Inferential Statistics and Predictive Analysis

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21AIC401T: Customer Churn Prediction - Case Study

Task 1: Data Preparation and Introduction

1.1 Load Libraries and Dataset

This first step involves importing the necessary Python libraries for data analysis and visualization (`pandas` , `matplotlib` , `seaborn`).

[cite_start]We will then load the **Telco Customer Churn dataset** downloaded from Kaggle[cite: 24]. [cite_start]We will perform three initial checks as required by the assignment[cite: 31, 32]:

1. **`.head()`** : View the first few rows to understand the columns and data structure.
2. **`.info()`** : Check for any missing (null) values and see the data types (e.g., object, int, float) for each column.
3. **`.duplicated().sum()`** : Check if there are any duplicate rows in the dataset.

In [1]:
```
# --- 1. Load Libraries ---
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Set a visual style for plots
sns.set(style="whitegrid")

# --- 2. Load Data ---
# Make sure you have the 'WA_Fn-UseC_-Telco-Customer-Churn.csv' file
# in the same directory as your notebook, or provide the full path.
try:
    df = pd.read_csv('WA_Fn-UseC_-Telco-Customer-Churn.csv')

    # --- 3. Initial Inspection (Data Description & Cleaning) [cite: 31, 32] ---
    print("--- 1. First 5 Rows of the Dataset ---")
    display(df.head())

    print("\n--- 2. Dataset Info (Checking for Missing Values & Data Types) ---"
    df.info()

    print("\n--- 3. Checking for Duplicate Rows ---")
    duplicate_count = df.duplicated().sum()
    print(f"Total duplicate rows found: {duplicate_count}")

except FileNotFoundError:
    print("Error: The file 'WA_Fn-UseC_-Telco-Customer-Churn.csv' was not found.
    print("Please download it from Kaggle and place it in the correct directory.
```

```
--- 1. First 5 Rows of the Dataset ---
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Multi
0	7590-VHVEG	Female	0	Yes	No	1	No	N
1	5575-GNVDE	Male	0	No	No	34	Yes	
2	3668-QPYBK	Male	0	No	No	2	Yes	
3	7795-CFOCW	Male	0	No	No	45	No	N
4	9237-HQITU	Female	0	No	No	2	Yes	

5 rows × 21 columns

```
--- 2. Dataset Info (Checking for Missing Values & Data Types) ---
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   object 
 1   gender            7043 non-null   object 
 2   SeniorCitizen     7043 non-null   int64  
 3   Partner           7043 non-null   object 
 4   Dependents        7043 non-null   object 
 5   tenure            7043 non-null   int64  
 6   PhoneService      7043 non-null   object 
 7   MultipleLines     7043 non-null   object 
 8   InternetService   7043 non-null   object 
 9   OnlineSecurity    7043 non-null   object 
 10  OnlineBackup      7043 non-null   object 
 11  DeviceProtection  7043 non-null   object 
 12  TechSupport       7043 non-null   object 
 13  StreamingTV       7043 non-null   object 
 14  StreamingMovies   7043 non-null   object 
 15  Contract          7043 non-null   object 
 16  PaperlessBilling  7043 non-null   object 
 17  PaymentMethod     7043 non-null   object 
 18  MonthlyCharges    7043 non-null   float64
 19  TotalCharges      7043 non-null   object 
 20  Churn             7043 non-null   object 
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB

--- 3. Checking for Duplicate Rows ---
Total duplicate rows found: 0
```

1.2 Data Cleaning & Target Variable Analysis

Based on the `.info()` output from the previous step, we observed two things:

1. The `TotalCharges` column is an `object` type, not a number. It needs to be converted to a numeric format. Any values that cannot be converted (like empty strings) will become `NaN` (missing values).
2. The `customerID` column is a unique identifier for each customer and is not a useful feature for prediction. We will drop it.

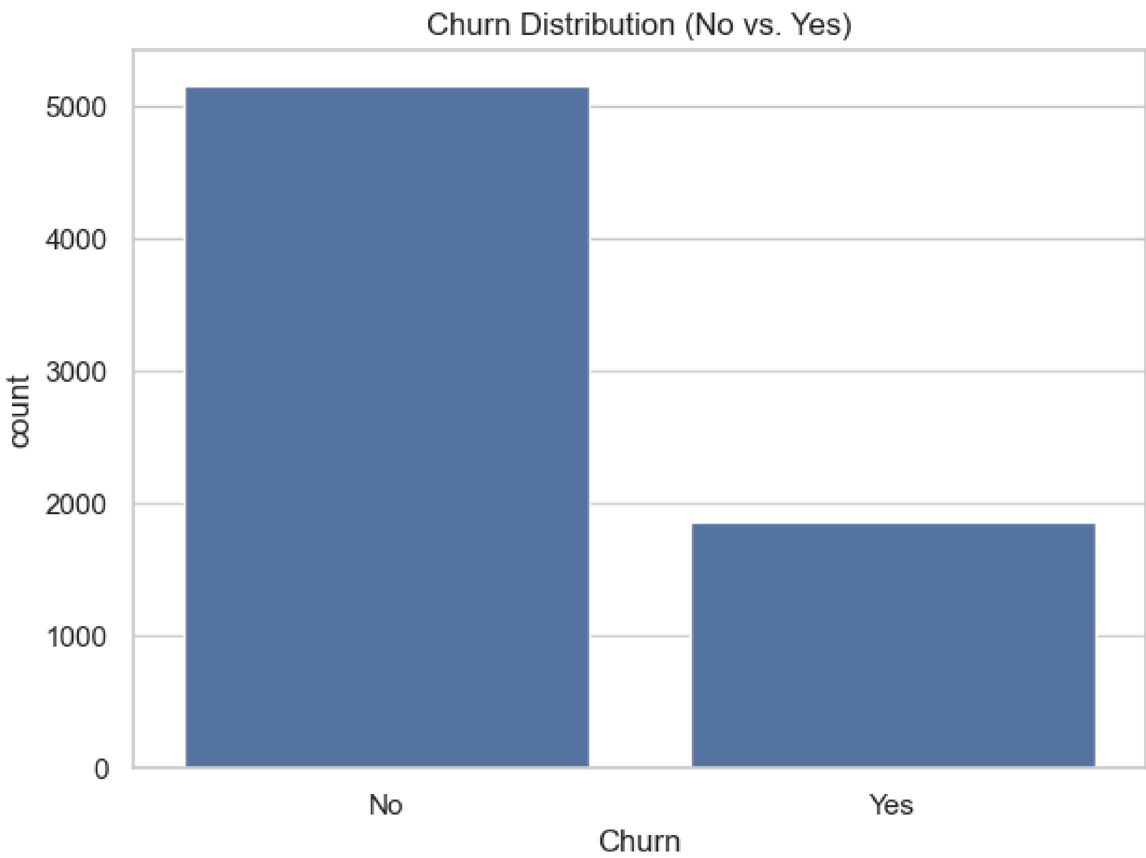
[cite_start]After conversion, we will handle the new missing values by simply dropping the rows, as it's the most straightforward cleaning method.

[cite_start]Finally, we will define our target variable `Churn` [cite_start]and create our first visualization to see the class distribution (i.e., how many customers churned vs. stayed). This is critical for understanding if our dataset is "imbalanced."

In [2]:

```
# --- 1. Data Cleaning: Convert 'TotalCharges' to numeric ---
# 'errors=coerce' will turn any non-numeric values (like empty strings) into NaN
df['TotalCharges'] = pd.to_numeric(df['TotalCharges'], errors='coerce')

# --- 2. Data Cleaning: Handle Missing Values ---
# Check how many missing values were created
print(f"Missing values in 'TotalCharges' after conversion: {df['TotalCharges'].i

# Drop rows with any missing values
df.dropna(inplace=True)

# --- 3. Feature Engineering: Drop 'customerID' ---
# Drop the customerID column as it's not a predictive feature
df = df.drop('customerID', axis=1)

# --- 4. Define Target and Predictor Variables (EDA) ---
# Define our target variable
target_variable = 'Churn'

# --- 5. Conduct EDA: Visualize the Target Variable  ---
print(f"\n--- Distribution of Target Variable: {target_variable} ---")

# Create a count plot to visualize the 'Churn' column
plt.figure(figsize=(7, 5))
sns.countplot(x=target_variable, data=df)
plt.title('Churn Distribution (No vs. Yes)')

# Calculate and print the percentage
churn_percentage = (df[target_variable].value_counts(normalize=True) * 100).rena
churn_counts = df[target_variable].value_counts().rename('Count')
print(pd.concat([churn_counts, churn_percentage], axis=1))

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

```
Missing values in 'TotalCharges' after conversion: 11

--- Distribution of Target Variable: Churn ---
       Count  Percentage
Churn
No      5163   73.421502
Yes     1869   26.578498
```



1.3 EDA: Numerical Variable Analysis

Now we perform Exploratory Data Analysis (EDA) on the numerical features to understand their relationship with `Churn`.

We will iterate through our main numerical columns (`tenure`, `MonthlyCharges`, `TotalCharges`) and create a Kernel Density Estimate (KDE) plot for each.

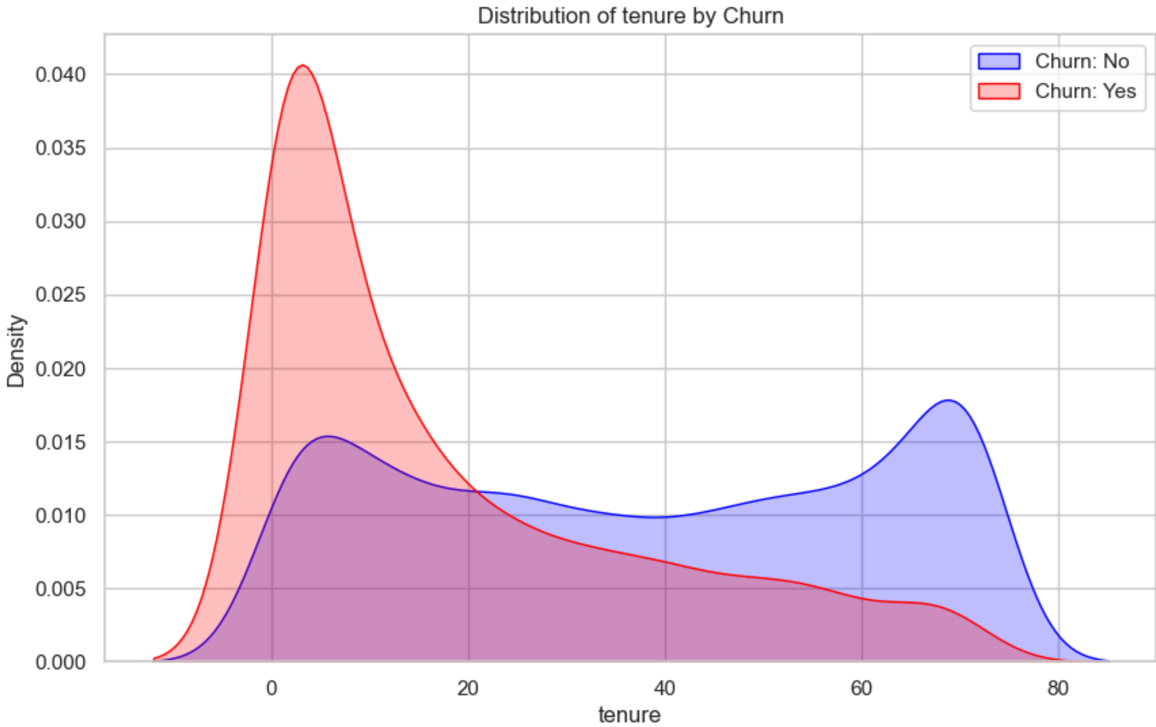
These plots will help us visualize the distribution of each feature, separated by customers who churned (`Churn` ='Yes') and those who stayed (`Churn` ='No'). This can reveal important patterns (e.g., "Do customers with lower tenure churn more?").

