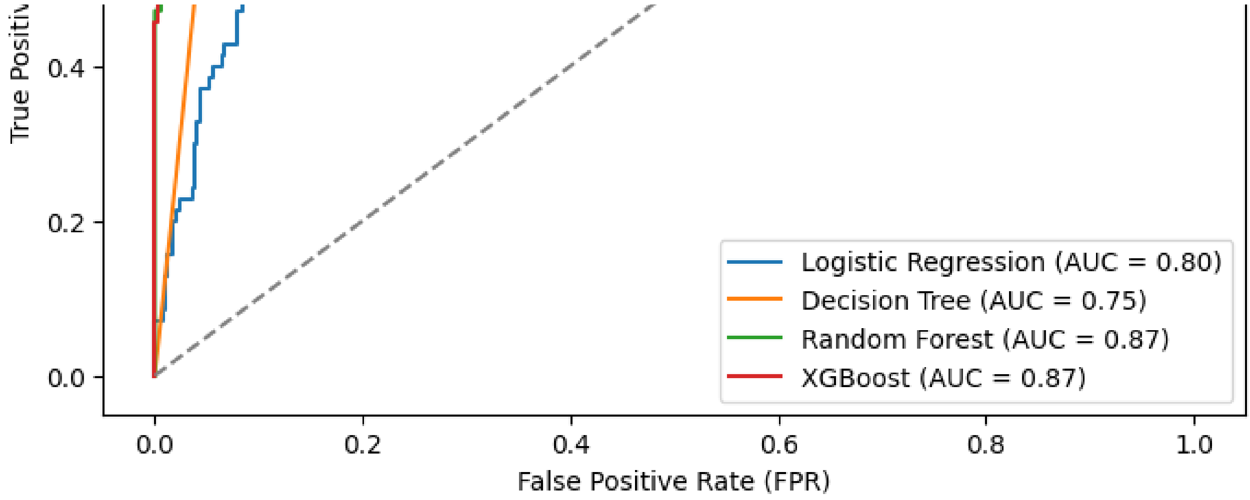



```
Model Evaluation Results:
                      Accuracy  Precision    Recall  F1 Score   ROC-AUC
Logistic Regression   0.882143   0.625000  0.142857  0.232558  0.798630
Decision Tree         0.905357   0.644068  0.542857  0.589147  0.750000
Random Forest         0.928571   0.875000  0.500000  0.636364  0.872172
XGBoost               0.932143   0.863636  0.542857  0.666667  0.874869
```

In [181]:

```python
plt.figure(figsize=(8, 6))

for name, model in models.items():
    if hasattr(model, "predict_proba"):
        y_prob = model.predict_proba(X_test)[:, 1]
        fpr, tpr, _ = roc_curve(y_test, y_prob)
        auc_score = roc_auc_score(y_test, y_prob)
        plt.plot(fpr, tpr, label=f"{name} (AUC = {auc_score:.2f})")

# Plot diagonal reference line
plt.plot([0, 1], [0, 1], linestyle="--", color="gray")

# visualize the plot
plt.xlabel("False Positive Rate (FPR)")
plt.ylabel("True Positive Rate (TPR)")
plt.title("ROC Curve Comparison")
plt.legend()
plt.show()
```



