CONNECTTEL CUSTOMER CHURN PREDICTION

Problem Overview

ConnectTel Telecom is facing a significant challenge as customers are leaving, posing a threat to its long-term success. Current retention strategies have proven ineffective, resulting in the loss of valuable customers to competitors. In response, ConnectTel aims to implement a data-driven solution, utilizing advanced analytics and machine learning to predict customer churn and execute targeted retention initiatives. The objective is to enhance customer loyalty and maintain competitiveness in the telecommunications industry.

Import Necessary Libraries

In [1]:
```
# Import libraries for data manipulation and visualization
import pandas as pd
import numpy as np

# For Data Visualization
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import plotly.express as px

# Import libraries for machine learning
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, roc_auc_score

import warnings
warnings.filterwarnings("ignore")
```

Loading the dataset

In [2]:
```
# Load Data
df = pd.read_csv('/Users/mac/Desktop/customer-churn.csv')
print('Data Imported Successfully')
```

```
Data Imported Successfully
```

In [3]:
```
# Loads the first five rows

df.head()
```

Out[3]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Cont
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...	No	No	No	No	Mo to-m
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...	Yes	No	No	No	One y
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...	No	No	No	No	Mo to-m

Loading [MathJax]/extensions/Safe.js

3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...	Yes	Yes	No	No	One y
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	...	No	No	No	No	Mo to-m

5 rows × 21 columns

In [4]:
```python
# Loads the last five rows

df.tail()
```

Out[4]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	C
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Yes	DSL	Yes	...	Yes	Yes	Yes	Yes	C
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Yes	Fiber optic	No	...	Yes	No	Yes	Yes	C
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phone service	DSL	Yes	...	No	No	No	No	t
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	Yes	Fiber optic	No	...	No	No	No	No	t
7042	3186-AJIEK	Male	0	No	No	66	Yes	No	Fiber optic	Yes	...	Yes	Yes	Yes	Yes	T

5 rows × 21 columns

In [5]:
```python
# Getting the shape of the dataset

df.shape
```

Out[5]:
```
(7043, 21)
```

In [6]:
```python
df.columns
```

Out[6]:
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

In [7]:
```python
# Provides a summary of the dataset

df.info()
```

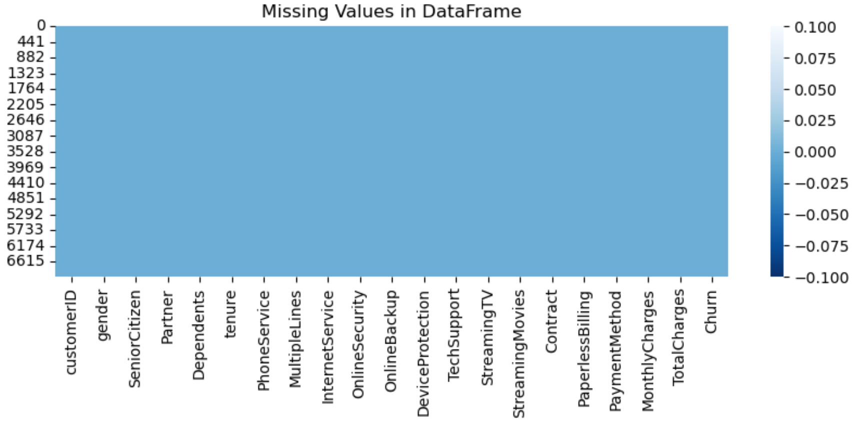
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7043 non-null   object 
 1   gender            7043 non-null   object 
 2   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
```

In [8]:
```python
# Checking for Descriptive statistics of numeric values

df.describe()
```

Out[8]:

	SeniorCitizen	tenure	MonthlyCharges
count	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692
std	0.368612	24.559481	30.090047
min	0.000000	0.000000	18.250000
25%	0.000000	9.000000	35.500000
50%	0.000000	29.000000	70.350000
75%	0.000000	55.000000	89.850000
max	1.000000	72.000000	118.750000

In [9]:
```python
# Check For Missing Values
df.isnull().sum()

# Visualizing the Missing Data
plt.figure(figsize=(10, 3))
sns.heatmap(df.isnull(), cbar=True, cmap="Blues_r" )
plt.title('Missing Values in DataFrame');
```



In [10]:
```
df.dtypes
```

Out[10]:
```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

Upon reviewing missing values, we found no null entries in the dataset. However, TotalCharges was identified as an object instead of a numeric variable, representing the total amount charged to customers. To correct this, we'll convert this column to a numeric data type using the pd.to_numeric function. Using errors='coerce' will replace non-numeric entries with NaN values.

In [11]:
```
# Drop the 'customerID' column from the DataFrame because it's not needed for our analysis

df = df.drop(['customerID'], axis=1)
df.head()
```

Out[11]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contra
0	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes	No	No	No	No	Mon to-mor
1	Male	0	No	No	34	Yes	No	DSL	Yes	No	Yes	No	No	No	One ye
2	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	No	No	No	No	Mon to-mor
3	Male	0	No	No	45	No	No phone service	DSL	Yes	No	Yes	Yes	No	No	One ye
4	Female	0	No	No	2	Yes	No	Fiber optic	No	No	No	No	No	No	Mon to-mor

In [12]:
```
# Convert 'TotalCharges' to numeric, coercing errors, and check for missing values

df['TotalCharges'] = pd.to_numeric(df.TotalCharges, errors='coerce')
df.isnull().sum()
```

Out[12]:
```
gender               0
SeniorCitizen        0
Partner              0
Dependents           0
tenure               0
PhoneService         0
MultipleLines        0
InternetService      0
OnlineSecurity       0
OnlineBackup         0
DeviceProtection     0
TechSupport          0
StreamingTV          0
StreamingMovies      0
Contract             0
PaperlessBilling     0
PaymentMethod        0
MonthlyCharges       0
TotalCharges        11
Churn                0
dtype: int64
```

In [13]:
```
# Displaying rows where 'TotalCharges' is NaN after numeric conversion

df[np.isnan(df['TotalCharges'])]
```

Out[13]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Co
488	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	No	Yes	Yes	Yes	No	Tw

Loading [MathJax]/extensions/Safe.js

753	Male	0	No	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Tw
936	Female	0	Yes	Yes	0	Yes	No	DSL	Yes	Yes	Yes	No	Yes	Yes	Tw
1082	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Tw
1340	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	Yes	Yes	Yes	Yes	No	Tw
3331	Male	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Tw
3826	Male	0	Yes	Yes	0	Yes	Yes	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Tw
4380	Female	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	Tw
5218	Male	0	Yes	Yes	0	Yes	No	No	No internet service	No internet service	No internet service	No internet service	No internet service	No internet service	On
6670	Female	0	Yes	Yes	0	Yes	Yes	DSL	No	Yes	Yes	Yes	Yes	No	Tw
6754	Male	0	No	Yes	0	Yes	Yes	DSL	Yes	Yes	No	Yes	No	No	Tw

We can observe that the 'Tenure' column is 0 for these entries, even though the 'MonthlyCharges' column is not empty. This information is unclear so we will remove it from the dataset.

In [14]:

```
# Dropping the rows with missing values

df.drop(labels=df[df['tenure'] == 0].index, axis=0, inplace=True)
df[df['tenure'] == 0].index
```

Out[14]:

```
Int64Index([], dtype='int64')
```

We've removed the rows with missing values in Tenure columns since there are only 11 rows and deleting them will not affect the data.

In [15]:

```
# To solve the problem of missing values in TotalCharges column, I fill it with the mean of TotalCharges values.

df.fillna(df["TotalCharges"].mean())
```

Out[15]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Co
0	Female	0	Yes	No	1	No	No phone service	DSL	No	Yes	No	No	No	No	to-
1	Male	0	No	No	34	Yes	No	DSL	Yes	No	Yes	No	No	No	On
2	Male	0	No	No	2	Yes	No	DSL	Yes	Yes	No	No	No	No	to-
3	Male	0	No	No	45	No	No phone service	DSL	Yes	No	Yes	Yes	No	No	On
4	Female	0	No	No	2	Yes	No	Fiber optic	No	No	No	No	No	No	to-
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
7038	Male	0	Yes	Yes	24	Yes	Yes	DSL	Yes	No	Yes	Yes	Yes	Yes	On
7039	Female	0	Yes	Yes	72	Yes	Yes	Fiber optic	No	Yes	Yes	No	Yes	Yes	On
7040	Female	0	Yes	Yes	11	No	No phone service	DSL	Yes	No	No	No	No	No	to-
7041	Male	1	Yes	No	4	Yes	Yes	Fiber optic	No	No	No	No	No	No	to-
7042	Male	0	No	No	66	Yes	No	Fiber optic	Yes	No	Yes	Yes	Yes	Yes	Tw

7032 rows × 20 columns

Handling Missing Values

To address missing values in the dataset, particularly in the 'TotalCharges' column, We will fill these gaps with the mean value of the 'TotalCharges' column. This approach was taken to maintain data integrity and prevent any significant impact on subsequent analyses.