In [3]:
```
# --- 1. Identify Numerical Predictor Variables ---
# From our .info() earlier, we know these are our numeric features
numerical_features = ['tenure', 'MonthlyCharges', 'TotalCharges']

print("--- EDA: Analyzing Numerical Features vs. Churn ---")

# --- 2. Loop and Plot (KDE Plots) ---
for col in numerical_features:
    plt.figure(figsize=(10, 6))

    # Plot KDE for customers who did NOT churn
    sns.kdeplot(df[df['Churn'] == 'No'][col], label='Churn: No', shade=True, col

    # Plot KDE for customers who DID churn
    sns.kdeplot(df[df['Churn'] == 'Yes'][col], label='Churn: Yes', shade=True, c

    # Add titles and labels
    plt.title(f'Distribution of {col} by Churn')
```

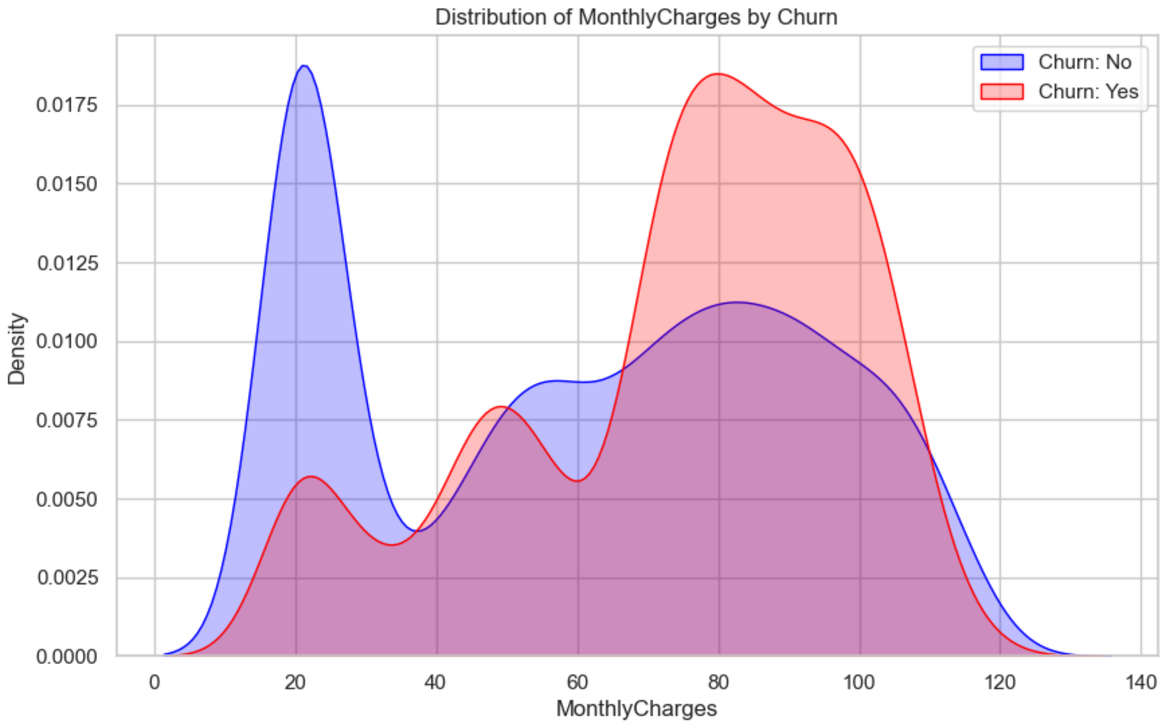
```python
    plt.xlabel(col)
    plt.ylabel('Density')
    plt.legend()

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

```
--- EDA: Analyzing Numerical Features vs. Churn ---
```

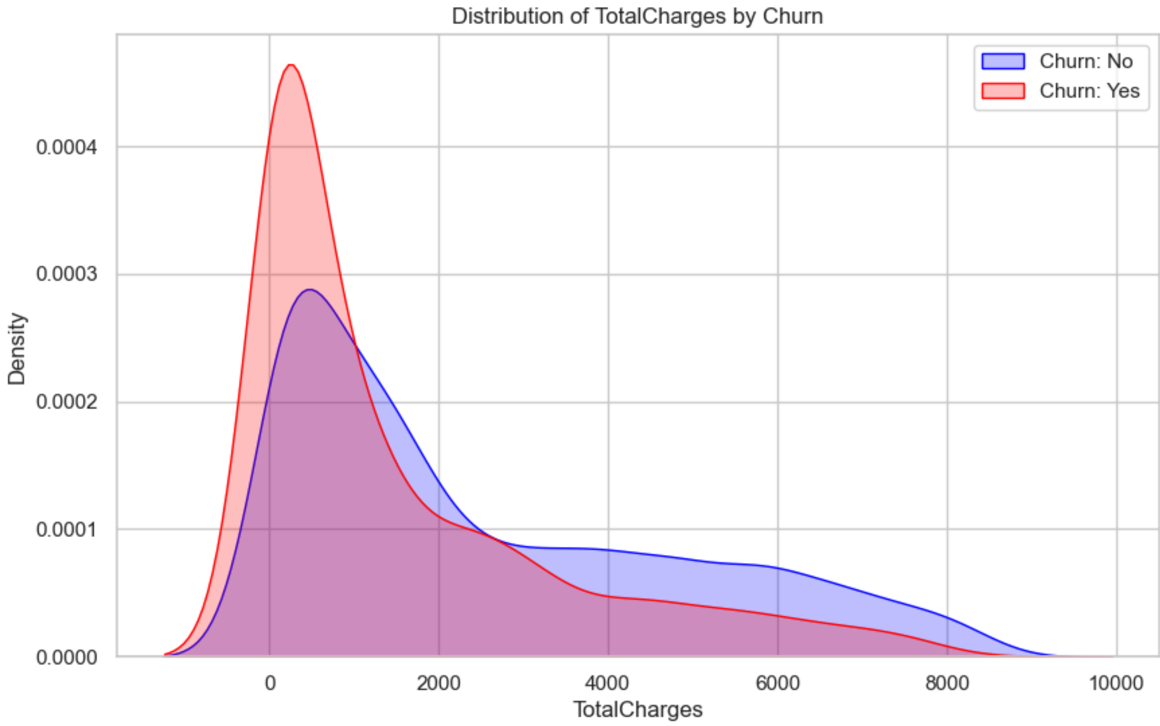
```
C:\Users\hp pavillion\AppData\Local\Temp\ipykernel_14092\1105170387.py:12: Future
Warning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(df[df['Churn'] == 'No'][col], label='Churn: No', shade=True, color
='blue')
C:\Users\hp pavillion\AppData\Local\Temp\ipykernel_14092\1105170387.py:15: Future
Warning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(df[df['Churn'] == 'Yes'][col], label='Churn: Yes', shade=True, colo
r='red')
```



```
C:\Users\hp pavillion\AppData\Local\Temp\ipykernel_14092\1105170387.py:12: Future
Warning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(df[df['Churn'] == 'No'][col], label='Churn: No', shade=True, color
='blue')
C:\Users\hp pavillion\AppData\Local\Temp\ipykernel_14092\1105170387.py:15: Future
Warning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(df[df['Churn'] == 'Yes'][col], label='Churn: Yes', shade=True, colo
r='red')
```




```
C:\Users\hp pavillion\AppData\Local\Temp\ipykernel_14092\1105170387.py:12: Future
Warning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(df[df['Churn'] == 'No'][col], label='Churn: No', shade=True, color
='blue')
C:\Users\hp pavillion\AppData\Local\Temp\ipykernel_14092\1105170387.py:15: Future
Warning:

`shade` is now deprecated in favor of `fill`; setting `fill=True`.
This will become an error in seaborn v0.14.0; please update your code.

  sns.kdeplot(df[df['Churn'] == 'Yes'][col], label='Churn: Yes', shade=True, colo
r='red')
```



1.4 EDA: Categorical Variable Analysis

Next, we analyze the categorical features to see their impact on churn.

We will iterate through our main categorical columns and create a `countplot` for each. We will use the `hue='Churn'` parameter in our plots.

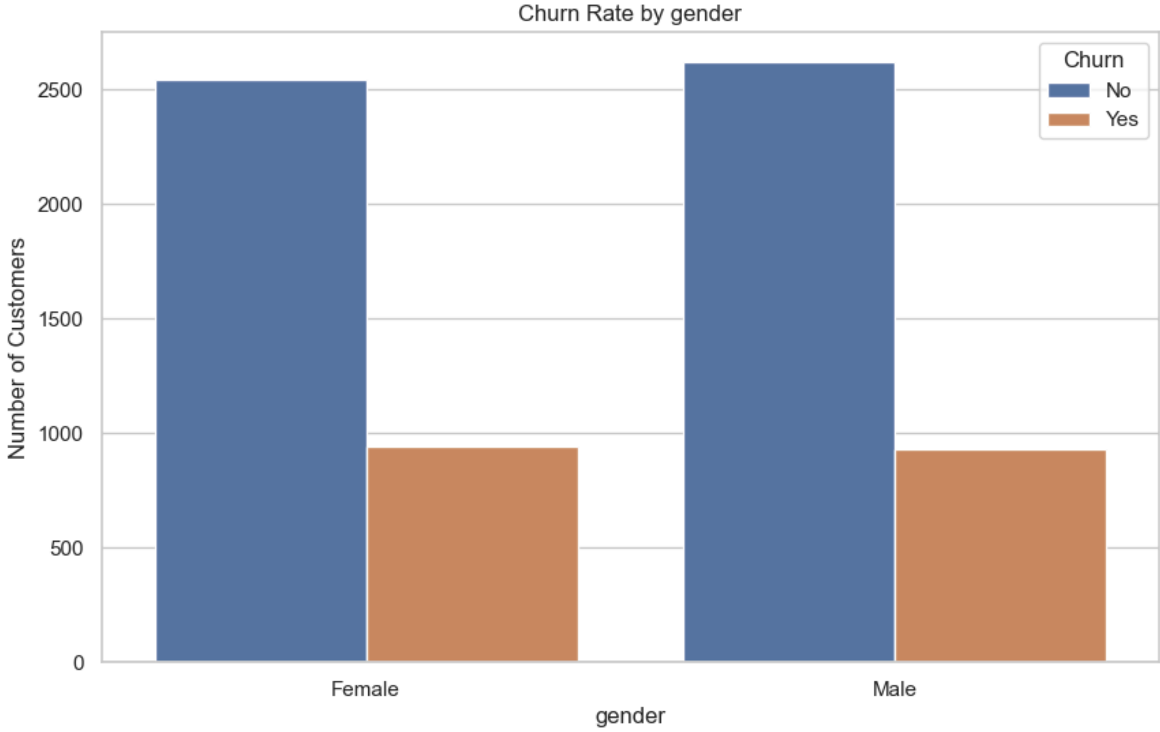
This will create stacked bar charts, allowing us to easily see not just the total number of customers in each category (e.g., "Month-to-month" contract), but also the proportion of those customers who churned vs. stayed. This is one of the most effective ways to find key drivers of churn.

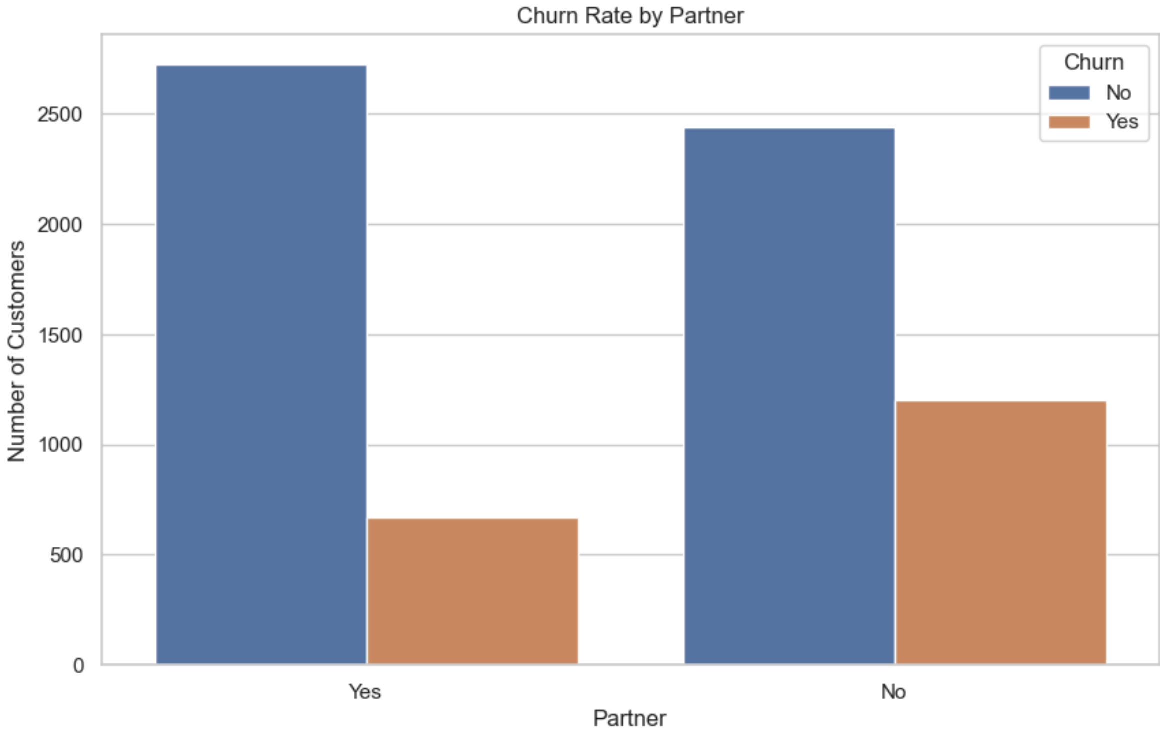
In [4]:

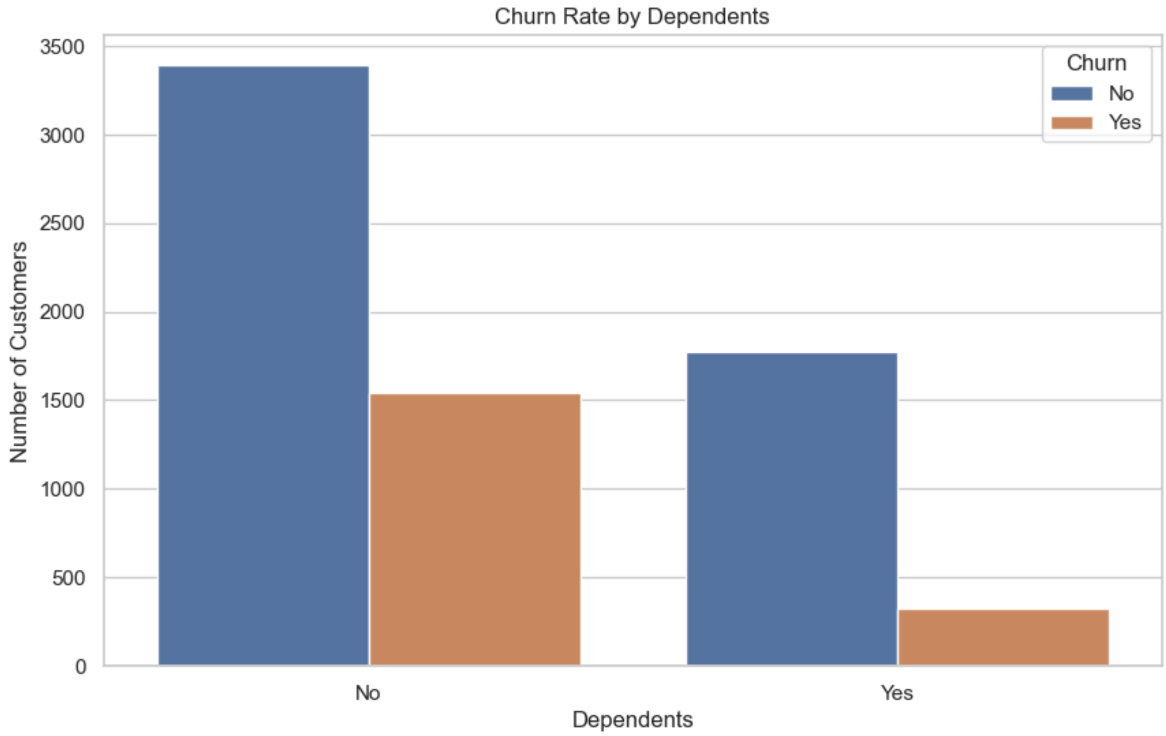
```
# --- 1. Identify Categorical Predictor Variables ---
# We list them manually for clarity, excluding our target 'Churn'
categorical_features = [
    'gender', 'Partner', 'Dependents', 'PhoneService', 'MultipleLines',
    'InternetService', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
    'TechSupport', 'StreamingTV', 'StreamingMovies', 'Contract',
    'PaperlessBilling', 'PaymentMethod'
]

print("--- EDA: Analyzing Categorical Features vs. Churn ---")