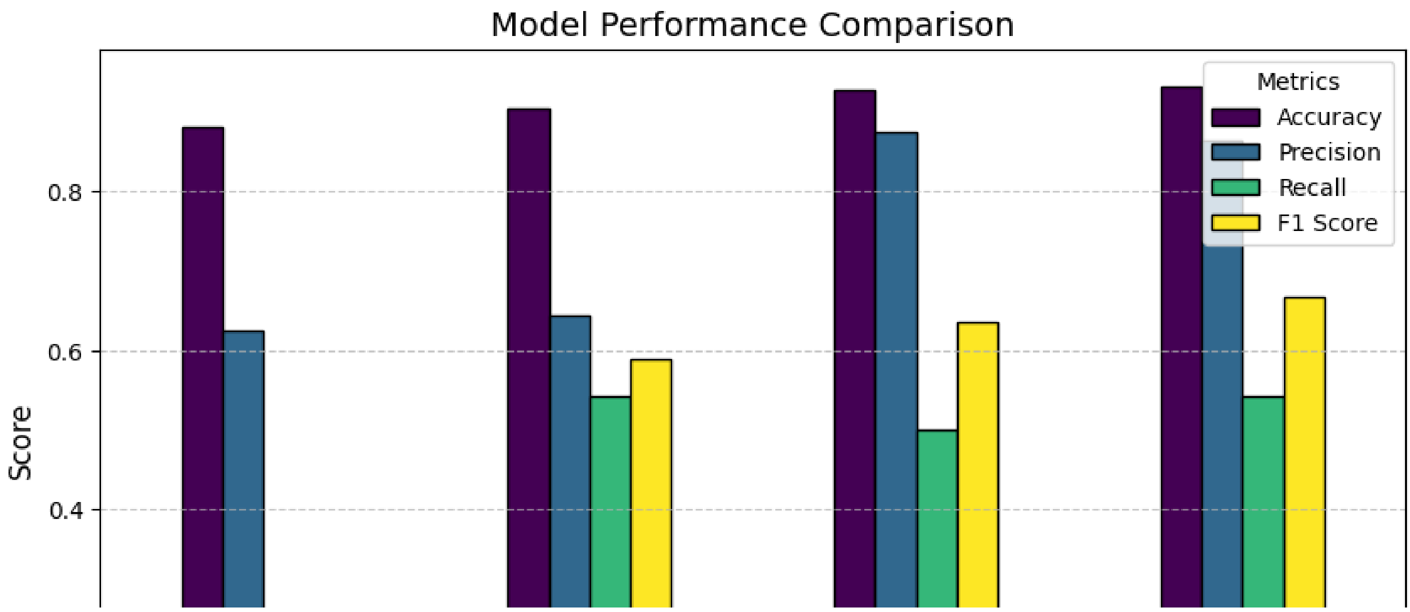


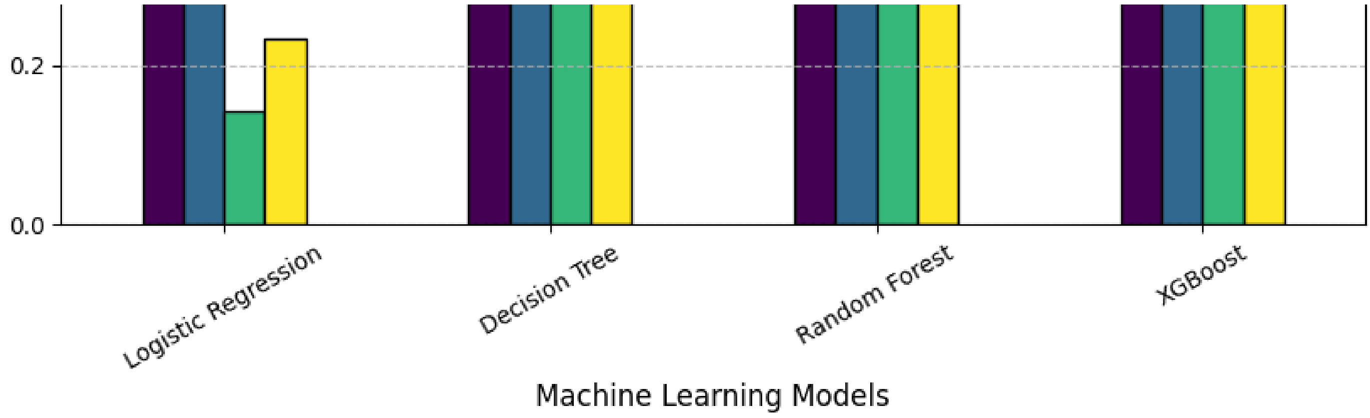
The best Model is XGBoost whihas an accuracy of 93.2143% Precision 86.3636% Recall of 54.2857% F1 Score of 66.6667% and ROC-AUC of 87.4869

In [184]:

```
# Model performance metrics
model_results = {
    "Logistic Regression": [0.882, 0.625, 0.143, 0.233],
    "Decision Tree": [0.905, 0.644, 0.543, 0.589],
    "Random Forest": [0.929, 0.875, 0.500, 0.636],
    "XGBoost": [0.932, 0.864, 0.543, 0.667]
}

# Convert to DataFrame
metrics_df = pd.DataFrame(model_results, index=["Accuracy", "Precision", "Recall", "F1 Sc
ore"]).T

# Plot
plt.figure(figsize=(8,5))
metrics_df.plot(kind="bar", figsize=(10,6), colormap="viridis", edgecolor='black')

# Labels and title
plt.title("Model Performance Comparison", fontsize=14)
plt.xlabel("Machine Learning Models", fontsize=12)
plt.ylabel("Score", fontsize=12)
plt.xticks(rotation=30)
plt.legend(title="Metrics", loc="upper right")
plt.grid(axis='y', linestyle="--", alpha=0.7)

# Show plot
plt.show()
```