By filling missing values with the mean, we aimed to provide a reasonable estimation of 'TotalCharges' for instances where the original data was absent. This method ensures a smooth flow in the dataset, crucial for tasks like exploratory data analysis and machine learning model training.

In [16]:

```
df.isnull().sum()
```

Out[16]:

```
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges        0
Churn               0
dtype: int64
```

In [17]:

```
# Counts of customers who did not churn by gender
```

```
df["Churn"][df["Churn"]=="No"].groupby(by=df["gender"]).count()
```

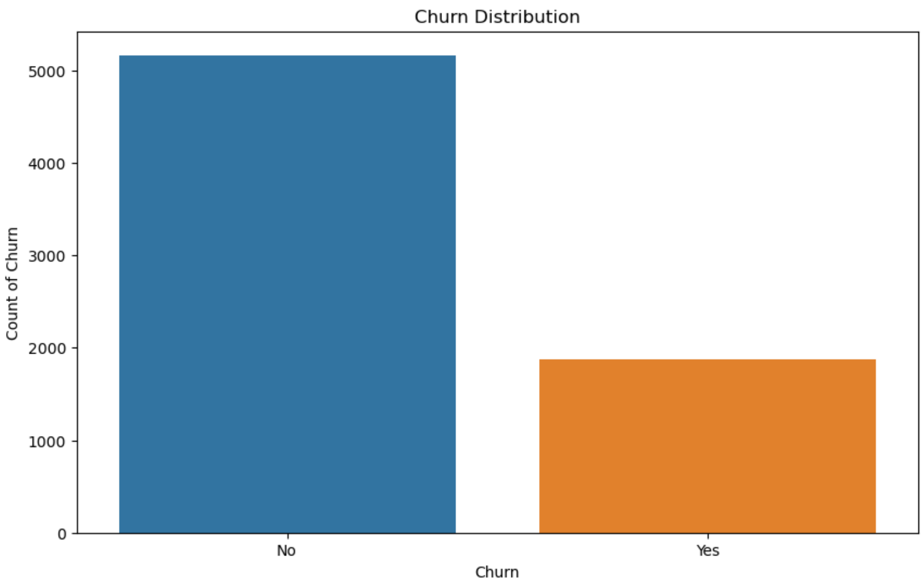
Out[17]:
```
gender
Female    2544
Male      2619
Name: Churn, dtype: int64
```

In [18]:
```
# Counts of customers who churned by gender

df["Churn"][df["Churn"]=="Yes"].groupby(by=df["gender"]).count()
```

Out[18]:
```
gender
Female    939
Male      930
Name: Churn, dtype: int64
```

Exploratory Data Analysis

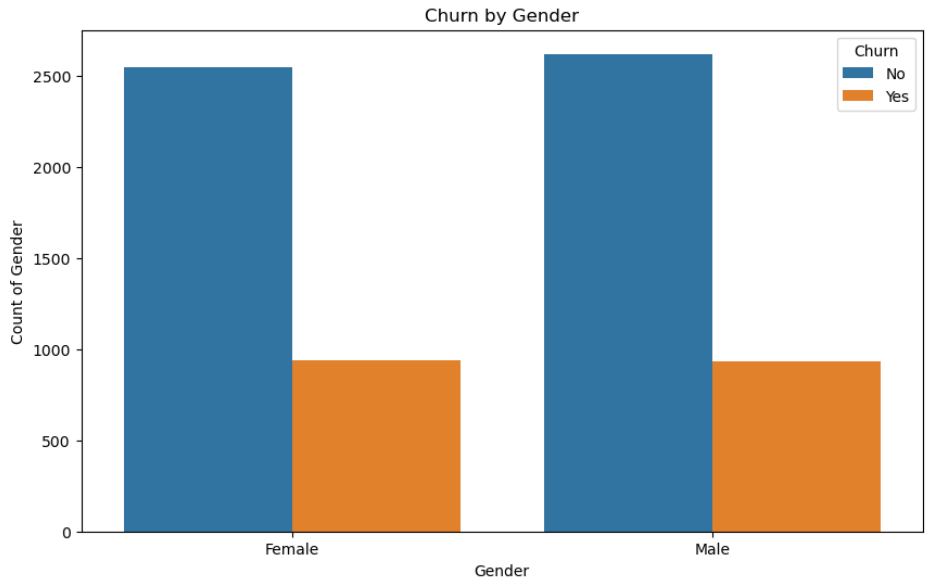
In [19]:
```
# Visualizing Churn

plt.figure(figsize=(10, 6))
sns.countplot(x='Churn', data=df)
plt.xlabel('Churn')
plt.ylabel('Count of Churn')
plt.title('Churn Distribution')
plt.show()

churn_count = df['Churn'].value_counts()
print("Count of Churn:")
print(churn_count)
```




```
Count of Churn:
No     5163
Yes    1869
Name: Churn, dtype: int64
```

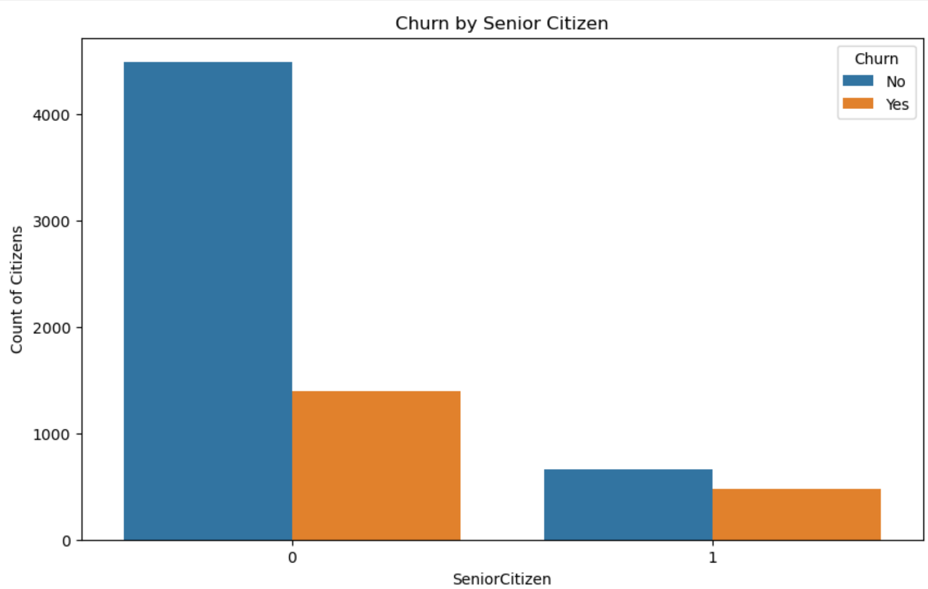
In [20]:
```
# Visualizing Churn with Gender

plt.figure(figsize=(10, 6))
sns.countplot(x='gender', hue='Churn', data=df)
plt.xlabel('Gender')
plt.ylabel('Count of Gender')
plt.title('Churn by Gender')
plt.show()
```

Loading [MathJax]/extensions/Safe.js

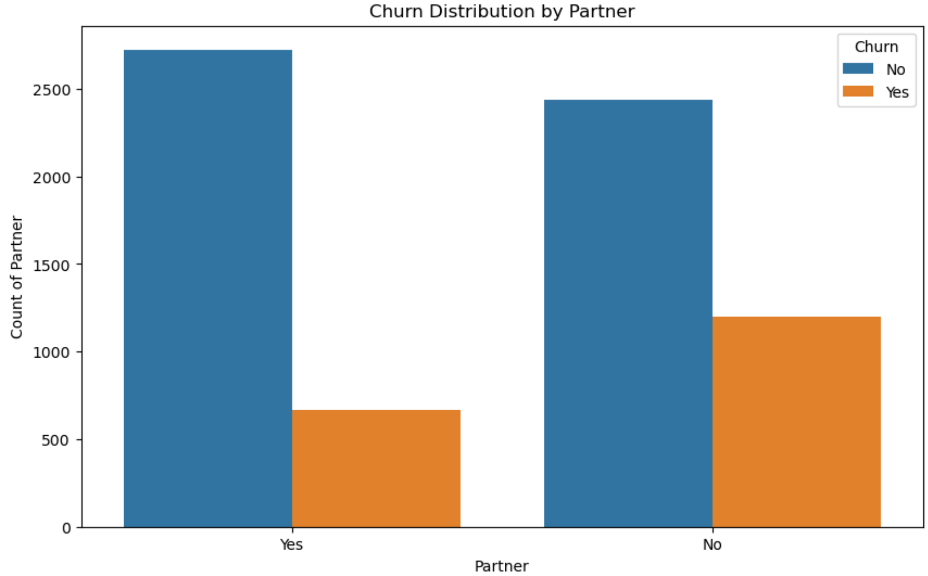


The gender distribution is nearly balanced for Male and Female. Regarding churn, Some of the customers switched to another firm.