# --- 2. Loop and Plot (Count Plots) ---
for col in categorical_features:
    plt.figure(figsize=(10, 6))

    # Create a count plot, splitting by the 'Churn' variable
    sns.countplot(data=df, x=col, hue='Churn')

    # Add titles and labels
    plt.title(f'Churn Rate by {col}')
    plt.xlabel(col)
    plt.ylabel('Number of Customers')
```

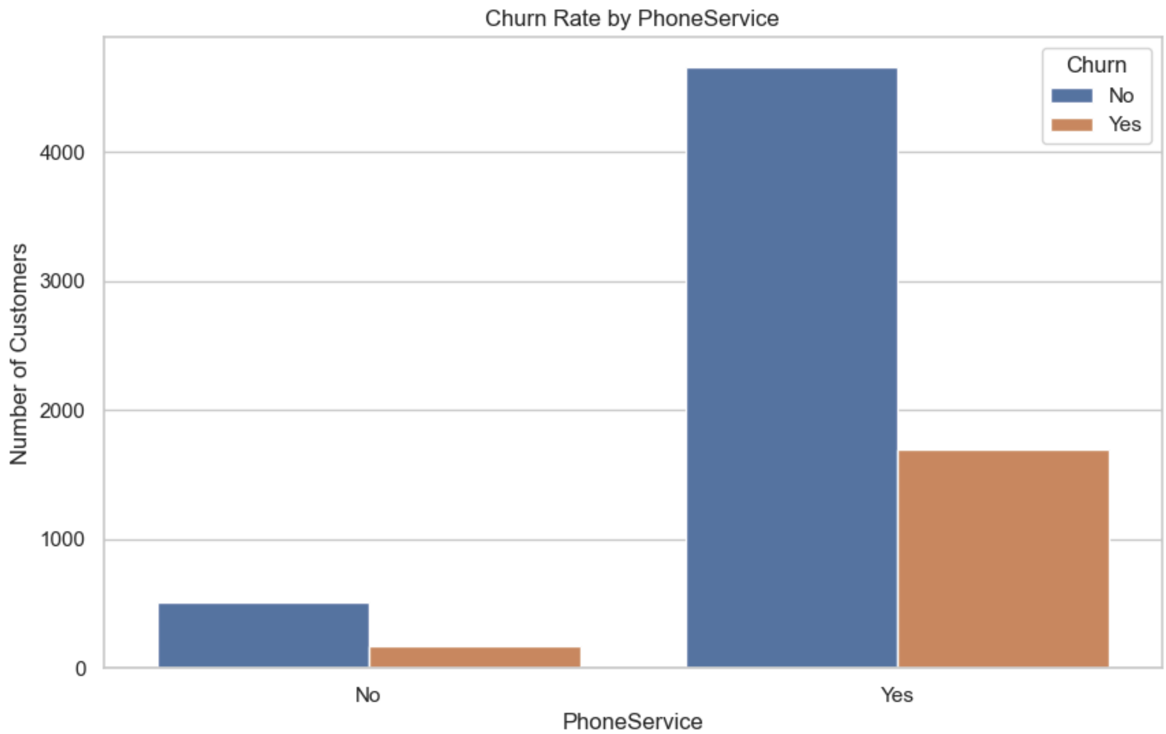
```
    # Rotate x-axis labels if they are long
    if df[col].nunique() > 4:
        plt.xticks(rotation=30)

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

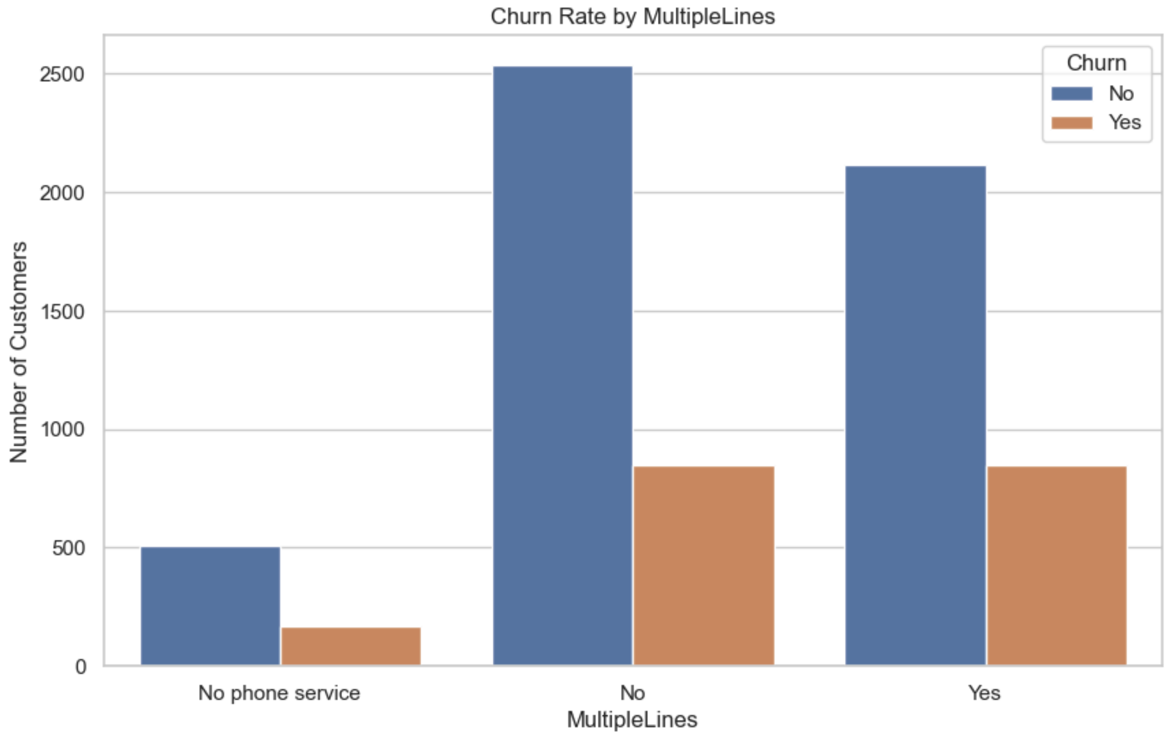
```
--- EDA: Analyzing Categorical Features vs. Churn ---
```

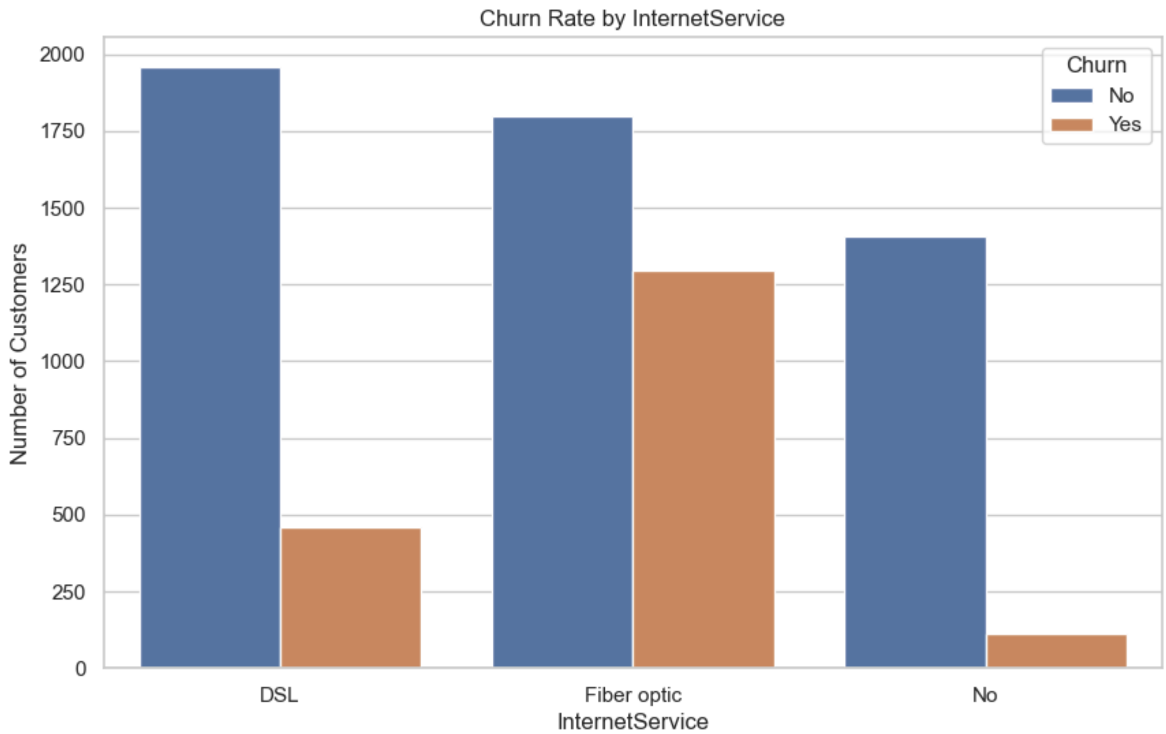


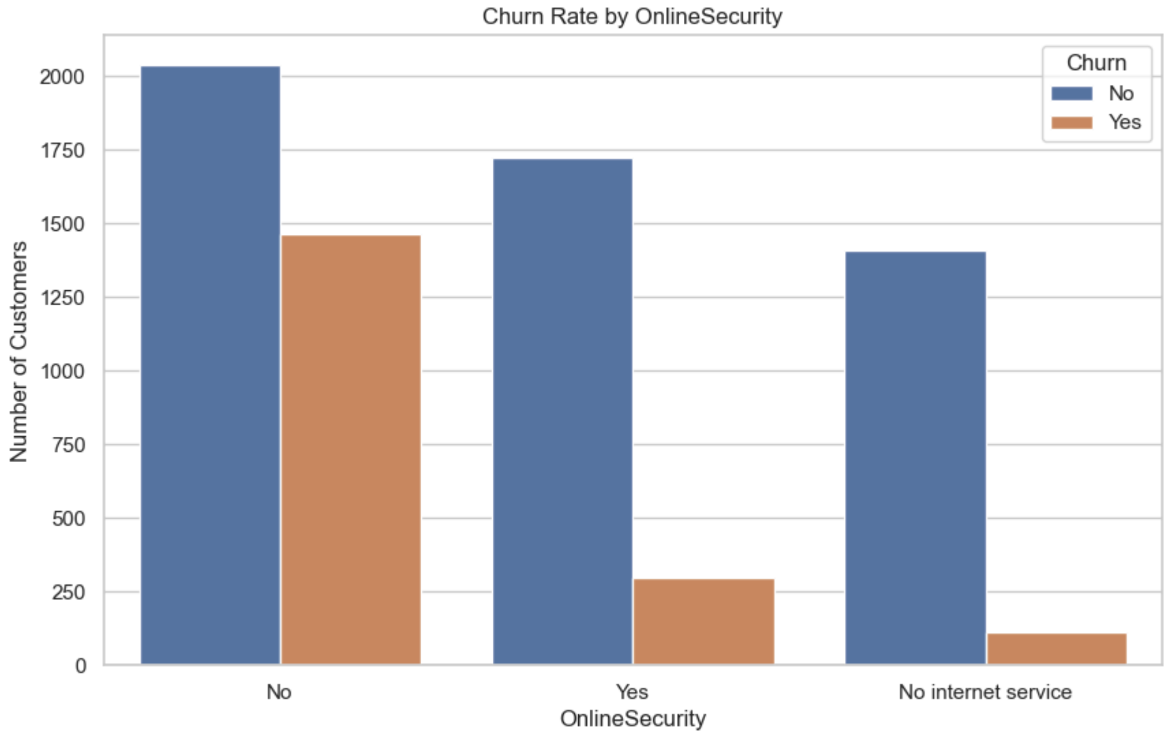


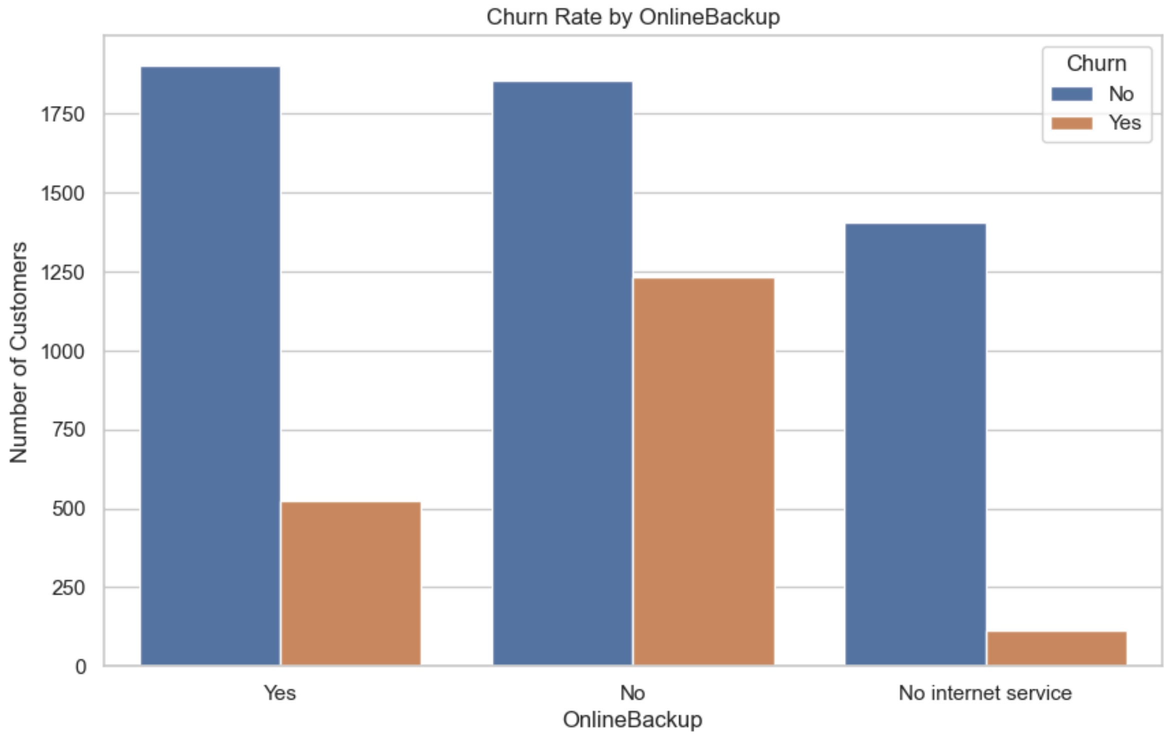

Churn Rate by Dependents
Churn
No
Yes
Number of Customers
3500
3000
2500
2000
1500
1000
500
0
No
Yes
Dependents