<Figure size 800x500 with 0 Axes>

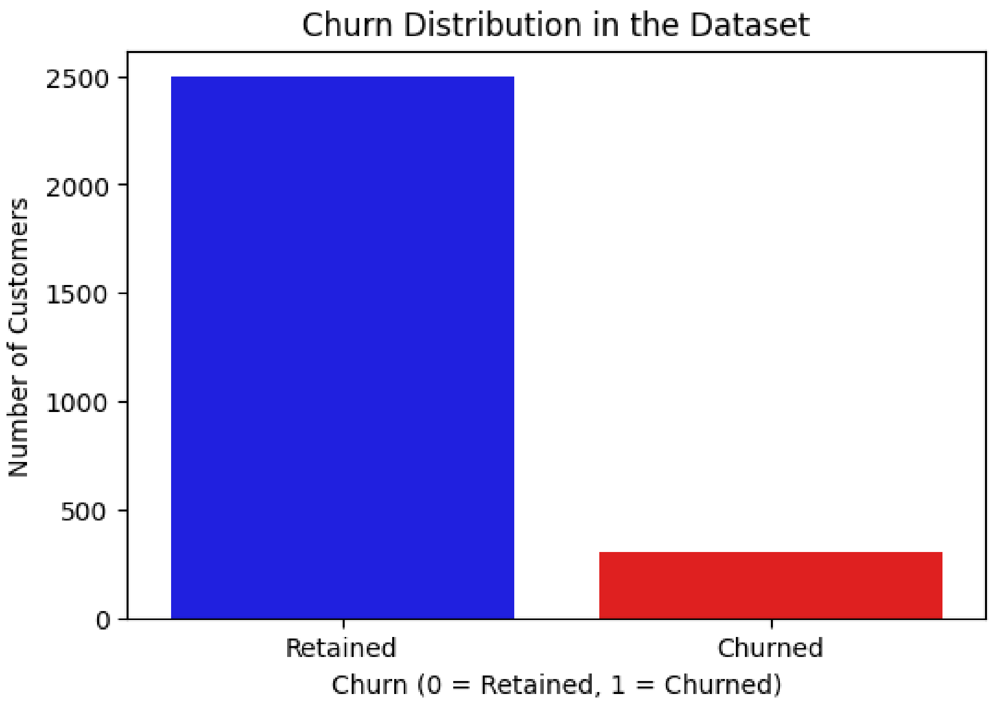




Conclusion and Recommendation

In [185]:

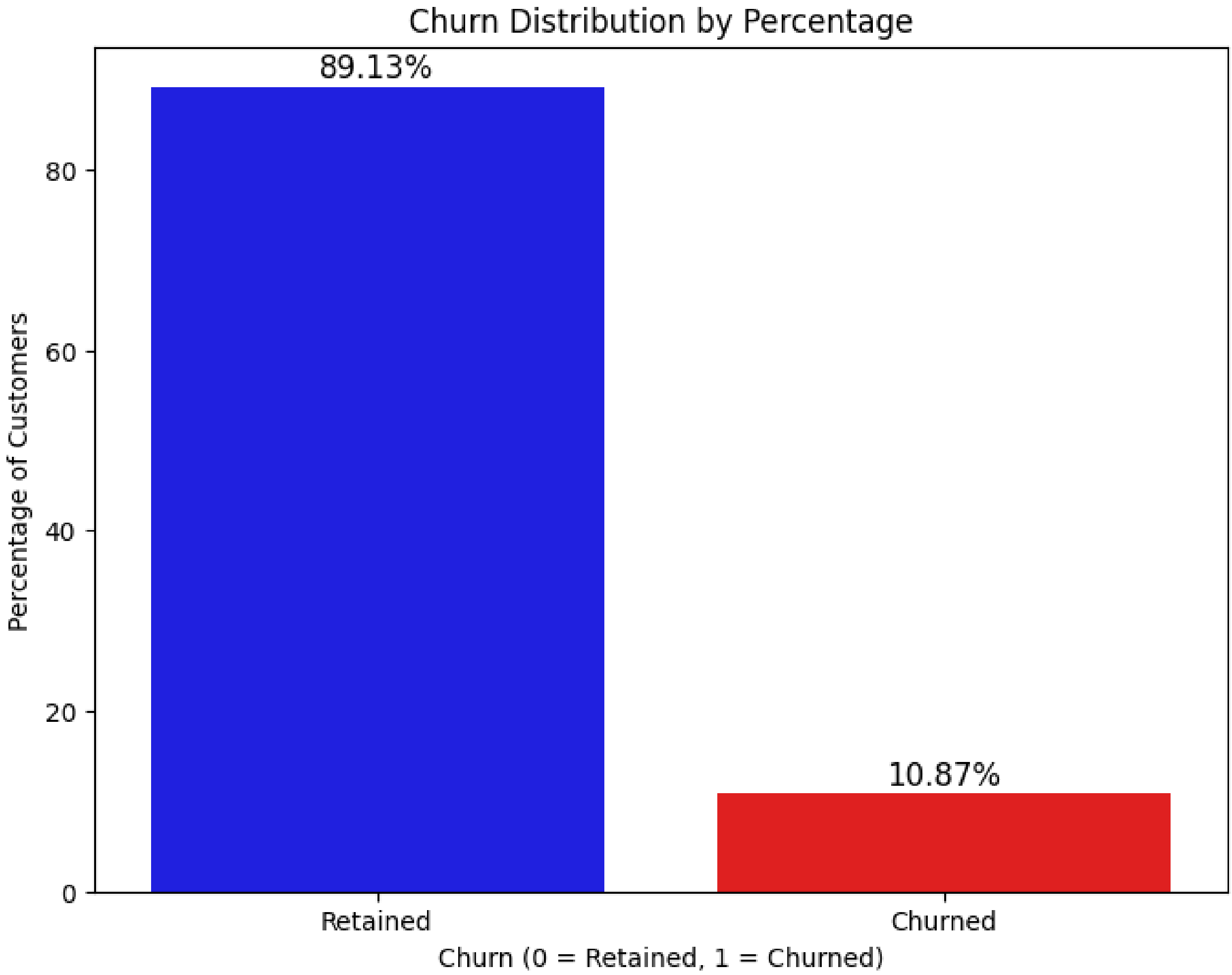
```
# Assuming 'churn' column contains 1 for churned and 0 for retained customers
plt.figure(figsize=(6,4))
sns.countplot(x=df_cleaned['churn'], palette=['blue', 'red'])

# Add labels
plt.title("Churn Distribution in the Dataset")
plt.xlabel("Churn (0 = Retained, 1 = Churned)")
plt.ylabel("Number of Customers")
plt.xticks(ticks=[0,1], labels=['Retained', 'Churned'])

# Show plot
plt.show()
```



In [188]:

```
# Calculate percentage of churned vs retained customers
churn_counts = df_cleaned['churn'].value_counts(normalize=True) * 100  # Convert to perc
entage

# Plot
plt.figure(figsize=(8,6))
sns.barplot(x=churn_counts.index, y=churn_counts.values, palette=['blue', 'red'])

# Add labels
plt.title("Churn Distribution by Percentage")
plt.xlabel("Churn (0 = Retained, 1 = Churned)")
```

```
plt.ylabel("Percentage of Customers")
plt.xticks(ticks=[0,1], labels=['Retained', 'Churned'])

# Display percentage values on bars
for i, percentage in enumerate(churn_counts.values):
    plt.text(i, percentage + 1, f"{percentage:.2f}%", ha='center', fontsize=12)

# Show plot
plt.show()
```



Conclusion

```
        *   Deploy XGBoost or Random Forest for real-time churn prediction
        *   Monitor customer behavior continuously to update the model with
        new insights
        *   Implement A/B testing to measure the effectiveness of retention
        strategies.
        *   Refine marketing campaigns based on churn predictions to optimize budg
et allocation
```

Recommendations

```
1. Integrate the churn prediction model into the company's CRM
system for automated alerts.
2. Develop personalized customer engagement strategies based on
churn risk levels.
3. Monitor and improve model performance periodically using
updated customer data.
```