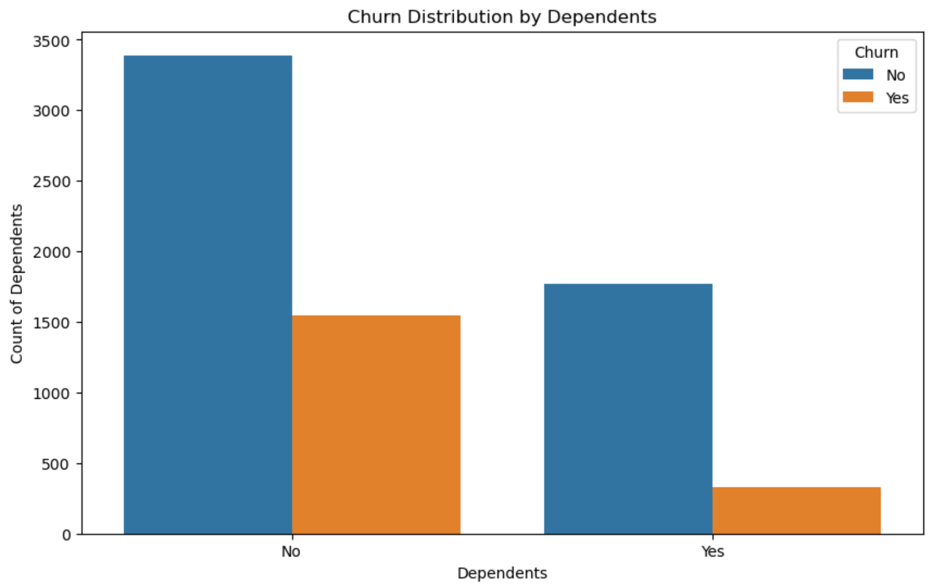
In [21]:
```
# Visualizing Churn for Senior Citizen

# plots
fig, ax = plt.subplots(figsize=(10, 6))

# Visualize Churn with SeniorCitizen
sns.countplot(x='SeniorCitizen', hue='Churn', data=df)
ax.set_title('Churn by Senior Citizen')
ax.set_ylabel('Count of Citizens')
plt.show()
```



In [22]:
```
# Visualizing Churn for Partner

# plots
fig, ax = plt.subplots(figsize=(10, 6))

# Visualize Churn with Partner
sns.countplot(x='Partner', hue='Churn', data=df)
ax.set_title('Churn Distribution by Partner')
ax.set_ylabel('Count of Partner')
plt.show()
```

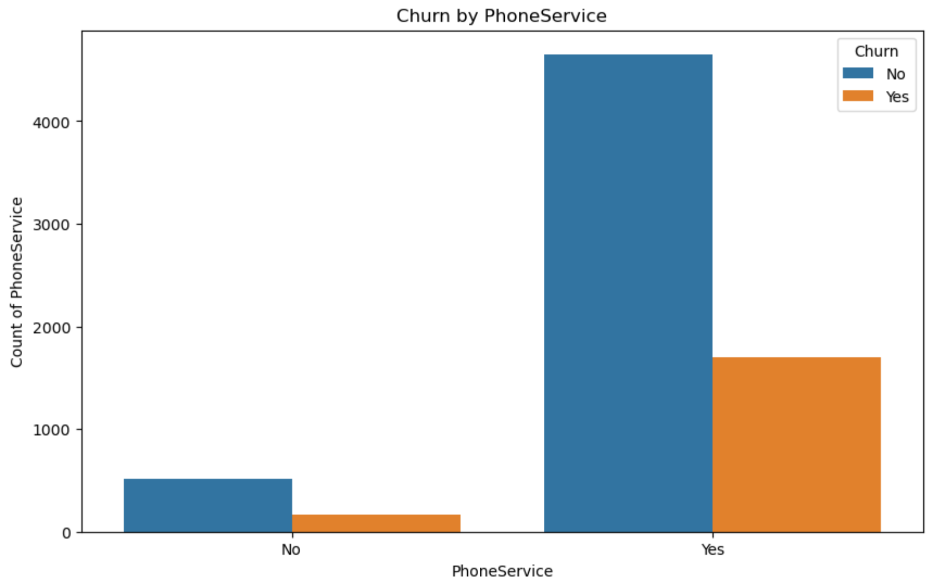


In [23]:
```
# Visualizing Churn for Dependents

# Plots
fig, ax = plt.subplots(figsize=(10, 6))

# Visualize Churn with Dependents
sns.countplot(x='Dependents', hue='Churn', data=df)
ax.set_title('Churn Distribution by Dependents')
ax.set_ylabel('Count of Dependents')
plt.show()
```



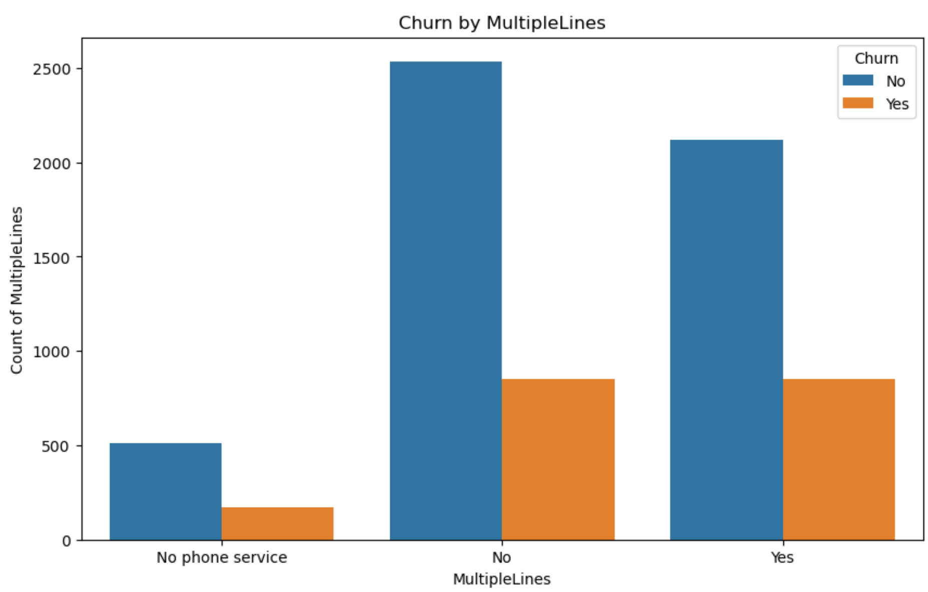
The rate of churn among senior citizens is nearly twice as high as that observed among younger citizens. Individuals with a partner exhibit lower churn rates compared to those without a partner. Customers without dependents are more likely to churn

In [24]:
```
# Visualizing Churn by PhoneService

plt.figure(figsize=(10, 6))
sns.countplot(x='PhoneService', hue='Churn', data=df)
plt.xlabel('PhoneService')
plt.ylabel('Count of PhoneService')
plt.title('Churn by PhoneService')
plt.show()
```



A very small number of customers do not have a phone service, and among them, a significant portion is more likely to leave or stop using our service.

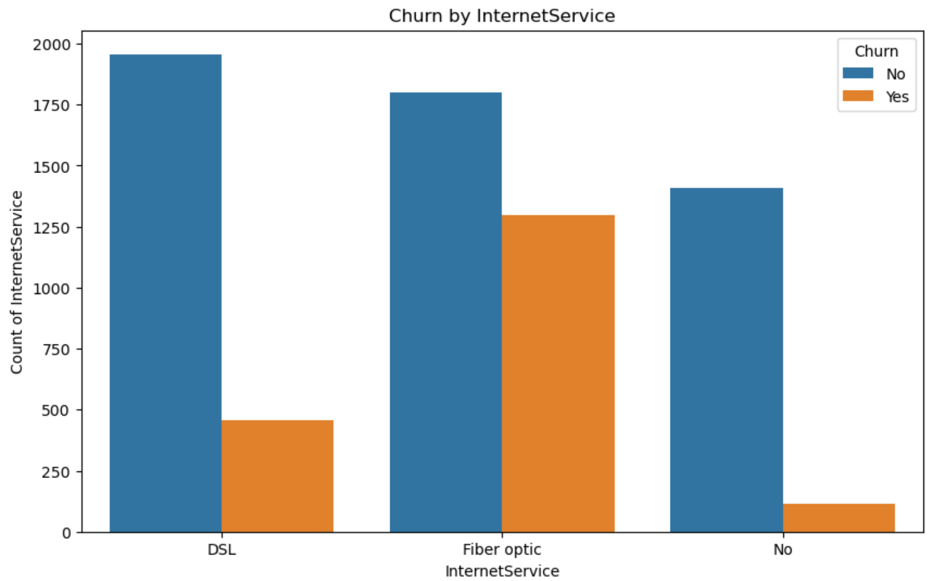
In [25]:
```
# Visualizing Churn with multiple lines

plt.figure(figsize=(10, 6))
sns.countplot(x='MultipleLines', hue='Churn', data=df)
plt.xlabel('MultipleLines')
plt.ylabel('Count of MultipleLines')
plt.title('Churn by MultipleLines')
plt.show()
```