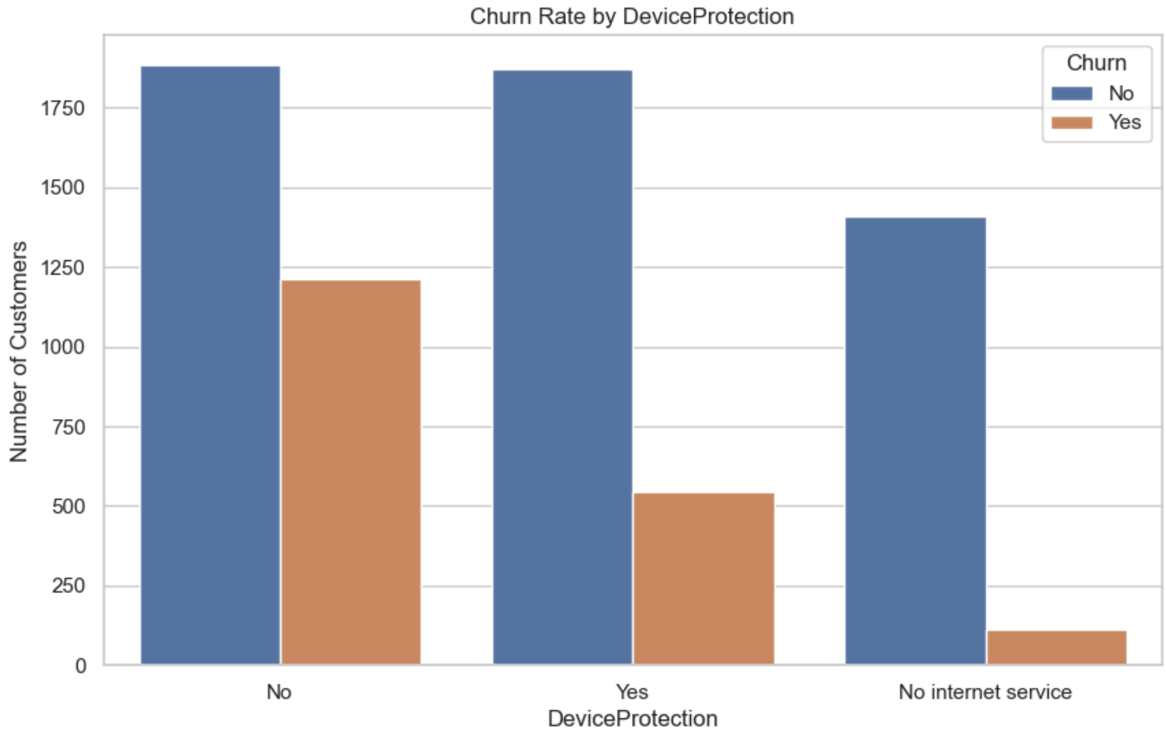

Churn Rate by PhoneService
Churn
No
Yes
Number of Customers
4000
3000
2000
1000
0
No
Yes
PhoneService

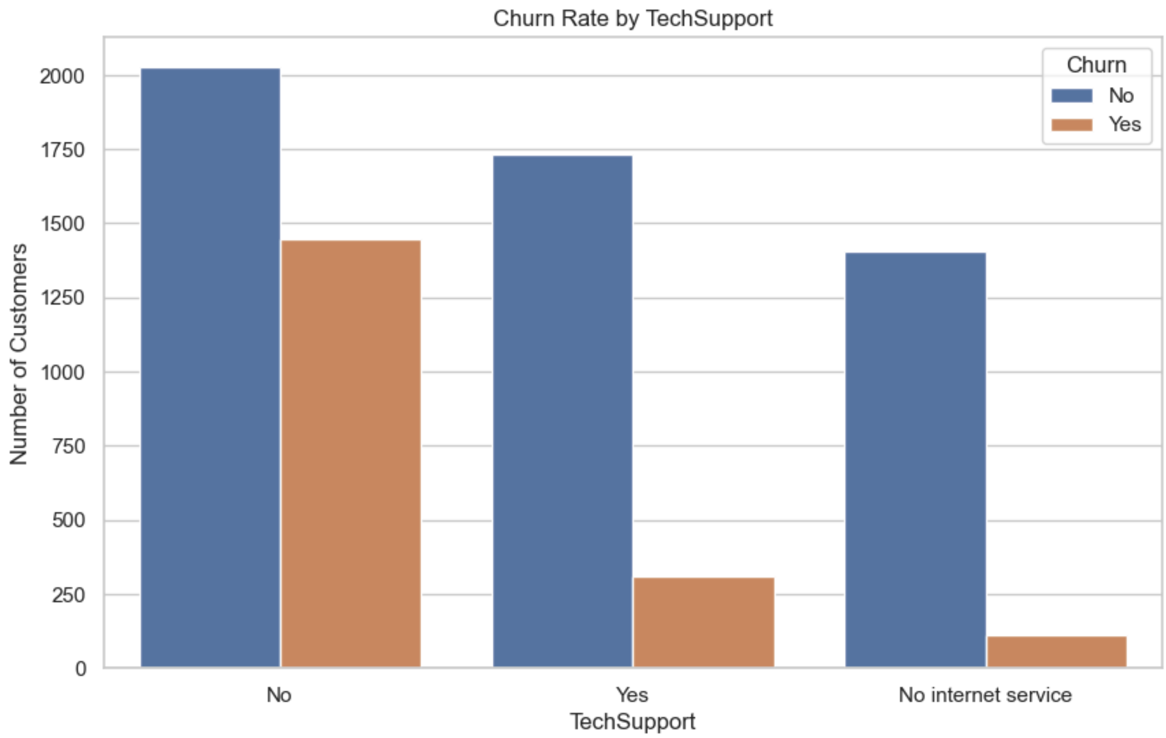

Churn Rate by MultipleLines
Number of Customers
0
500
1000
1500
2000
2500
No phone service
No
Yes
MultipleLines
Churn
No
Yes

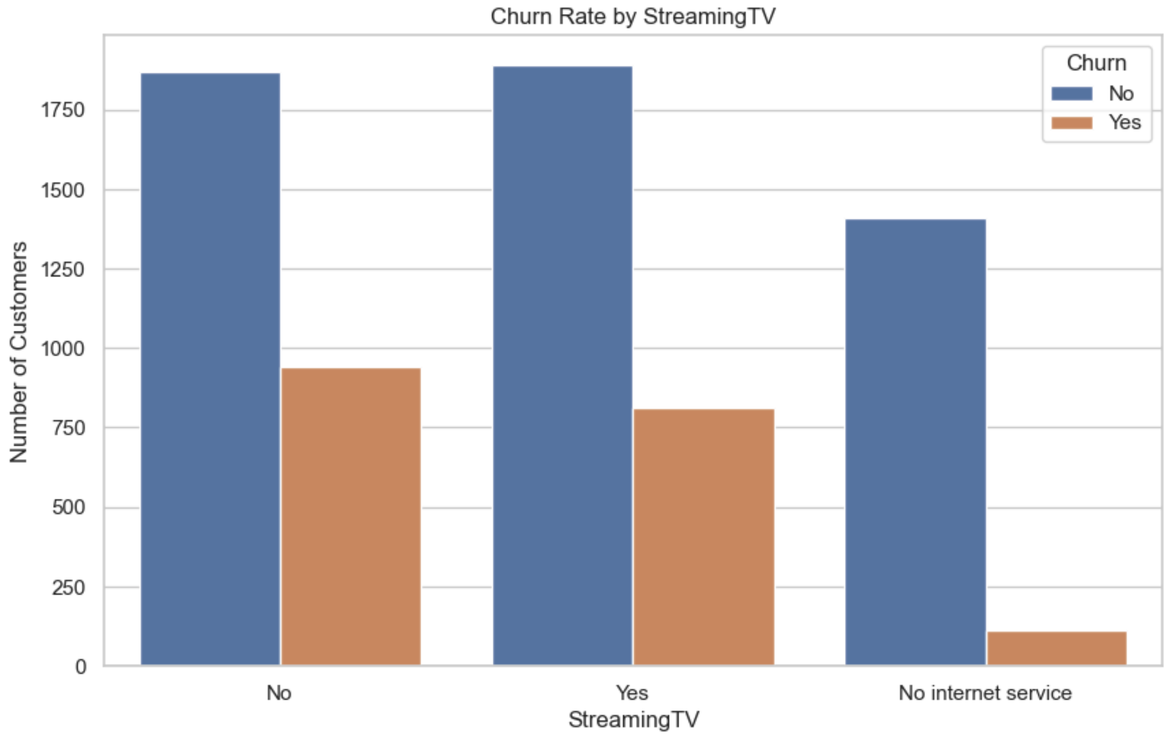

Churn Rate by InternetService
Number of Customers
0
250
500
750
1000
1250
1500
1750
2000
DSL
Fiber optic
No
InternetService
Churn
No
Yes

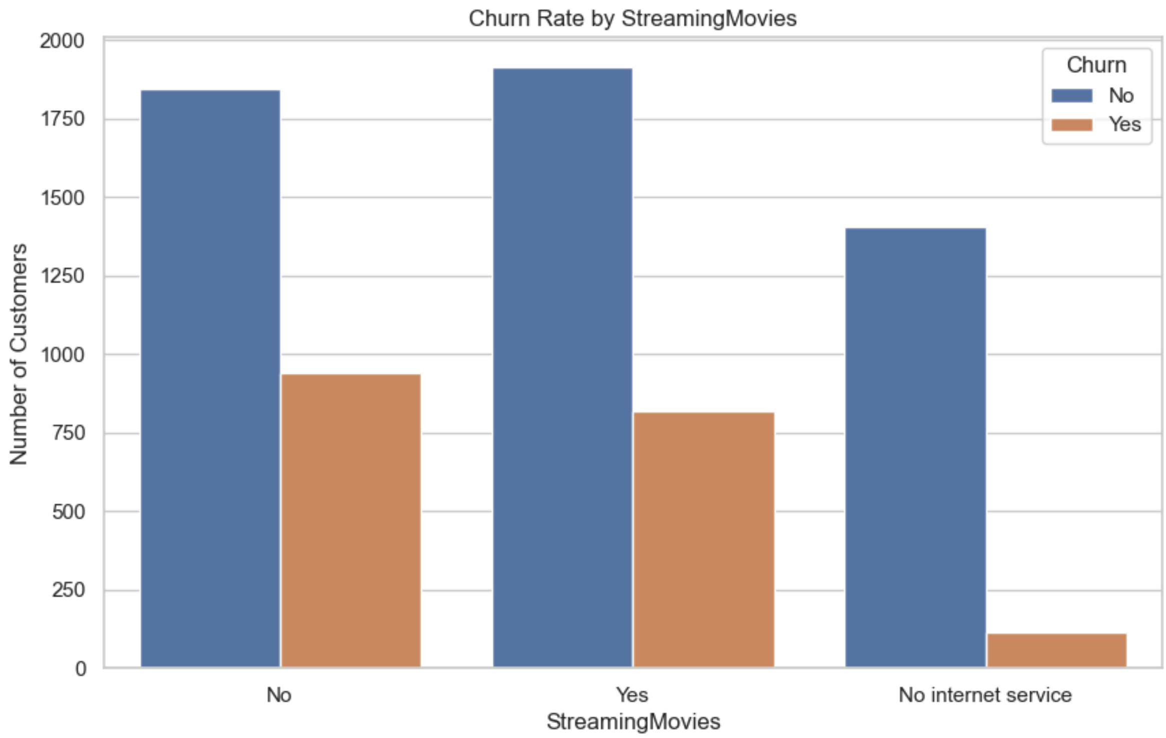

Churn Rate by OnlineSecurity
Churn
No
Yes
Number of Customers
2000
1750
1500
1250
1000
750
500
250
0
No
Yes
No internet service
OnlineSecurity

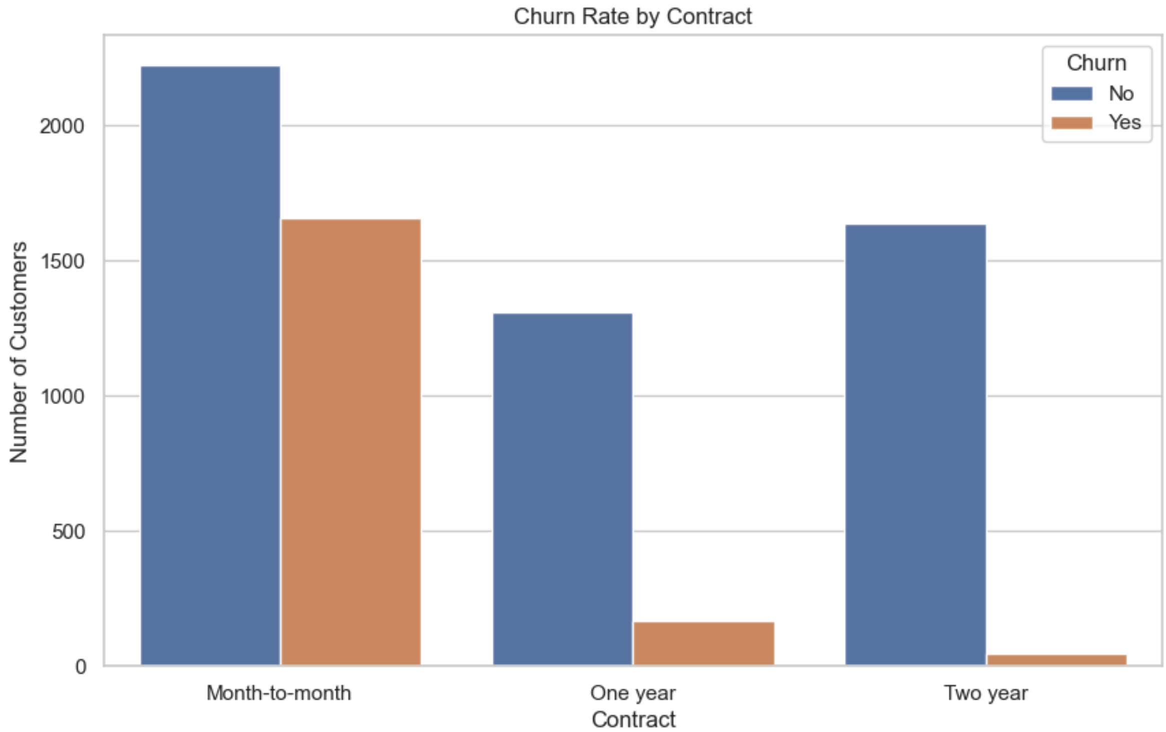

Churn Rate by OnlineBackup
Churn
No
Yes
Number of Customers
1750
1500
1250
1000
750
500
250
0
Yes
No
No internet service
OnlineBackup


Churn Rate by DeviceProtection
Churn
No
Yes
Number of Customers
0
250
500
750
1000
1250
1500
1750
No
Yes
No internet service
DeviceProtection

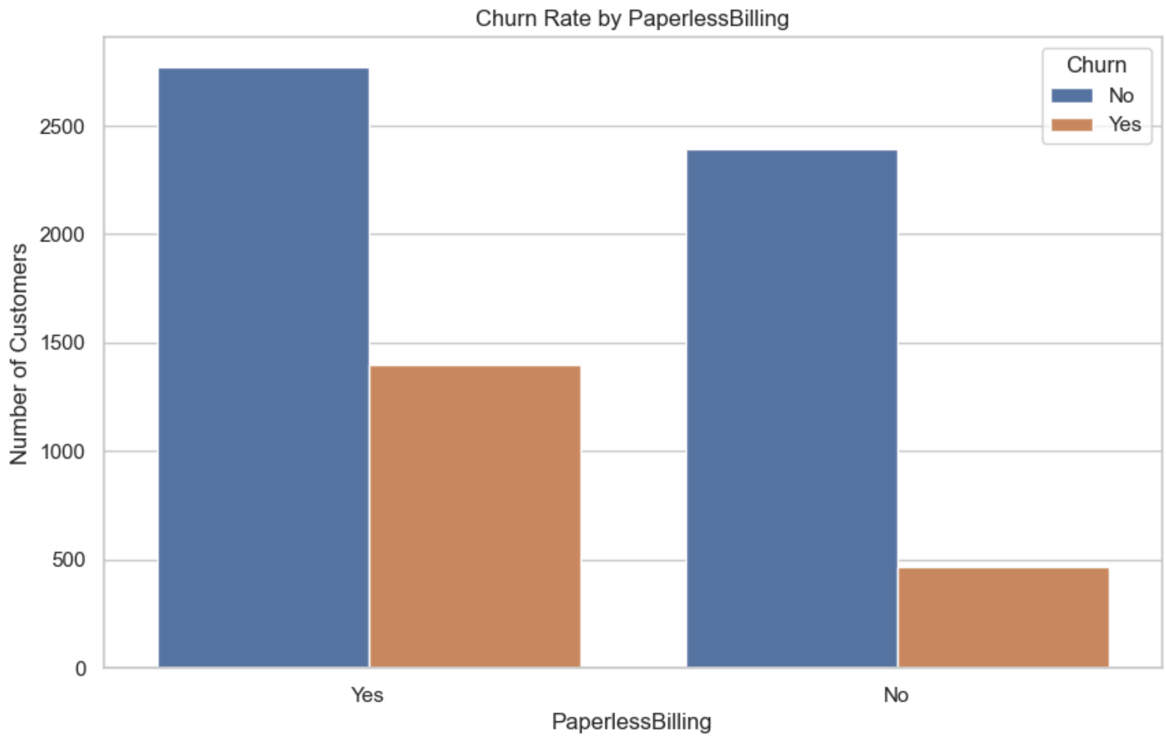

Churn Rate by TechSupport
Churn
No
Yes
Number of Customers
0
250
500
750
1000
1250
1500
1750
2000
No
Yes
No internet service
TechSupport


Churn Rate by StreamingTV
Churn
No
Yes
Number of Customers
1750
1500
1250
1000
750
500
250
0
No
Yes
No internet service
StreamingTV

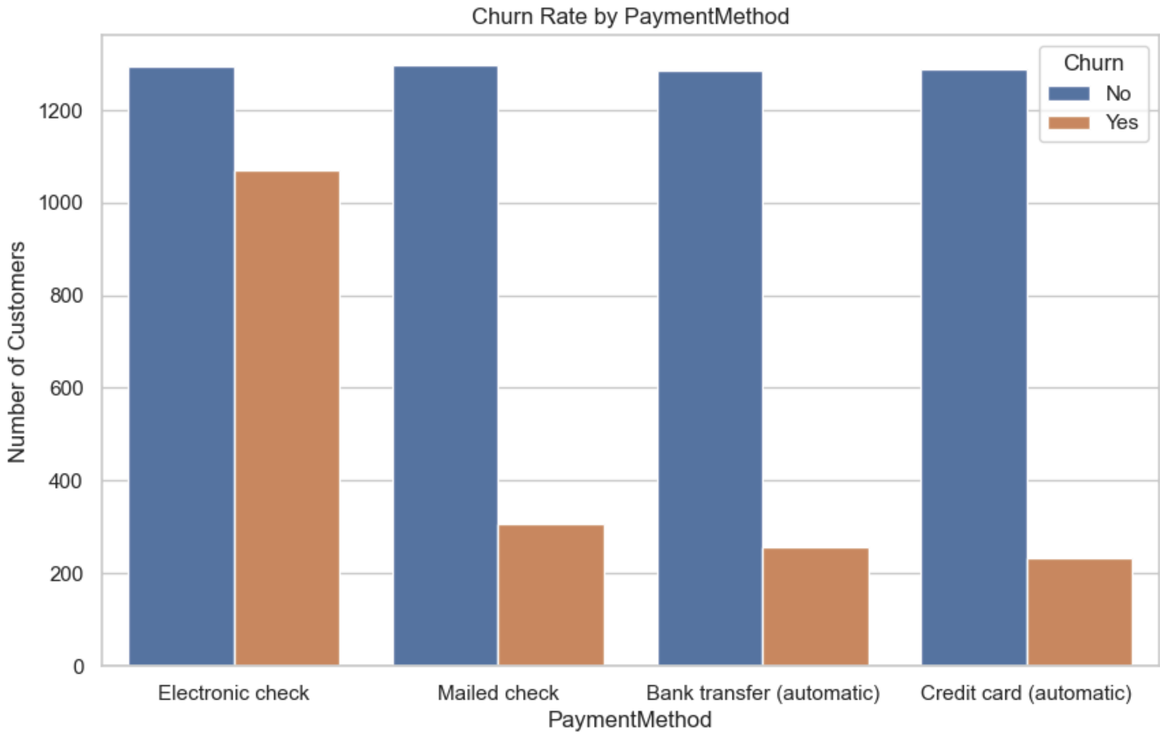

Churn Rate by StreamingMovies
Churn
No
Yes
Number of Customers
2000
1750
1500
1250
1000
750
500
250
0
No
Yes
No internet service
StreamingMovies



Churn Rate by Contract
Churn
No
Yes
Number of Customers
0
500
1000
1500
2000
Month-to-month
One year
Two year
Contract



Churn Rate by PaperlessBilling
Churn
No
Yes
Number of Customers
0
500
1000
1500
2000
2500
Yes
No
PaperlessBilling



Task 2 (Part 1): Data Preprocessing for CHAID

We are now starting Task 2: Model Development using CHAID.

The CHAID algorithm requires all of its predictor variables to be categorical. Our dataset currently has a mix of numerical and categorical features.

Our plan is to:

1. **Discretize (Bin) Numerical Features**: Convert `tenure`, `MonthlyCharges`, and `TotalCharges` into categorical bins (e.g., 4 groups based on quantiles).
2. **Encode All Features**: Apply `LabelEncoder` to *all* predictor columns. This will convert text categories (like 'Yes', 'No', 'DSL') into integers (like 1, 0, 2), which the CHAID library requires.
3. **Split Data**: Separate our data into a training set (to build the model) and a testing set (to evaluate it later).

In [5]:

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

# --- 1. Create a copy of the dataframe for CHAID preprocessing ---
# This ensures our original 'df' remains unchanged for other models
df_chaid = df.copy()

# --- 2. Discretize (Bin) Numerical Features ---
# We will use 'qcut' (quantile-cut) to split them into 4 equal-sized groups
numerical_features = ['tenure', 'MonthlyCharges', 'TotalCharges']
for col in numerical_features:
    df_chaid[col] = pd.qcut(df_chaid[col], q=4, duplicates='drop').astype(str)

# --- 3. Encode All Features (Predictors and Target) ---
# Separate predictors (X) and target (y)
```

```python
X = df_chaid.drop('Churn', axis=1)
y = df_chaid['Churn']

# Apply LabelEncoder to all predictor columns in X
X_encoded = X.apply(LabelEncoder().fit_transform)

# Apply LabelEncoder to the target variable y
y_encoded = LabelEncoder().fit_transform(y)
# (In 'y', 'No' will become 0 and 'Yes' will become 1)

print("--- Data after Encoding (First 5 Rows) ---")
display(X_encoded.head())

# --- 4. Split Data into Training and Testing Sets ---
# We'll use 80% for training and 20% for testing
X_train, X_test, y_train, y_test = train_test_split(
    X_encoded,
    y_encoded,
    test_size=0.2,
    random_state=42
)

print(f"\nData split successfully:")
print(f"X_train shape: {X_train.shape}")
print(f"X_test shape: {X_test.shape}")
print(f"y_train shape: {y_train.shape}")
print(f"y_test shape: {y_test.shape}")
```

```
--- Data after Encoding (First 5 Rows) ---
```

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Inte
0	0	0	1	0	0	0	1	
1	1	0	0	0	1	1	0	
2	1	0	0	0	0	1	0	
3	1	0	0	0	1	0	1	
4	0	0	0	0	0	1	0	

```
Data split successfully:
X_train shape: (5625, 19)
X_test shape: (1407, 19)
y_train shape: (5625,)
y_test shape: (1407,)
```

Task 2 (Part 2): Build CHAID Model & Extract Rules

Now that our data is preprocessed, we can build the CHAID model.

1. **Install Library**: We will first install the `CHAID` library, as it is not a default part of `scikit-learn`.
2. **Build Tree**: We will instantiate the `Tree` object from the library and fit it on our training data (`X_train` , `y_train`). We'll set a `max_depth` (e.g., 5) to keep the tree from getting too large and to make the rules easier to interpret.

3. **Extract Rules**: The key output of this model is the set of human-readable decision rules. We will print the resulting tree structure, which shows the "IF-THEN" logic that the model discovered. [cite_start]This directly addresses the assignment's requirement to "extract decision rules"[cite: 36].

In [8]:

```
# --- 1. Define Model Inputs ---
# We use 'df_chaid', the dataframe with binned numerical features
# and original string categories (e.g., 'Yes', 'No')
from CHAID import Tree

predictor_columns = [col for col in df_chaid.columns if col != 'Churn']
target_column = 'Churn'
column_types = {col: 'nominal' for col in predictor_columns}

# --- 2. Build the CHAID Tree (on the full dataset) ---
# The goal here is rule discovery, not prediction, so
# we use the full dataset to find all possible patterns.
print("--- Building CHAID Tree (max_depth=5) ---")
chaid_tree = Tree.from_pandas_df(
    df_chaid,                    # The dataframe with raw categories
    column_types,                # The dictionary mapping predictors to 'nominal'
    target_column,               # The name of the target column
    max_depth=5                  # Set the maximum depth to 5
)

# --- 3. Print the Decision Rules ---
print("\n--- CHAID Decision Rules (for Task 2 Report) ---")
chaid_tree.print_tree()

print("\nTask 2 complete. Please copy the rules above for your report.")
```

```
c:\Users\hp pavillion\AppData\Local\Programs\Python\Python310\lib\site-packages\C
HAID\graph.py:13: UserWarning: Imports of optional packages needed to generate gr
aphs failed. Please install with the "graph" option.
  warnings.warn(UserWarning('Imports of optional packages needed to generate grap
hs failed. Please install with the "graph" option.'))
```