In [26]:
```
df["InternetService"].unique()
```

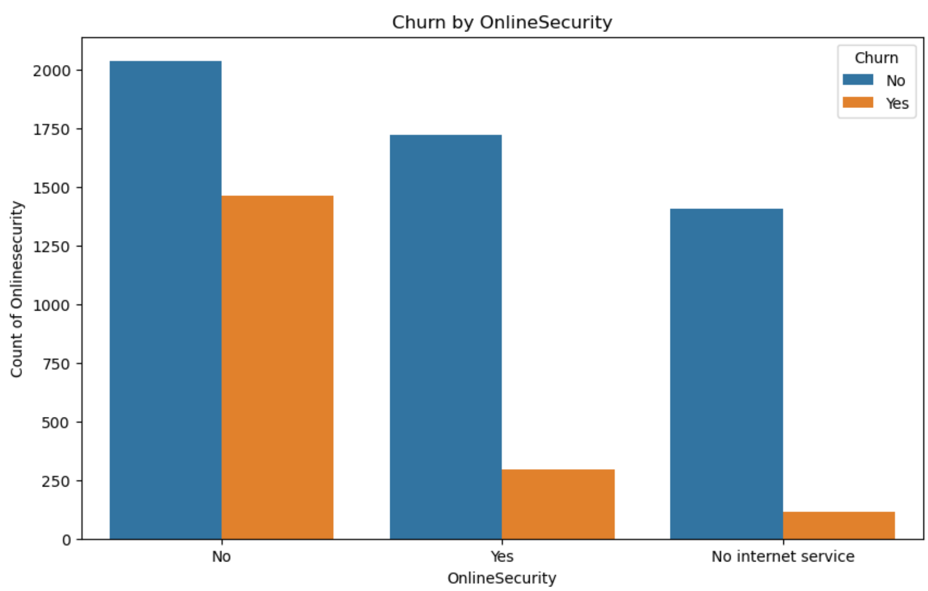
Out[26]:
```
array(['DSL', 'Fiber optic', 'No'], dtype=object)
```

In [27]:
```
# Visualizing Churn by InternetService

plt.figure(figsize=(10, 6))
sns.countplot(x='InternetService', hue='Churn', data=df)
plt.xlabel('InternetService')
plt.ylabel('Count of InternetService')
plt.title('Churn by InternetService')
plt.show()
```

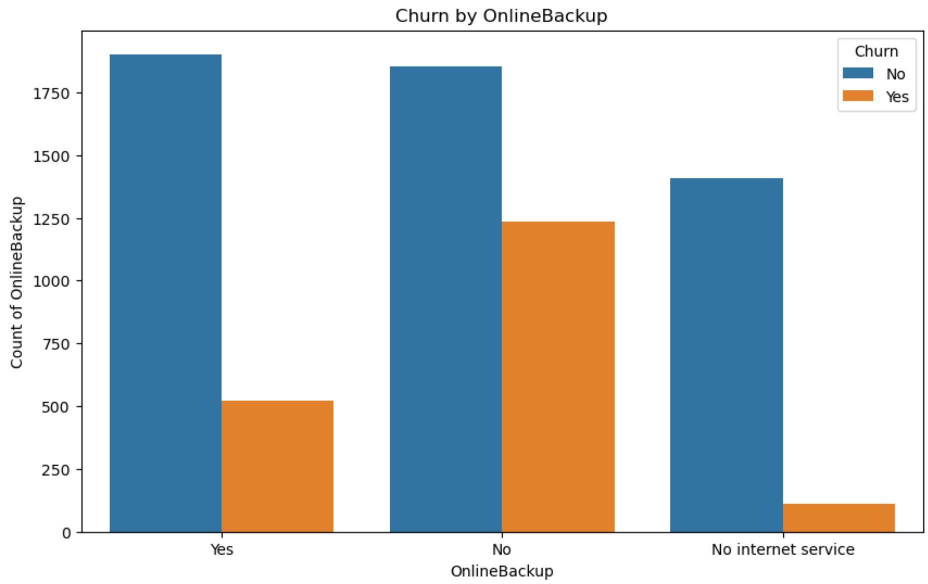


Many customers choose for Fiber optic internet service. However, it's noticeable that customers using Fiber optic have a higher churn rate, indicating potential dissatisfaction with this type of internet service. In contrast, customers with DSL service are more numerous and show a lower churn rate compared to Fiber optic service.

In [28]:
```
# Visualizing Churn by OnlineSecurity

plt.figure(figsize=(10, 6))
sns.countplot(x='OnlineSecurity', hue='Churn', data=df)
plt.xlabel('OnlineSecurity')
plt.ylabel('Count of Onlinesecurity')
plt.title('Churn by OnlineSecurity')
plt.show()
```

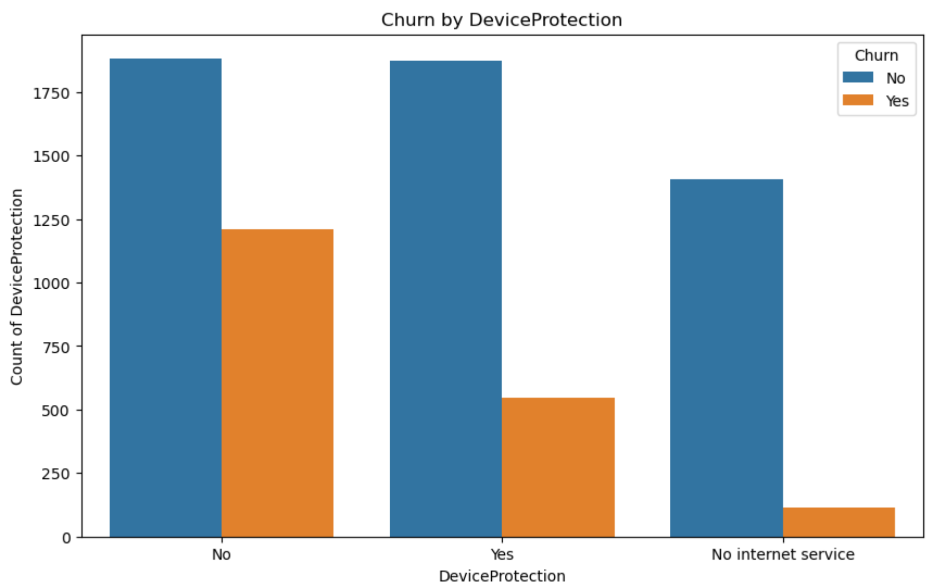


In [29]:
```
# Visualizing Churn by OnlineBackup

plt.figure(figsize=(10, 6))
sns.countplot(x='OnlineBackup', hue='Churn', data=df)
plt.xlabel('OnlineBackup')
plt.ylabel('Count of OnlineBackup')
plt.title('Churn by OnlineBackup')
plt.show()
```



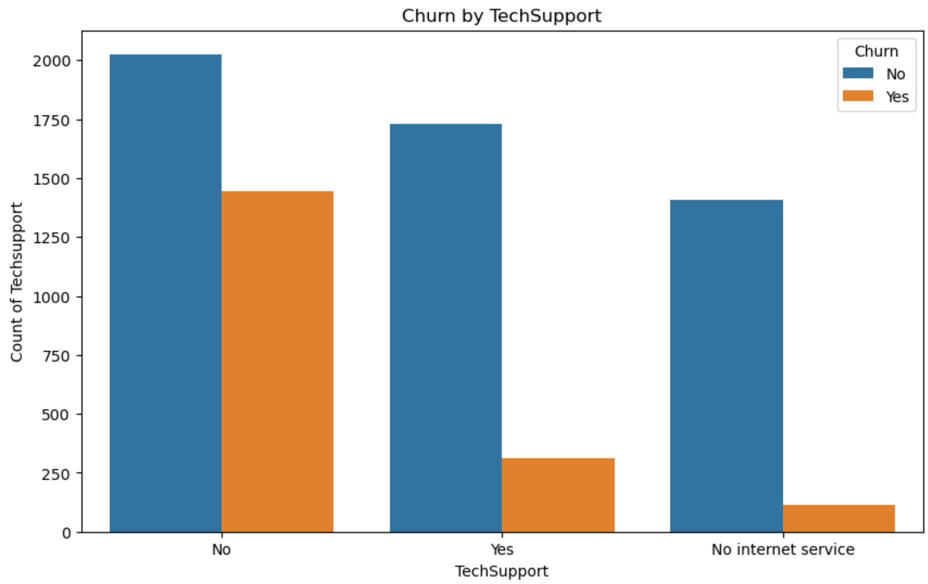
In [30]:

```
# Visualizing Churn by DeviceProtection

plt.figure(figsize=(10, 6))
sns.countplot(x='DeviceProtection', hue='Churn', data=df)
plt.xlabel('DeviceProtection')
plt.ylabel('Count of DeviceProtection')
plt.title('Churn by DeviceProtection')
plt.show()
```