```
--- Building CHAID Tree (max_depth=5) ---

--- CHAID Decision Rules (for Task 2 Report) ---
([], {'No': 5163.0, 'Yes': 1869.0}, (Contract, p=7.326182186265472e-257, score=11
79.5458287339445, groups=[['Month-to-month'], ['One year'], ['Two year']]), dof=
2))
|-- (['Month-to-month'], {'No': 2220.0, 'Yes': 1655.0}, (InternetService, p=8.853
102500484912e-66, score=299.5796963499884, groups=[['DSL'], ['Fiber optic'], ['N
o']]), dof=2))
|   |-- (['DSL'], {'No': 829.0, 'Yes': 394.0}, (TotalCharges, p=6.320879510155006
e-25, score=111.44153792675088, groups=[['(1397.475, 3794.738]', '(3794.738, 868
4.8]'], ['(18.799, 401.45]'], ['(401.45, 1397.475]']]), dof=2))
|   |   |-- (['(1397.475, 3794.738]', '(3794.738, 8684.8]'], {'No': 229.0, 'Yes':
38.0}, (PhoneService, p=0.001875614417503133, score=9.667450235354163, groups=
[['No'], ['Yes']]), dof=1))
|   |   |   |-- (['No'], {'No': 58.0, 'Yes': 19.0}, <Invalid Chaid Split> - the n
ode only contains single category respondents)
|   |   |   +-- (['Yes'], {'No': 171.0, 'Yes': 19.0}, <Invalid Chaid Split> - p-v
alue greater than alpha merge)
|   |   |-- (['(18.799, 401.45]'], {'No': 294.0, 'Yes': 263.0}, (PaymentMethod, p
=0.0014564321619320209, score=10.132936247419636, groups=[['Bank transfer (automa
tic)', 'Credit card (automatic)', 'Mailed check'], ['Electronic check']]), dof=
1))
|   |   |   |-- (['Bank transfer (automatic)', 'Credit card (automatic)', 'Mailed
check'], {'No': 189.0, 'Yes': 134.0}, (OnlineSecurity, p=0.007403242048135513, sc
ore=7.172430147442203, groups=[['No'], ['Yes']]), dof=1))
|   |   |   |   |-- (['No'], {'No': 137.0, 'Yes': 114.0}, <Invalid Chaid Split> -
the max depth has been reached)
|   |   |   |   +-- (['Yes'], {'No': 52.0, 'Yes': 20.0}, <Invalid Chaid Split> -
the max depth has been reached)
|   |   |   +-- (['Electronic check'], {'No': 105.0, 'Yes': 129.0}, (SeniorCitize
n, p=0.011972888128015327, score=6.31487951011844, groups=[[0], [1]]), dof=1))
|   |   |       |-- ([0], {'No': 95.0, 'Yes': 101.0}, <Invalid Chaid Split> - the
max depth has been reached)
|   |   |       +-- ([1], {'No': 10.0, 'Yes': 28.0}, <Invalid Chaid Split> - the
max depth has been reached)
|   |   +-- (['(401.45, 1397.475]'], {'No': 306.0, 'Yes': 93.0}, (OnlineBackup, p
=0.0005570716992938892, score=11.914216275767004, groups=[['No'], ['Yes']]), dof=
1))
|   |       |-- (['No'], {'No': 203.0, 'Yes': 79.0}, (SeniorCitizen, p=0.00455809
02310967, score=8.046927195146937, groups=[[0], [1]]), dof=1))
|   |       |   |-- ([0], {'No': 188.0, 'Yes': 64.0}, <Invalid Chaid Split> - the
max depth has been reached)
|   |       |   +-- ([1], {'No': 15.0, 'Yes': 15.0}, <Invalid Chaid Split> - the
minimum parent node size threshold has been reached)
|   |       +-- (['Yes'], {'No': 103.0, 'Yes': 14.0}, <Invalid Chaid Split> - the
node only contains single category respondents)
|   |-- (['Fiber optic'], {'No': 966.0, 'Yes': 1162.0}, (tenure, p=6.085068284360
564e-41, score=190.00621994037962, groups=[['(0.999, 9.0]'], ['(29.0, 55.0]'],
['(55.0, 72.0]'], ['(9.0, 29.0]']]), dof=3))
|   |   |-- (['(0.999, 9.0]'], {'No': 226.0, 'Yes': 559.0}, (OnlineSecurity, p=0.
00012134122323093427, score=14.7717271650391, groups=[['No'], ['Yes']]), dof=1))
|   |   |   |-- (['No'], {'No': 195.0, 'Yes': 528.0}, (TotalCharges, p=0.00091645
62189801672, score=10.989174497523898, groups=[['(18.799, 401.45]'], ['(401.45, 1
397.475]']]), dof=1))
|   |   |   |   |-- (['(18.799, 401.45]'], {'No': 116.0, 'Yes': 382.0}, <Invalid
Chaid Split> - the max depth has been reached)
|   |   |   |   +-- (['(401.45, 1397.475]'], {'No': 79.0, 'Yes': 146.0}, <Invalid
Chaid Split> - the max depth has been reached)
|   |   |   +-- (['Yes'], {'No': 31.0, 'Yes': 31.0}, <Invalid Chaid Split> - p-va
```

```
lue greater than alpha merge)
|   |   |-- (['(29.0, 55.0]'], {'No': 299.0, 'Yes': 204.0}, (PaymentMethod, p=0.0
008613048375408288, score=11.104242024179086, groups=[['Bank transfer (automati
c)', 'Credit card (automatic)', 'Mailed check'], ['Electronic check']]), dof=1))
|   |   |   |-- (['Bank transfer (automatic)', 'Credit card (automatic)', 'Mailed
check'], {'No': 158.0, 'Yes': 77.0}, (SeniorCitizen, p=0.015368010211948608, scor
e=5.873780991394172, groups=[[0], [1]]), dof=1))
|   |   |   |   |-- ([0], {'No': 124.0, 'Yes': 49.0}, <Invalid Chaid Split> - the
max depth has been reached)
|   |   |   |   +-- ([1], {'No': 34.0, 'Yes': 28.0}, <Invalid Chaid Split> - the
max depth has been reached)
|   |   |   +-- (['Electronic check'], {'No': 141.0, 'Yes': 127.0}, (OnlineBacku
p, p=0.023531903042689425, score=5.128806526025489, groups=[['No'], ['Yes']]), do
f=1))
|   |   |       |-- (['No'], {'No': 66.0, 'Yes': 77.0}, <Invalid Chaid Split> - t
he max depth has been reached)
|   |   |       +-- (['Yes'], {'No': 75.0, 'Yes': 50.0}, <Invalid Chaid Split> -
the max depth has been reached)
|   |   |-- (['(55.0, 72.0]'], {'No': 121.0, 'Yes': 37.0}, (StreamingTV, p=0.0031
252887067114853, score=8.732842651714124, groups=[['No'], ['Yes']]), dof=1))
|   |   |   |-- (['No'], {'No': 52.0, 'Yes': 6.0}, <Invalid Chaid Split> - the no
de only contains single category respondents)
|   |   |   +-- (['Yes'], {'No': 69.0, 'Yes': 31.0}, (TechSupport, p=0.0087230699
42273122, score=6.878664906790146, groups=[['No'], ['Yes']]), dof=1))
|   |   |       |-- (['No'], {'No': 42.0, 'Yes': 27.0}, <Invalid Chaid Split> - t
he max depth has been reached)
|   |   |       +-- (['Yes'], {'No': 27.0, 'Yes': 4.0}, <Invalid Chaid Split> - t
he max depth has been reached)
|   |   +-- (['(9.0, 29.0]'], {'No': 320.0, 'Yes': 362.0}, (PaymentMethod, p=1.85
75843171978175e-05, score=18.330003854262397, groups=[['Bank transfer (automati
c)', 'Mailed check', 'Credit card (automatic)'], ['Electronic check']]), dof=1))
|   |       |-- (['Bank transfer (automatic)', 'Mailed check', 'Credit card (auto
matic)'], {'No': 153.0, 'Yes': 115.0}, (StreamingMovies, p=7.150171298599028e-06,
score=20.15263410455226, groups=[['No'], ['Yes']]), dof=1))
|   |       |   |-- (['No'], {'No': 107.0, 'Yes': 49.0}, <Invalid Chaid Split> -
the max depth has been reached)
|   |       |   +-- (['Yes'], {'No': 46.0, 'Yes': 66.0}, <Invalid Chaid Split> -
the max depth has been reached)
|   |       +-- (['Electronic check'], {'No': 167.0, 'Yes': 247.0}, (MultipleLine
s, p=0.0014082648476866737, score=10.194940754992746, groups=[['No'], ['Yes']]),
dof=1))
|   |           |-- (['No'], {'No': 83.0, 'Yes': 84.0}, <Invalid Chaid Split> - t
he max depth has been reached)
|   |           +-- (['Yes'], {'No': 84.0, 'Yes': 163.0}, <Invalid Chaid Split> -
the max depth has been reached)
|   +-- (['No'], {'No': 425.0, 'Yes': 99.0}, (tenure, p=7.939471301056829e-06, sc
ore=19.952388453619644, groups=[['(0.999, 9.0]', '(55.0, 72.0]'], ['(29.0, 55.
0]', '(9.0, 29.0]']]), dof=1))
|       |-- (['(0.999, 9.0]', '(55.0, 72.0]'], {'No': 260.0, 'Yes': 84.0}, <Inval
id Chaid Split> - p-value greater than alpha merge)
|       +-- (['(29.0, 55.0]', '(9.0, 29.0]'], {'No': 165.0, 'Yes': 15.0}, (TotalC
harges, p=0.037915871054459316, score=4.308792253043124, groups=[['(18.799, 401.4
5]'], ['(401.45, 1397.475]']]), dof=1))
|           |-- (['(18.799, 401.45]'], {'No': 86.0, 'Yes': 12.0}, <Invalid Chaid
Split> - the node only contains single category respondents)
|           +-- (['(401.45, 1397.475]'], {'No': 79.0, 'Yes': 3.0}, <Invalid Chaid
Split> - the node only contains single category respondents)
|-- (['One year'], {'No': 1306.0, 'Yes': 166.0}, (StreamingMovies, p=2.2256538457
43632e-18, score=81.29296187637681, groups=[['No'], ['No internet service'], ['Ye
s']]), dof=2))
```

```
|   |-- (['No'], {'No': 418.0, 'Yes': 29.0}, (PaymentMethod, p=0.0002788586453788
878, score=13.207314577437081, groups=[['Bank transfer (automatic)', 'Credit card
(automatic)', 'Mailed check'], ['Electronic check']]), dof=1))
|   |   |-- (['Bank transfer (automatic)', 'Credit card (automatic)', 'Mailed che
ck'], {'No': 336.0, 'Yes': 15.0}, (TotalCharges, p=0.009704976340340725, score=6.
6882621951219505, groups=[['(1397.475, 3794.738]', '(18.799, 401.45]', '(401.45,
1397.475]'], ['(3794.738, 8684.8]']]), dof=1))
|   |   |   |-- (['(1397.475, 3794.738]', '(18.799, 401.45]', '(401.45, 1397.47
5]'], {'No': 231.0, 'Yes': 15.0}, <Invalid Chaid Split> - p-value greater than al
pha merge)
|   |   |   +-- (['(3794.738, 8684.8]'], {'No': 105.0, 'Yes': 0}, <Invalid Chaid
Split> - the node only contains single category respondents)
|   |   +-- (['Electronic check'], {'No': 82.0, 'Yes': 14.0}, <Invalid Chaid Spli
t> - p-value greater than alpha merge)
|   |-- (['No internet service'], {'No': 354.0, 'Yes': 9.0}, (PaymentMethod, p=0.
03731426562874419, score=4.336010257794574, groups=[['Bank transfer (automatic)',
'Electronic check'], ['Credit card (automatic)', 'Mailed check']]), dof=1))
|   |   |-- (['Bank transfer (automatic)', 'Electronic check'], {'No': 118.0, 'Ye
s': 6.0}, <Invalid Chaid Split> - p-value greater than alpha merge)
|   |   +-- (['Credit card (automatic)', 'Mailed check'], {'No': 236.0, 'Yes': 3.
0}, (tenure, p=0.0006516610816516224, score=14.67197188921042, groups=[['(0.999,
9.0]'], ['(29.0, 55.0]', '(55.0, 72.0]'], ['(9.0, 29.0]']]), dof=2))
|   |       |-- (['(0.999, 9.0]'], {'No': 38.0, 'Yes': 3.0}, <Invalid Chaid Split
> - the node only contains single category respondents)
|   |       |-- (['(29.0, 55.0]', '(55.0, 72.0]'], {'No': 88.0, 'Yes': 0}, <Inval
id Chaid Split> - the node only contains single category respondents)
|   |       +-- (['(9.0, 29.0]'], {'No': 110.0, 'Yes': 0}, <Invalid Chaid Split>
- the node only contains single category respondents)
|   +-- (['Yes'], {'No': 534.0, 'Yes': 128.0}, (InternetService, p=0.001185609188
2215625, score=10.51263738147573, groups=[['DSL'], ['Fiber optic']]), dof=1))
|       |-- (['DSL'], {'No': 225.0, 'Yes': 34.0}, <Invalid Chaid Split> - p-value
greater than alpha merge)
|       +-- (['Fiber optic'], {'No': 309.0, 'Yes': 94.0}, (StreamingTV, p=0.03093
7030512007014, score=4.656453438543821, groups=[['No'], ['Yes']]), dof=1))
|           |-- (['No'], {'No': 59.0, 'Yes': 9.0}, (DeviceProtection, p=0.0158956
60876330597, score=5.814379468616755, groups=[['No'], ['Yes']]), dof=1))
|           |   |-- (['No'], {'No': 27.0, 'Yes': 8.0}, <Invalid Chaid Split> - th
e max depth has been reached)
|           |   +-- (['Yes'], {'No': 32.0, 'Yes': 1.0}, <Invalid Chaid Split> - t
he max depth has been reached)
|           +-- (['Yes'], {'No': 250.0, 'Yes': 85.0}, <Invalid Chaid Split> - p-v
alue greater than alpha merge)
+-- (['Two year'], {'No': 1637.0, 'Yes': 48.0}, (InternetService, p=2.74362621097
35596e-10, score=39.84908551133631, groups=[['DSL', 'No'], ['Fiber optic']]), dof
=1))
    |-- (['DSL', 'No'], {'No': 1239.0, 'Yes': 17.0}, (SeniorCitizen, p=0.00187404
91036021263, score=9.668984114864745, groups=[[0], [1]]), dof=1))
    |   |-- ([0], {'No': 1169.0, 'Yes': 13.0}, (PaymentMethod, p=0.00021216545788
49526, score=13.720154144172987, groups=[['Bank transfer (automatic)', 'Credit ca
rd (automatic)', 'Mailed check'], ['Electronic check']]), dof=1))
    |   |   |-- (['Bank transfer (automatic)', 'Credit card (automatic)', 'Mailed
check'], {'No': 1100.0, 'Yes': 9.0}, <Invalid Chaid Split> - p-value greater than
alpha merge)
    |   |   +-- (['Electronic check'], {'No': 69.0, 'Yes': 4.0}, <Invalid Chaid S
plit> - p-value greater than alpha merge)
    |   +-- ([1], {'No': 70.0, 'Yes': 4.0}, (StreamingTV, p=0.03462664031644337,
score=4.463492063492064, groups=[['No', 'No internet service'], ['Yes']]), dof=
1))
    |       |-- (['No', 'No internet service'], {'No': 38.0, 'Yes': 0}, <Invalid
Chaid Split> - the node only contains single category respondents)
```

```
    |       +-- (['Yes'], {'No': 32.0, 'Yes': 4.0}, <Invalid Chaid Split> - p-val
ue greater than alpha merge)
    +-- (['Fiber optic'], {'No': 398.0, 'Yes': 31.0}, (PaymentMethod, p=0.0321835
3990434876, score=4.58869337798977, groups=[['Bank transfer (automatic)', 'Electr
onic check'], ['Credit card (automatic)', 'Mailed check']]), dof=1))
        |-- (['Bank transfer (automatic)', 'Electronic check'], {'No': 230.0, 'Ye
s': 24.0}, <Invalid Chaid Split> - p-value greater than alpha merge)
        +-- (['Credit card (automatic)', 'Mailed check'], {'No': 168.0, 'Yes': 7.
0}, (Partner, p=0.031601199059749494, score=4.6200021235287, groups=[['No'], ['Ye
s']]), dof=1))
            |-- (['No'], {'No': 37.0, 'Yes': 4.0}, <Invalid Chaid Split> - p-valu
e greater than alpha merge)
            +-- (['Yes'], {'No': 131.0, 'Yes': 3.0}, <Invalid Chaid Split> - p-va
lue greater than alpha merge)


Task 2 complete. Please copy the rules above for your report.
```

Task 3 (Part 2): Build & Train Models (Decision Tree and Logistic Regression)

Now that our data is fully numeric and split, we can build the two models for our comparison.

1. **Model 1: Decision Tree Classifier**: This is our functional replacement for CHAID, as it's a tree-based model that can be used for prediction.
2. [cite_start]**Model 2: Logistic Regression**: This is the second model required by the assignment[cite: 44].

We will:

1. Import, initialize, and train both models on our `X_train` data.
2. Get two types of predictions from each model on the `X_test` data:
   - **Class Predictions (`.predict()`)**: The final 'Yes' (1) or 'No' (0) guess. Used for calculating **Accuracy**.
   - **Probability Predictions (`.predict_proba()`)**: The model's confidence (e.g., "70% chance of churn"). This is required to calculate **ROC-AUC** and draw **Lift/Gains charts**.

In [9]:
```python
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler

# --- 1. Scale the Data (Important for Logistic Regression) ---

# Logistic Regression performs better when features are on a similar scale.
# Decision Trees don't require scaling, but it doesn't hurt them.
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# --- 2. Build and Train Model 1: Decision Tree ---
print("--- Training Decision Tree ---")
# We set max_depth=5 to match our CHAID tree and prevent overfitting
```

```
dt_model = DecisionTreeClassifier(max_depth=5, random_state=42)
dt_model.fit(X_train_scaled, y_train)

# --- 3. Build and Train Model 2: Logistic Regression ---
print("--- Training Logistic Regression ---")
# 'max_iter' is increased to 1000 to ensure the model converges
lr_model = LogisticRegression(max_iter=1000, random_state=42)
lr_model.fit(X_train_scaled, y_train)

# --- 4. Get Predictions from Both Models ---
print("--- Generating predictions ---")

# Decision Tree predictions
y_pred_dt = dt_model.predict(X_test_scaled)
y_proba_dt = dt_model.predict_proba(X_test_scaled)[:, 1] # Get probability of ch

# Logistic Regression predictions
y_pred_lr = lr_model.predict(X_test_scaled)
y_proba_lr = lr_model.predict_proba(X_test_scaled)[:, 1] # Get probability of ch

print("Models trained and predictions generated successfully.")
```

```
--- Training Decision Tree ---
--- Training Logistic Regression ---
--- Generating predictions ---
Models trained and predictions generated successfully.
```

Task 3 (Part 3): Model Comparison & Evaluation (Metrics)

This is the core of Task 3. We will now use the predictions we generated in the previous step to evaluate and compare our two models.

[cite_start]As required by the assignment, we will use the following metrics:

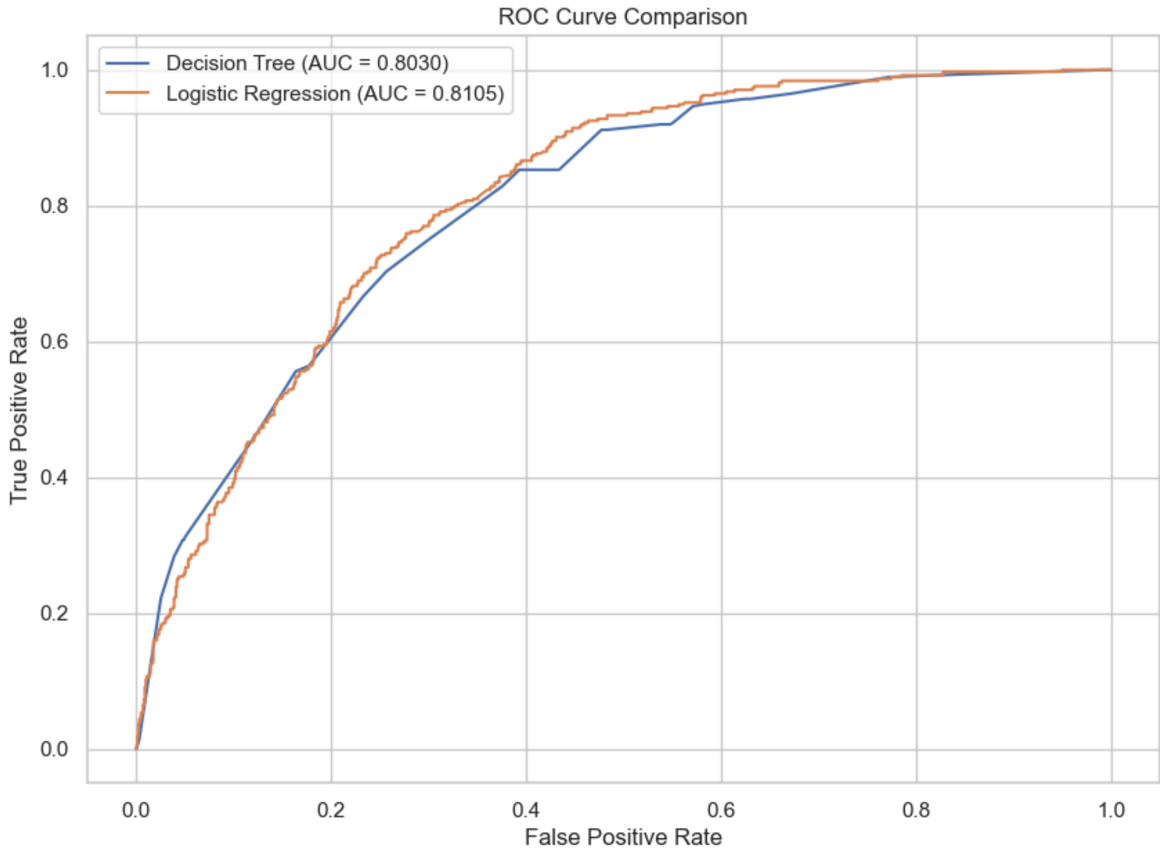
1. **Accuracy**: The percentage of correct predictions.
2. **ROC-AUC Score**: A measure of how well the model can distinguish between churners and non-churners.
3. **ROC Curve**: A visual plot of the model's performance.
4. **Gains and Lift Charts**: These are used to show the "lift" or "gain" from using the model, which is a key business metric.

We will need to install the `scikit-plot` library to easily create the Gains and Lift charts.

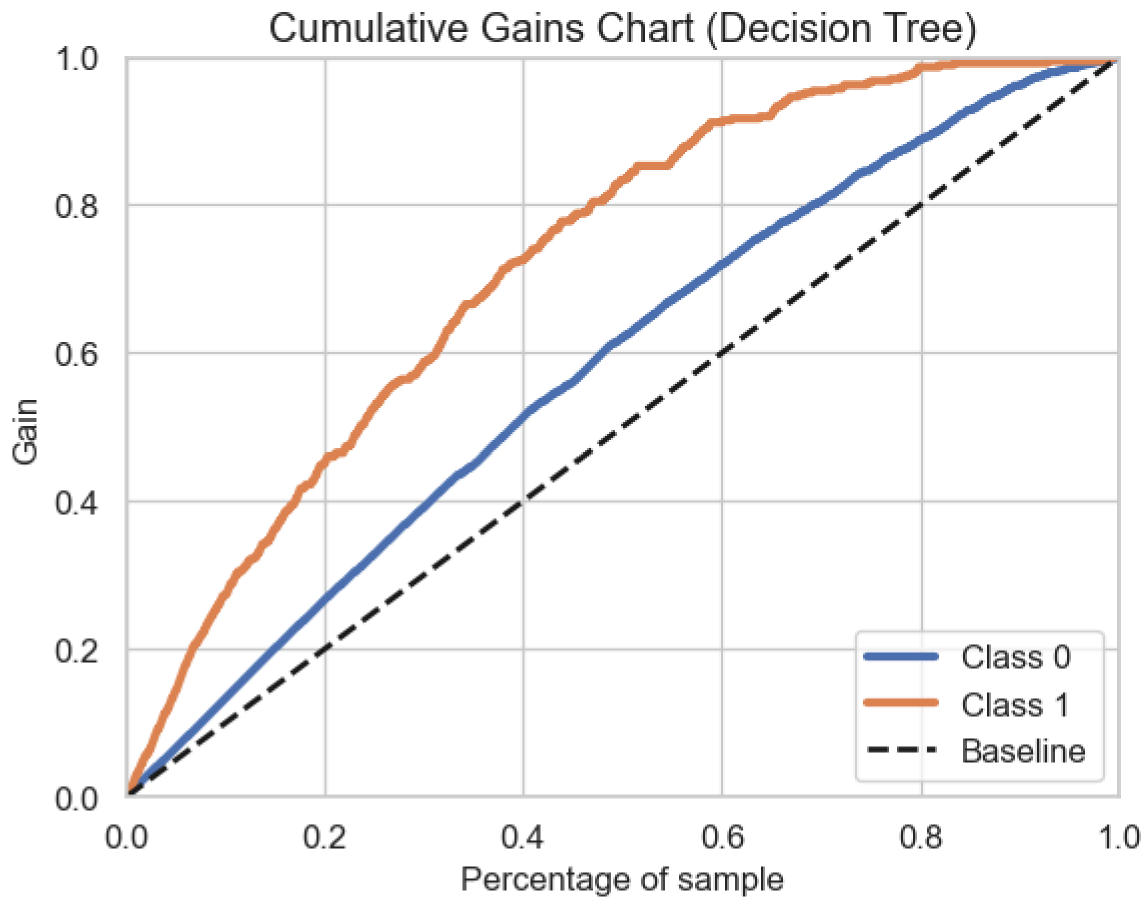
In [11]:
```
# --- 1. Import all necessary metrics libraries ---
from sklearn.metrics import accuracy_score, roc_auc_score, roc_curve
import scikitplot as skplt
import matplotlib.pyplot as plt