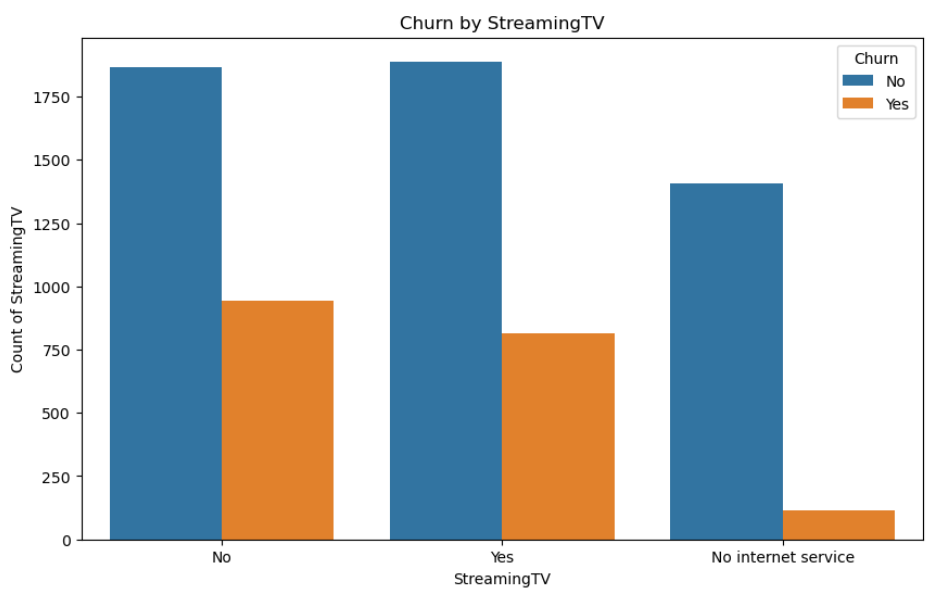


In [31]:

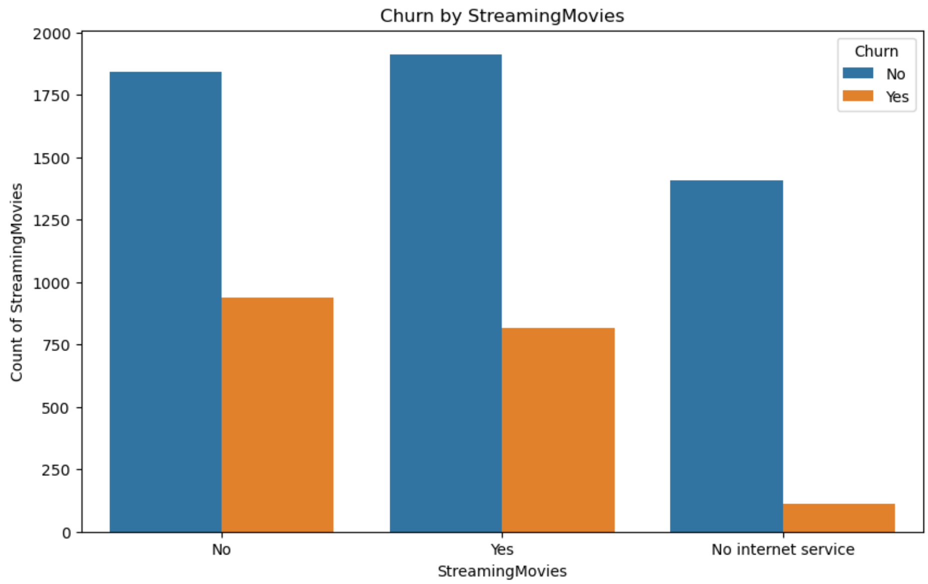
```
# Visualizing Churn by TechSupport

plt.figure(figsize=(10, 6))
sns.countplot(x='TechSupport', hue='Churn', data=df)
plt.xlabel('TechSupport')
plt.ylabel('Count of Techsupport')
plt.title('Churn by TechSupport')
plt.show()
```



In [32]:
```
# Visualizing Churn by StreamingTV

plt.figure(figsize=(10, 6))
sns.countplot(x='StreamingTV', hue='Churn', data=df)
plt.xlabel('StreamingTV')
plt.ylabel('Count of StreamingTV')
plt.title('Churn by StreamingTV')
plt.show()
```

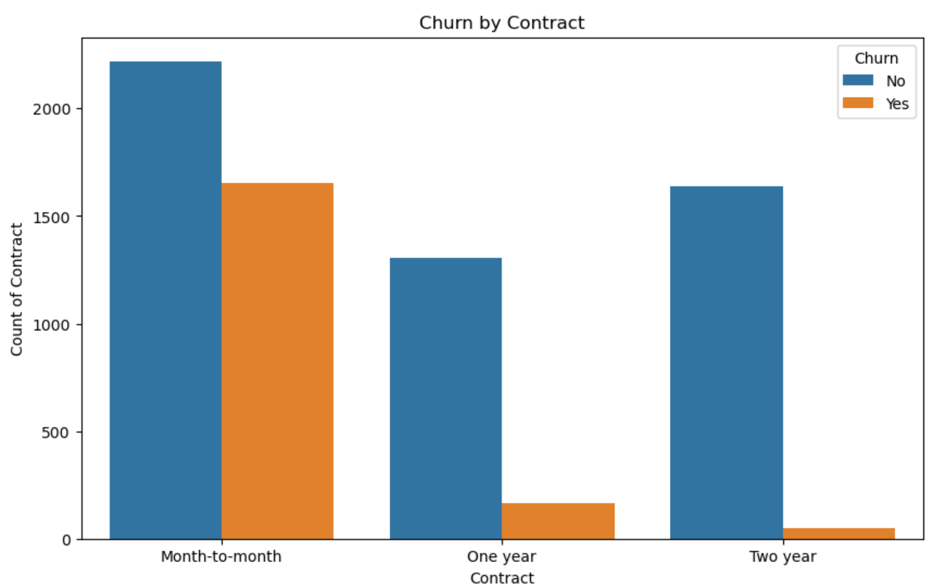


In [33]:
```
# Visualizing Churn by StreamingMovies

plt.figure(figsize=(10, 6))
sns.countplot(x='StreamingMovies', hue='Churn', data=df)
plt.xlabel('StreamingMovies')
plt.ylabel('Count of StreamingMovies')
plt.title('Churn by StreamingMovies')
plt.show()
```



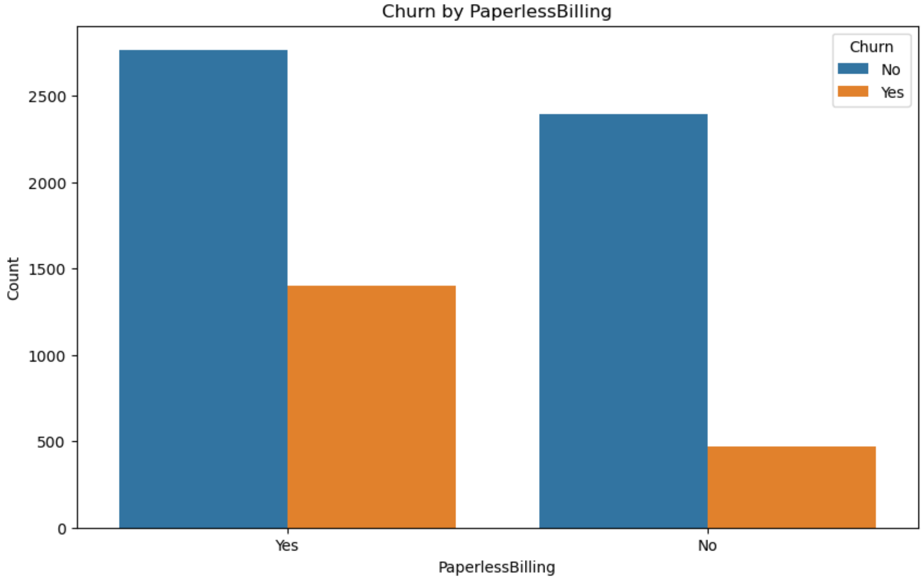
Customers who don't have TechSupport are more likely to switch to another service provider. Customers who choose Paperless Billing are more likely to churn. The majority of customers tend to churn when they don't have online security services.