# --- 2. Calculate Accuracy ---
acc_dt = accuracy_score(y_test, y_pred_dt)
acc_lr = accuracy_score(y_test, y_pred_lr)

print("--- Model Comparison ---")
print(f"Decision Tree Accuracy: {acc_dt:.4f}")
```

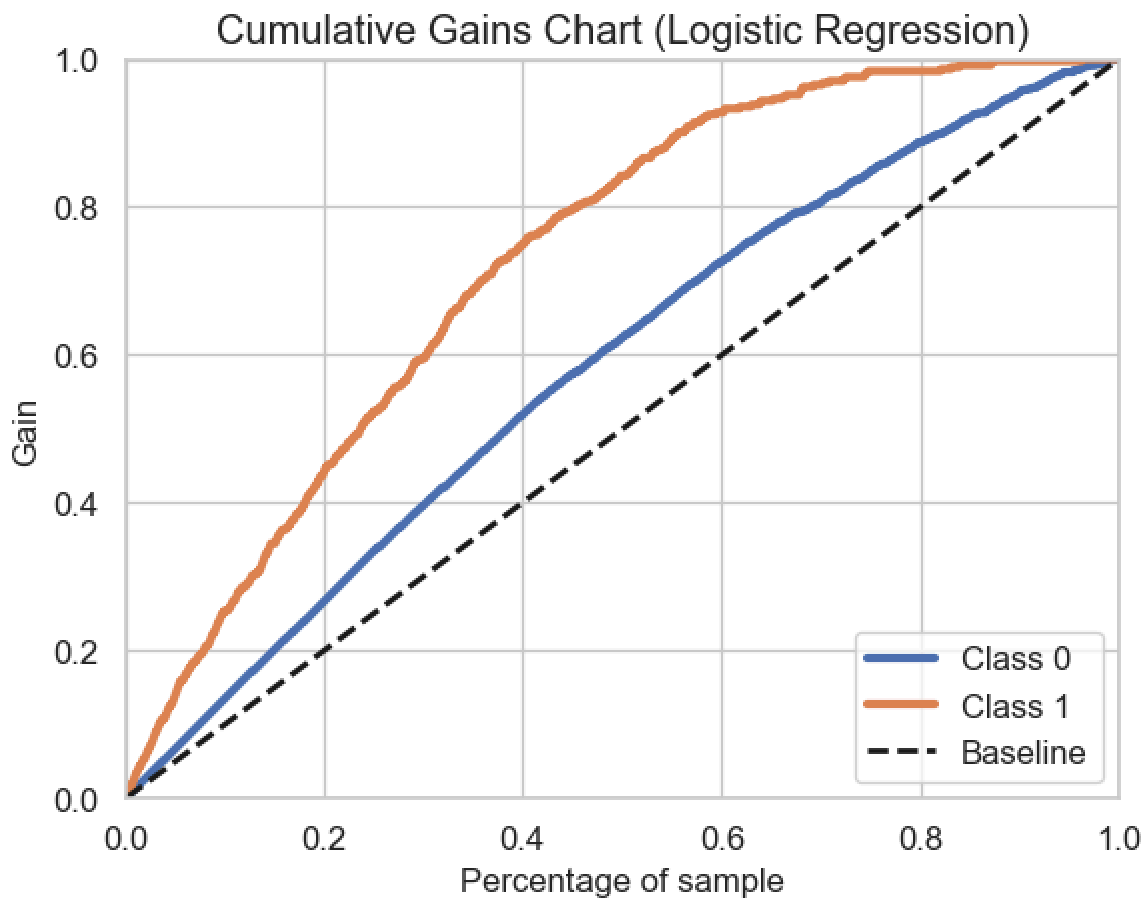
```python
print(f"Logistic Regression Accuracy: {acc_lr:.4f}")

# --- 3. Calculate ROC-AUC Score ---
auc_dt = roc_auc_score(y_test, y_proba_dt)
auc_lr = roc_auc_score(y_test, y_proba_lr)

print(f"\nDecision Tree ROC-AUC Score: {auc_dt:.4f}")
print(f"Logistic Regression ROC-AUC Score: {auc_lr:.4f}")

# --- 4. Plot ROC Curve ---
# (Removed the 'Random Guess' line as requested)
fpr_dt, tpr_dt, _ = roc_curve(y_test, y_proba_dt)
fpr_lr, tpr_lr, _ = roc_curve(y_test, y_proba_lr)

plt.figure(figsize=(10, 7))
plt.plot(fpr_dt, tpr_dt, label=f'Decision Tree (AUC = {auc_dt:.4f})')
plt.plot(fpr_lr, tpr_lr, label=f'Logistic Regression (AUC = {auc_lr:.4f})')
# plt.plot([0, 1], [0, 1], 'k--', label='Random Guess') # This line is now remov
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison')
plt.legend()
plt.show()

# --- 5. Plot Gains and Lift Charts (Corrected Method) ---
# The previous ValueError is a bug. We will fix it by
# plotting each model's chart in its own figure.

# Get the 2D probability arrays for both models
probas_dt = dt_model.predict_proba(X_test_scaled)
probas_lr = lr_model.predict_proba(X_test_scaled)

print("\n--- Gains Charts ---")
skplt.metrics.plot_cumulative_gain(y_test, probas_dt, title='Cumulative Gains Ch
plt.show()
skplt.metrics.plot_cumulative_gain(y_test, probas_lr, title='Cumulative Gains Ch
plt.show()

print("\n--- Lift Charts ---")
skplt.metrics.plot_lift_curve(y_test, probas_dt, title='Lift Curve (Decision Tre
plt.show()
skplt.metrics.plot_lift_curve(y_test, probas_lr, title='Lift Curve (Logistic Reg
plt.show()

print("\nTask 3 (Evaluation) complete.")
```

```
--- Model Comparison ---
Decision Tree Accuracy: 0.7669
Logistic Regression Accuracy: 0.7676

Decision Tree ROC-AUC Score: 0.8030
Logistic Regression ROC-AUC Score: 0.8105
```

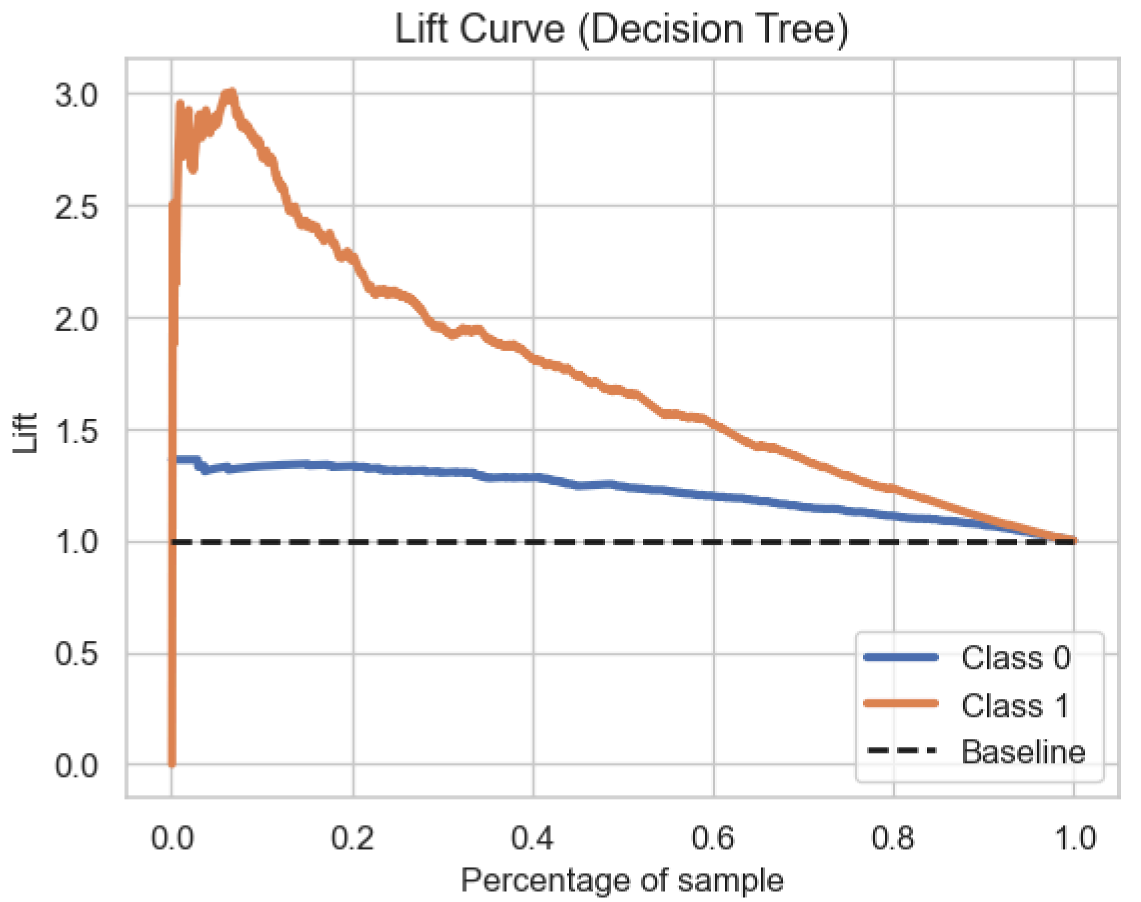


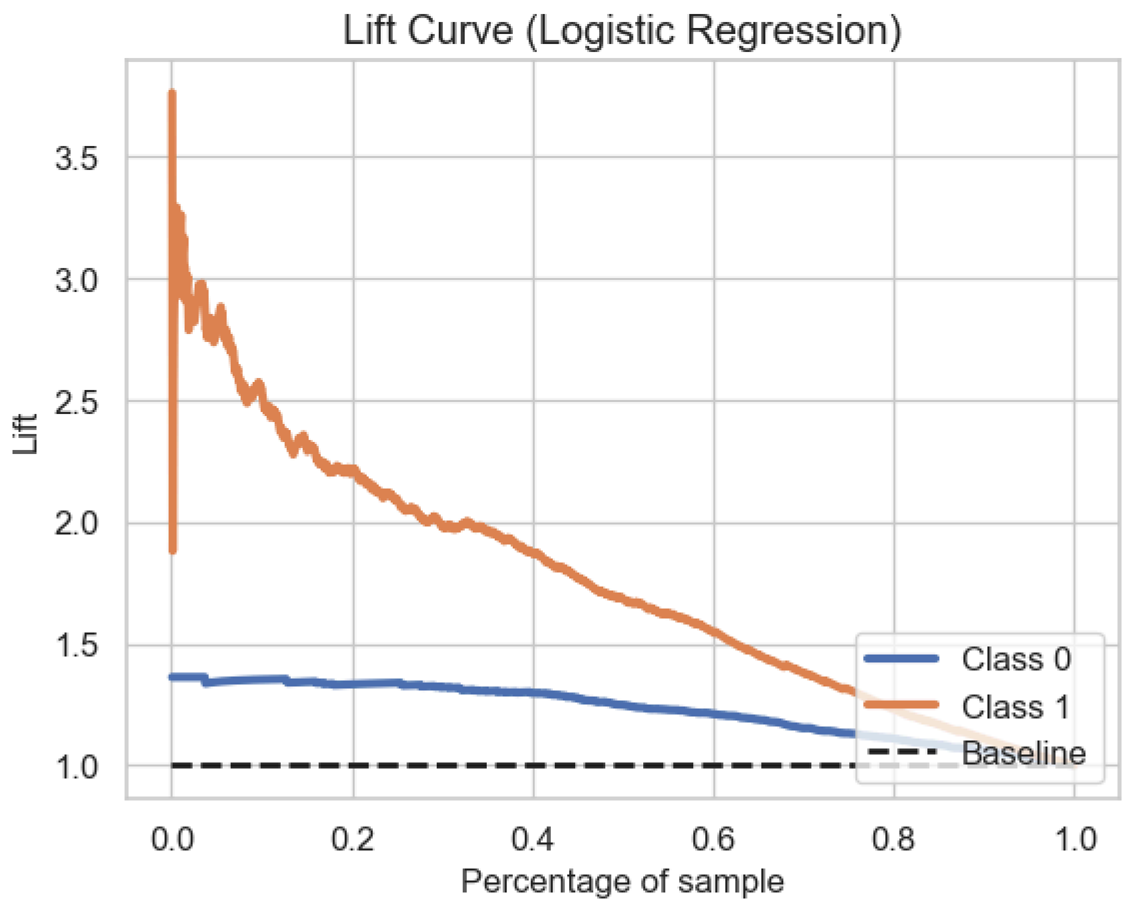

```
--- Gains Charts ---
```




Cumulative Gains Chart (Logistic Regression)
1.0
0.8
0.6
0.4
0.2
0.0
Gain
0.0
0.2
0.4
0.6
0.8
1.0
Percentage of sample
Class 0
Class 1
Baseline

```
--- Lift Charts ---
```


Lift Curve (Decision Tree)
3.0
2.5
2.0
1.5
1.0
0.5
0.0
Lift
0.0
0.2
0.4
0.6
0.8
1.0
Percentage of sample
Class 0
Class 1
Baseline




```
Task 3 (Evaluation) complete.
```

Task 4: Model Deployment and Updating

This task requires us to *explain* the process for deploying and updating our churn model. We do not need to build a full application.

4.1 Model Deployment Process

The first step in deployment is to save (or "pickle") our best-performing model. Based on our ROC-AUC scores, the **Logistic Regression** model was our best model.

We will use the `joblib` library to save our trained `lr_model` and the `scaler` object (which is required for preprocessing new data) to disk.

My Deployment Plan (for the report):

1. **Save Model:** Save the trained `lr_model` and `scaler` objects as `.joblib` files.
2. **Build API:** Create a simple web API (using a framework like **Flask** or **FastAPI**).
3. **Load Model:** The API will load the saved `lr_model` and `scaler` files when it starts.
4. **Create Endpoint:** The API will have an endpoint (e.g., `/predict`) that accepts new customer data (as JSON).
5. **Process & Predict:** The API will:
   - Receive the new data.
   - Apply the same One-Hot Encoding and scaling (using the saved `scaler`).

- Pass the processed data to the `lr_model.predict_proba()` method.
- Return a JSON response with the churn probability.

4.2 Model Updating Process

Models grow "stale" as new customer data and behaviors emerge.

My Updating Plan (for the report):

1. **Collect New Data:** Set up a process to automatically collect and label new customer data (e.g., customers who churned in the last month).
2. **Schedule Retraining:** Create a scheduled script (e.g., a monthly **CRON job** or **Airflow DAG**) that re-runs this entire notebook (from preprocessing to training) on the *new, combined* dataset.
3. **Validate & Deploy:** After retraining, the script would automatically test the new model. If its performance (e.g., ROC-AUC) on a test set is better than the old model, the script will automatically save it, replacing the old `.joblib` file in the API.

In [12]:
```python
import joblib

# --- 1. Save the Logistic Regression Model ---
# This was our best model
model_filename = 'churn_model_lr.joblib'
joblib.dump(lr_model, model_filename)

# --- 2. Save the Scaler ---
# We MUST save the scaler, as new data needs to be scaled
# in the exact same way as the training data.
scaler_filename = 'data_scaler.joblib'
joblib.dump(scaler, scaler_filename)

print(f"--- Task 4: Deployment ---")
print(f"Model saved as: {model_filename}")
print(f"Scaler saved as: {scaler_filename}")
print("\nThese two files are all you need for your API.")
print("You can now write the descriptive part of Task 4 in your report.")
```

```
--- Task 4: Deployment ---
Model saved as: churn_model_lr.joblib
Scaler saved as: data_scaler.joblib

These two files are all you need for your API.
You can now write the descriptive part of Task 4 in your report.
```