In [34]:
```
# Visualizing Churn by Contract

plt.figure(figsize=(10, 6))
sns.countplot(x='Contract', hue='Churn', data=df)
plt.xlabel('Contract')
plt.ylabel('Count of Contract')
plt.title('Churn by Contract')
plt.show()
```

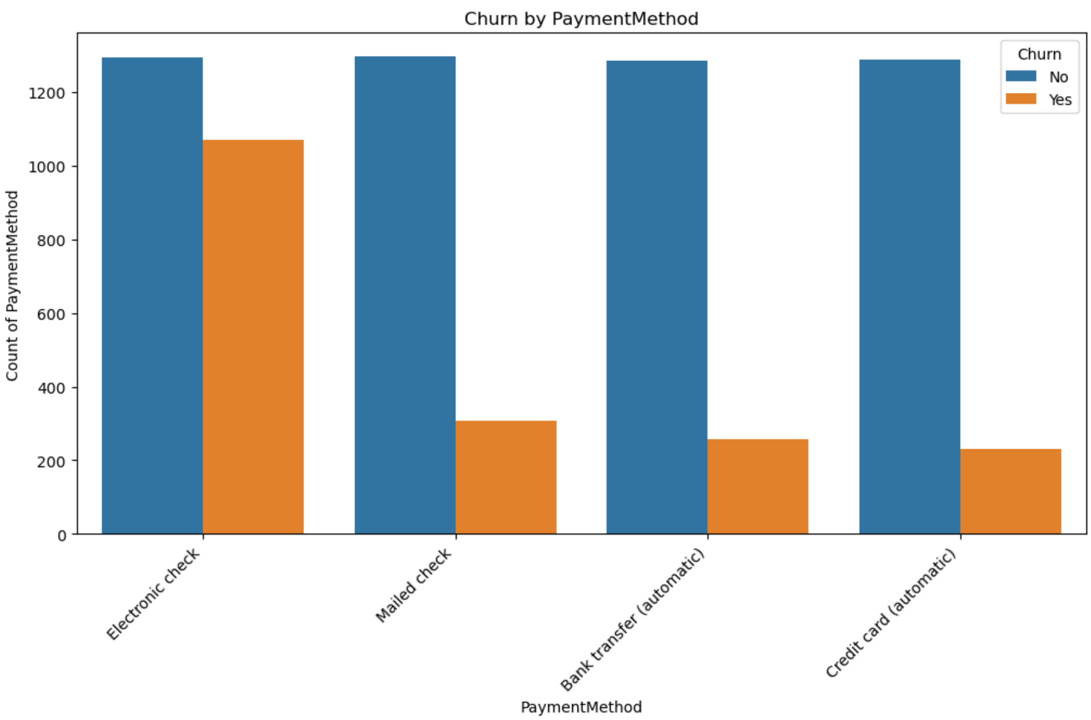


Large amount of customer with Month-to-Month Contract opted to move out as compared to customrs with One Year Contract and few with Two Year Contract

In [35]:
```
# Visualizing Churn by PaperlessBilling

plt.figure(figsize=(10, 6))
sns.countplot(x='PaperlessBilling', hue='Churn', data=df)
plt.xlabel('PaperlessBilling')
plt.ylabel('Count')
plt.title('Churn by PaperlessBilling')
plt.show()
```



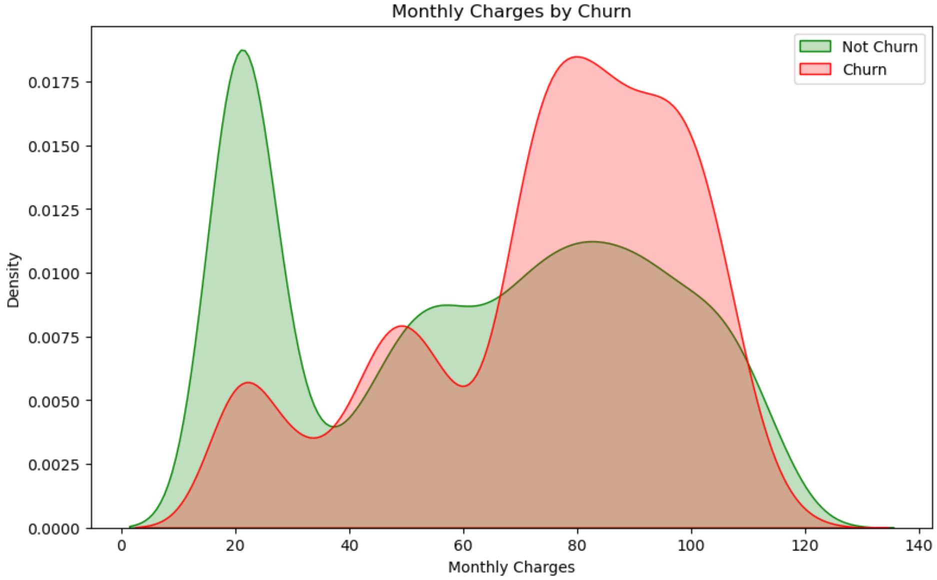
In [36]:
```
# Visualizing Churn by PaymentMethod

plt.figure(figsize=(12, 6))
sns.countplot(x='PaymentMethod', hue='Churn', data=df)
plt.xlabel('PaymentMethod')
plt.ylabel('Count of PaymentMethod')
plt.title('Churn by PaymentMethod')
plt.xticks(rotation=45, ha='right')  # Rotate x-axis labels for better visibility
plt.show()
```



The main group of customers who decided to leave were those who used Electronic Check as their payment method. On the other hand, customers who chose Credit-Card automatic transfer, Bank Automatic Transfer, or Mailed Check as their payment method were less likely to move out or switch to another service.

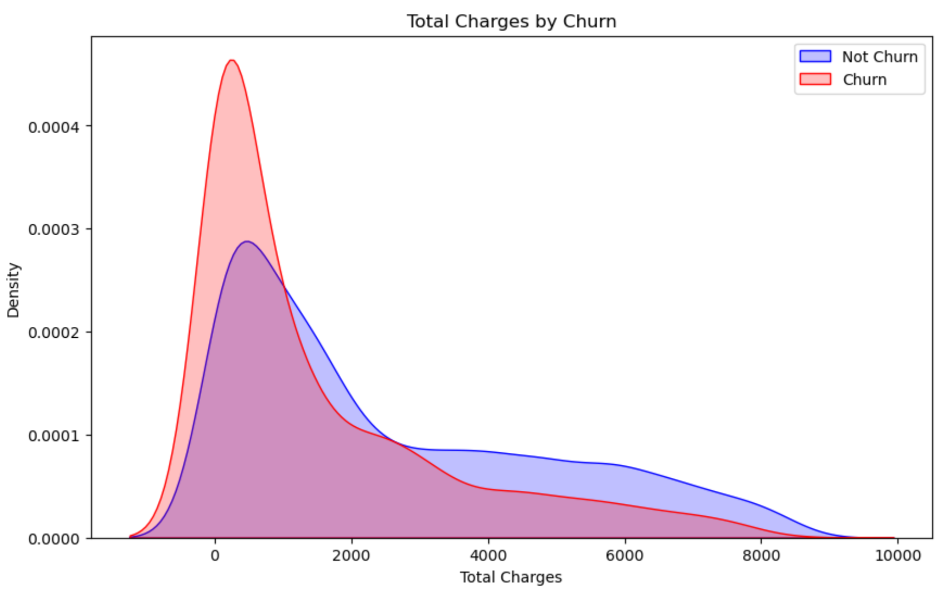
In [ ]:

In [37]:
```
# Visualizing Monthly Charges by Churn

plt.figure(figsize=(10, 6))

# Monthly Charges by Churn
sns.kdeplot(df.MonthlyCharges[df["Churn"] == 'No'], color="Green", shade=True, label="Not Churn")
sns.kdeplot(df.MonthlyCharges[df["Churn"] == 'Yes'], color="Red", shade=True, label="Churn")
plt.ylabel('Density')
plt.xlabel('Monthly Charges')
plt.title('Monthly Charges by Churn')
plt.legend()
plt.show()
```



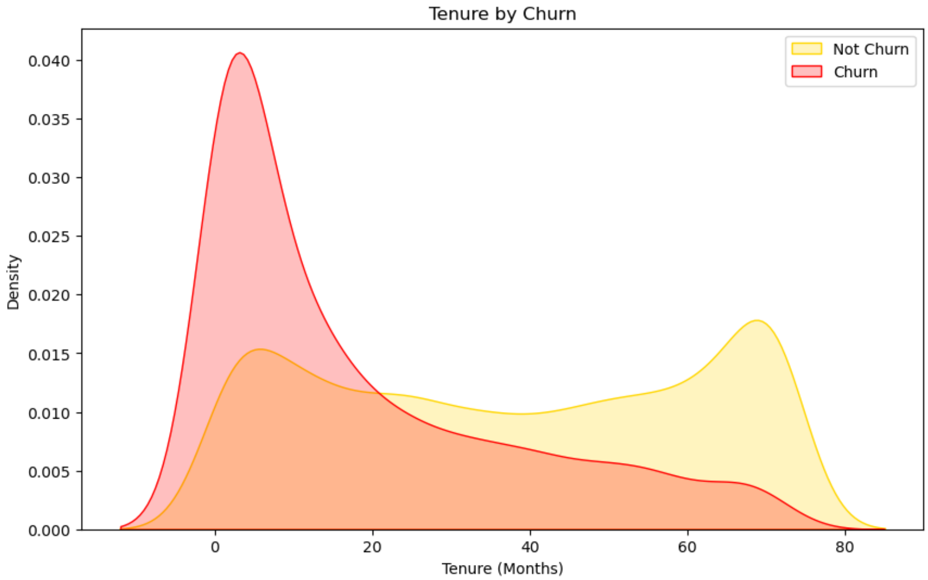
Customers with higher monthly charges are more likely to Churn.

In [38]:
```
# Visualizing Total Charges by Churn

plt.figure(figsize=(10, 6))

# Total Charges by Churn
sns.kdeplot(df.TotalCharges[df["Churn"] == 'No'], color="Blue", shade=True, label="Not Churn")
sns.kdeplot(df.TotalCharges[df["Churn"] == 'Yes'], color="Red", shade=True, label="Churn")
plt.ylabel('Density')
plt.xlabel('Total Charges')
plt.title('Total Charges by Churn')
plt.legend()
plt.show()
```



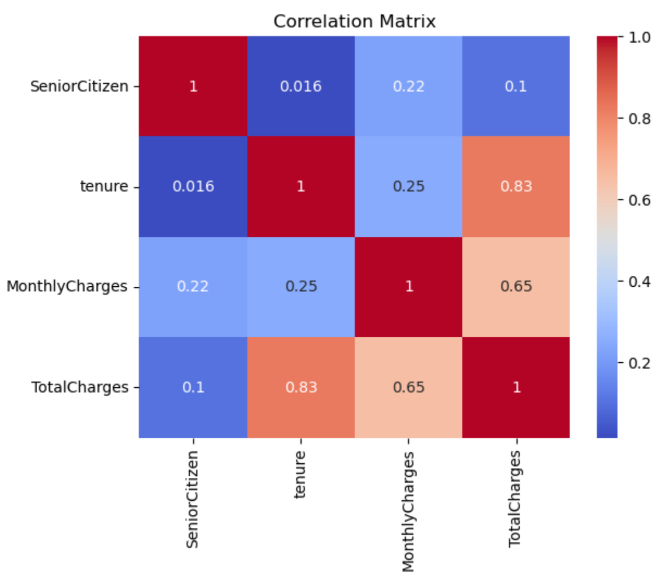
Customers with high total charges are less likely to leave the company.

In [39]:
```
# Visualizing Tenue by Churn

plt.figure(figsize=(10, 6))

# Tenure by Churn
sns.kdeplot(df.tenure[df["Churn"] == 'No'], color="Gold", shade=True, label="Not Churn")
sns.kdeplot(df.tenure[df["Churn"] == 'Yes'], color="Red", shade=True, label="Churn")
plt.ylabel('Density')
plt.xlabel('Tenure (Months)')
plt.title('Tenure by Churn')
plt.legend()
plt.show()
```



New customers (low tenure) are more likely to churn.

In [40]:
```
# Correlation matrix

corr_matrix = df.corr()

sns.heatmap(corr_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix',)
plt.show()
```



In the heatmap, we noticed a strong connection (0.83) between TotalCharges and tenure. Moreover, there's a solid correlation (0.65) between TotalCharges and MonthlyCharges.

Feature Engineering/Data Preprocessing

In [41]:
```
def object_to_int(dataframe_series):
    if dataframe_series.dtype=='object':
        dataframe_series = LabelEncoder().fit_transform(dataframe_series)
    return dataframe_series
```

In [42]:
```
df = df.apply(lambda x: object_to_int(x))
df.head()
```

Out[42]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	StreamingTV	StreamingMovies	Contra
0	0	0	1	0	1	0	1	0	0	2	0	0	0	0	
1	1	0	0	0	34	1	0	0	2	0	2	0	0	0	
2	1	0	0	0	2	1	0	0	2	2	0	0	0	0	
3	1	0	0	0	45	0	1	0	2	0	2	2	0	0	
4	0	0	0	0	2	1	0	1	0	0	0	0	0	0	

In [43]:
```
plt.figure(figsize=(14,7))
df.corr()['Churn'].sort_values(ascending = False)
```

Loading [MathJax]/extensions/Safe.js

Out[43]:
```
Churn               1.000000
MonthlyCharges      0.192858
PaperlessBilling    0.191454
SeniorCitizen       0.150541
PaymentMethod       0.107852
MultipleLines       0.038043
PhoneService        0.011691
gender             -0.008545
StreamingTV        -0.036303
StreamingMovies    -0.038802
InternetService    -0.047097
Partner            -0.149982
Dependents         -0.163128
DeviceProtection   -0.177883
OnlineBackup       -0.195290
TotalCharges       -0.199484
TechSupport        -0.282232
OnlineSecurity     -0.289050
tenure             -0.354049
Contract           -0.396150
Name: Churn, dtype: float64
<Figure size 1400x700 with 0 Axes>
```

Observations on Correlation with Churn

- Higher MonthlyCharges and PaperlessBilling are positively correlated with Churn.
- SeniorCitizen and certain PaymentMethods show positive correlations with Churn.
- MultipleLines and PhoneService have weak positive correlations with Churn.
- Gender, StreamingTV, StreamingMovies, InternetService, and Partner have weak negative correlations with Churn.
- TotalCharges, TechSupport, OnlineSecurity, tenure, and Contract show moderate negative correlations with Churn.
- Longer tenure, higher total charges, and specific services (tech support, online security) are associated with lower churn.
- Longer-term contracts are also associated with lower churn.

Machine Learning

Splitting the data in training and testing sets

In [44]:
```
X = df.drop(columns = ['Churn'])
y = df['Churn'].values
```

In [45]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size = 0.30, random_state = 42, stratify=y)

print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("y_train shape:", y_train.shape)
print("y_test shape:", y_test.shape)
```

```
X_train shape: (4922, 19)
X_test shape: (2110, 19)
y_train shape: (4922,)
y_test shape: (2110,)
```

In [46]:
```
#importing predictive models
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
```

In [47]:
```
#instantiate models
log_reg = LogisticRegression()
dec_tree = DecisionTreeClassifier()
gb_clf = GradientBoostingClassifier()
svc = SVC()
rand_forest = RandomForestClassifier()
```

In [48]:
```
# Train Logistic Regression
log_reg.fit(X_train, y_train)
log_reg_predictions = log_reg.predict(X_test)
log_reg_accuracy = accuracy_score(y_test, log_reg_predictions)
print(f"Logistic Regression Accuracy: {log_reg_accuracy}")
```

```
Logistic Regression Accuracy: 0.7895734597156399
```

In [49]:
```
print(classification_report(y_test, log_reg_predictions))
```

```
              precision    recall  f1-score   support

           0       0.84      0.88      0.86      1549
           1       0.62      0.55      0.58       561

    accuracy                           0.79      2110
   macro avg       0.73      0.71      0.72      2110
weighted avg       0.78      0.79      0.79      2110
```

In [50]:
```
# Train Decision Tree
dec_tree.fit(X_train, y_train)
dec_tree_predictions = dec_tree.predict(X_test)
dec_tree_accuracy = accuracy_score(y_test, dec_tree_predictions)
print(f"Decision Tree Accuracy: {dec_tree_accuracy}")
```

```
Decision Tree Accuracy: 0.7355450236966825
```

In [51]:
```
print(classification_report(y_test, dec_tree_predictions))
```

```
              precision    recall  f1-score   support

           0       0.83      0.81      0.82      1549
           1       0.50      0.53      0.51       561

    accuracy                           0.74      2110
Loading [MathJax]/extensions/Safe.js
                   0.66      0.67      0.67      2110
```

```
weighted avg       0.74      0.74      0.74      2110
```

In [52]:
```python
# Train Gradient Boosting Classifier
gb_clf.fit(X_train, y_train)
gb_clf_predictions = gb_clf.predict(X_test)
gb_clf_accuracy = accuracy_score(y_test, gb_clf_predictions)
print(f"Gradient Boosting Classifier Accuracy: {gb_clf_accuracy}")
```

```
Gradient Boosting Classifier Accuracy: 0.795260663507109
```

In [53]:
```python
print(classification_report(y_test, gb_clf_predictions))
```

```
              precision    recall  f1-score   support

           0       0.83      0.90      0.87      1549
           1       0.65      0.50      0.57       561

    accuracy                           0.80      2110
   macro avg       0.74      0.70      0.72      2110
weighted avg       0.78      0.80      0.79      2110
```

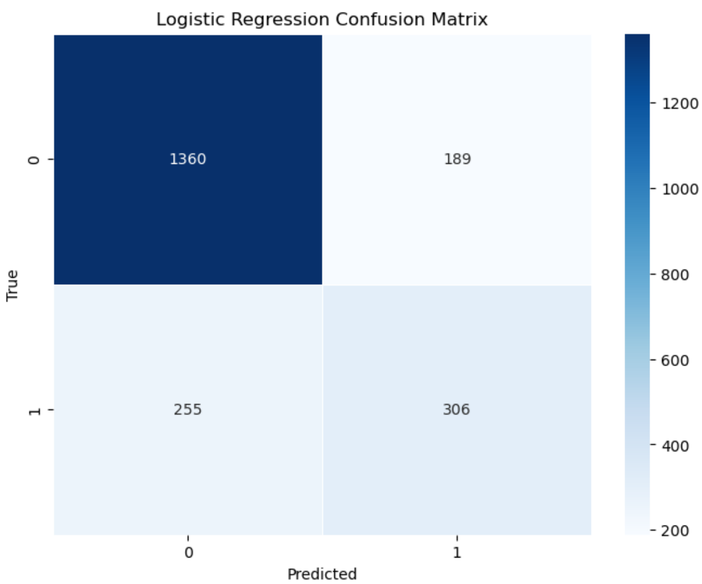
In [54]:
```python
# Train Random Forest

rand_forest.fit(X_train, y_train)
rand_forest_predictions = rand_forest.predict(X_test)
rand_forest_accuracy = accuracy_score(y_test, rand_forest_predictions)
print(f"Random Forest Accuracy: {rand_forest_accuracy}")
```

```
Random Forest Accuracy: 0.7843601895734598
```

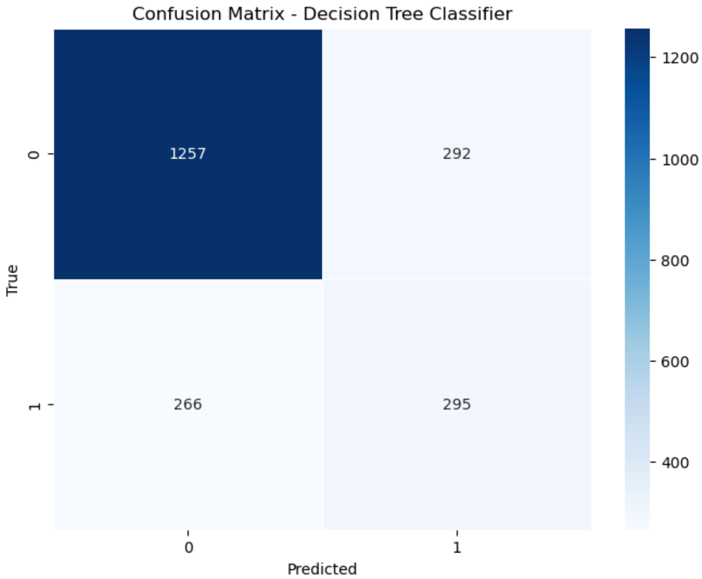
In [55]:
```python
print(classification_report(y_test, rand_forest_predictions))
```

```
              precision    recall  f1-score   support

           0       0.83      0.89      0.86      1549
           1       0.62      0.48      0.54       561

    accuracy                           0.78      2110
   macro avg       0.72      0.69      0.70      2110
weighted avg       0.77      0.78      0.78      2110
```

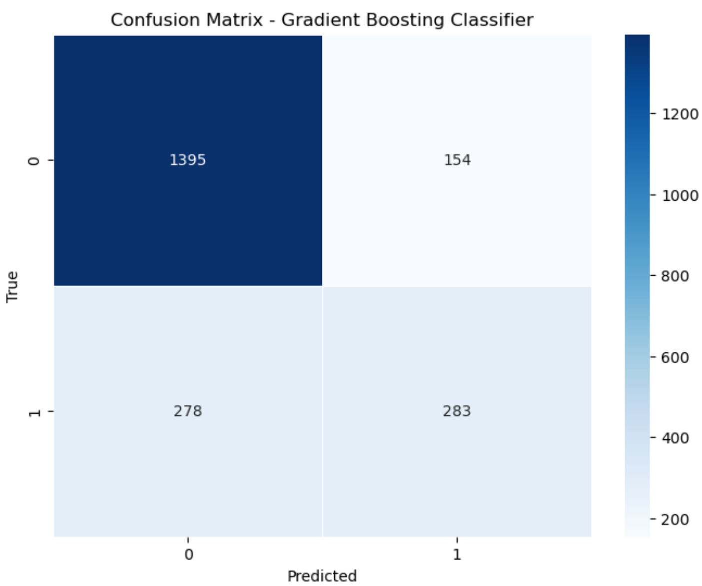
In [56]:
```python
# Confusion matrix
cm = confusion_matrix(y_test, log_reg_predictions)

# Plotting the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', linewidths=.5)
plt.title('Logistic Regression Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```



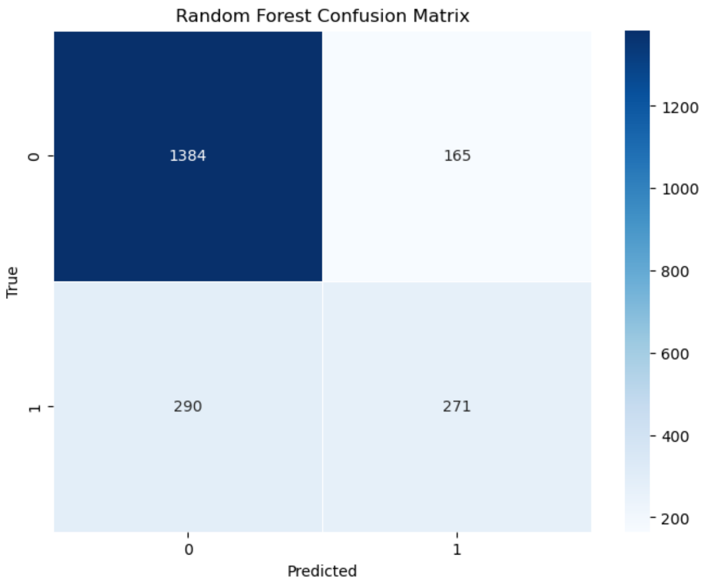
In [57]:
```python
# Confusion matrix for Decision Tree Classifier
dec_tree_cm = confusion_matrix(y_test, dec_tree_predictions)

# Plotting the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(dec_tree_cm, annot=True, fmt='d', cmap='Blues', linewidths=.5)
plt.title('Confusion Matrix - Decision Tree Classifier')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```



In [58]:
```
# Confusion matrix for Gradient Boosting Classifier
gb_clf_cm = confusion_matrix(y_test, gb_clf_predictions)

# Plotting the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(gb_clf_cm, annot=True, fmt='d', cmap='Blues', linewidths=.5)
plt.title('Confusion Matrix - Gradient Boosting Classifier')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```



In [59]:
```
# Confusion matrix for Random Forest
conf_matrix_rf = confusion_matrix(y_test, rand_forest_predictions)

# Plotting the confusion matrix
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix_rf, annot=True, fmt='d', cmap='Blues', linewidths=.5)
plt.title('Random Forest Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
```



Trained Model Performance:

Logistic Regression

- **Accuracy:** 78.96%
- **Precision (Class 1):** 62%
- **Recall (Class 1):** 55%
- **F1-Score (Class 1):** 58%

Decision Tree

- **Accuracy:** 73.74%
- **Precision (Class 1):** 51%
- **Recall (Class 1):** 51%
- **F1-Score (Class 1):** 51%

Gradient Boosting Classifier

- **Accuracy:** 79.53%
- **Precision (Class 1):** 65%
- **Recall (Class 1):** 50%
- **F1-Score (Class 1):** 57%

Random Forest

- **Accuracy:** 78.34%
- **Precision (Class 1):** 62%
- **Recall (Class 1):** 48%
- **F1-Score (Class 1):** 54%

Insights

- The Gradient Boosting Classifier achieved the highest accuracy among the models.
- Precision and recall metrics bring attention to the balance between minimizing incorrect positive predictions and capturing all positive instances.
- When analyzing these results, take into account the unique business context and priorities to derive meaningful insights.
- Further exploration of feature importance in the Gradient Boosting model may provide insights.

Recommendations:

- The Gradient Boosting Classifier appears to be the best choice for customer churn prediction among the models. Minimizing customer churn is crucial for a firm's profitability. To achieve this, understanding and identifying at-risk customers are key. Prioritizing customer service improvement and building loyalty through personalized experiences are effective strategies. Proactive measures, such as surveying departed customers, help prevent future churn.

In [ ]:

In [ ]:

Loading [MathJax]/extensions/Safe.js