1.Importing the dependencies

In [3]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import pearsonr, chi2_contingency
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import  LinearRegression
from imblearn.over_sampling import SMOTE
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
import pickle
import warnings
warnings.filterwarnings("ignore")
```

2. Data Loading

In [5]:

```
df = pd.read_csv("Telco-Customer-Churn.csv")
pd.set_option("display.max_columns", None)
df
```

Out[5]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	
4	9237-HQITU	Female	0	No	No	2	Yes	No	
...	...	...	...	...	...	...	...	...	
7038	6840-RESVB	Male	0	Yes	Yes	24	Yes	Yes	
7039	2234-XADUH	Female	0	Yes	Yes	72	Yes	Yes	
7040	4801-JZAZL	Female	0	Yes	Yes	11	No	No phone service	
7041	8361-LTMKD	Male	1	Yes	No	4	Yes	Yes	

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
7042	3186-AJIEK	Male	0	No	No	66	Yes	No	

7043 rows × 21 columns

3. Exploratory Data Analysis(EDA)

In [7]:

```
df.shape
```

Out[7]:

```
(7043, 21)
```

In [8]:

```
df.head()
```

Out[8]:

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

In [9]:

```
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 [10]:

```
df.describe()
```

Out[10]:

	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 [11]:

```
# Printing the unique values in columns
numerical_features_list = ["tenure","MonthlyCharges","TotalCharges"]
for col in df.columns:
  if col not in numerical_features_list:
    print(col,df[col].unique())
    print("-"*50)
```

```
customerID ['7590-VHVEG' '5575-GNVDE' '3668-QPYBK' ... '4801-JZAZL' '8361-LTMKD'
 '3186-AJIEK']
--------------------------------------------------
gender ['Female' 'Male']
--------------------------------------------------
SeniorCitizen [0 1]
--------------------------------------------------
Partner ['Yes' 'No']
--------------------------------------------------
Dependents ['No' 'Yes']
--------------------------------------------------
PhoneService ['No' 'Yes']
--------------------------------------------------
MultipleLines ['No phone service' 'No' 'Yes']
--------------------------------------------------
InternetService ['DSL' 'Fiber optic' 'No']
--------------------------------------------------
OnlineSecurity ['No' 'Yes' 'No internet service']
--------------------------------------------------
OnlineBackup ['Yes' 'No' 'No internet service']
--------------------------------------------------
DeviceProtection ['No' 'Yes' 'No internet service']
--------------------------------------------------
```

```
TechSupport ['No' 'Yes' 'No internet service']
--------------------------------------------------
StreamingTV ['No' 'Yes' 'No internet service']
--------------------------------------------------
StreamingMovies ['No' 'Yes' 'No internet service']
--------------------------------------------------
Contract ['Month-to-month' 'One year' 'Two year']
--------------------------------------------------
PaperlessBilling ['Yes' 'No']
--------------------------------------------------
PaymentMethod ['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']
--------------------------------------------------
Churn ['No' 'Yes']
--------------------------------------------------
```

In [12]:

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

Out[12]:

```
customerID          0
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 [13]:

```
df.columns
```

Out[13]:

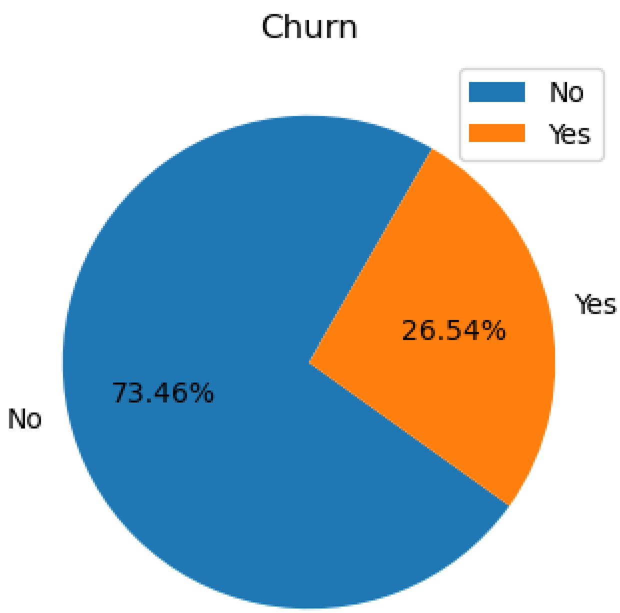
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
     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

Numerical featuer - Analysis

In [15]:

```
plt.figure(figsize=(5,4))
x = df["Churn"].value_counts().index
y = df["Churn"].value_counts().values
```

```
plt.pie(y,labels=x,startangle= 60, autopct="%.2f%%")
plt.title("Churn")
plt.legend()
plt.show()
```



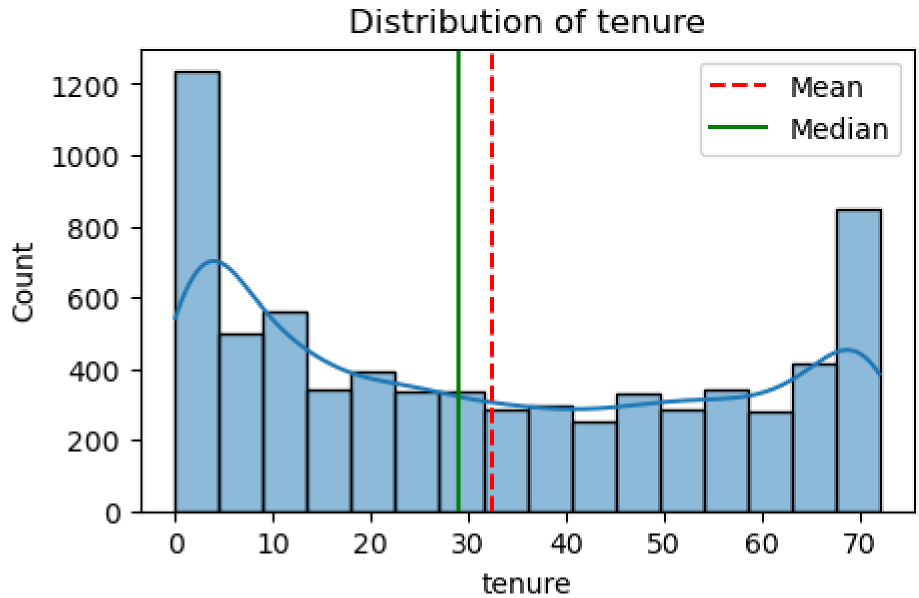
understand the distribution of the numerical features

In [17]:

```
def plot_histogram(dataset, columns_name):

  plt.figure(figsize=(5,3))
  sns.histplot(dataset[columns_name], kde=True)
  plt.title(f"Distribution of {columns_name}")

  # calculate the mean and median value for columns
  col_mean = dataset[columns_name].mean()
  col_median = dataset[columns_name].median()

  # add vertical lines for mean and median
  plt.axvline(col_mean, c="red", linestyle="--", label="Mean")
  plt.axvline(col_median, c="green", linestyle="-", label="Median")

  plt.legend()

  plt.show()
```

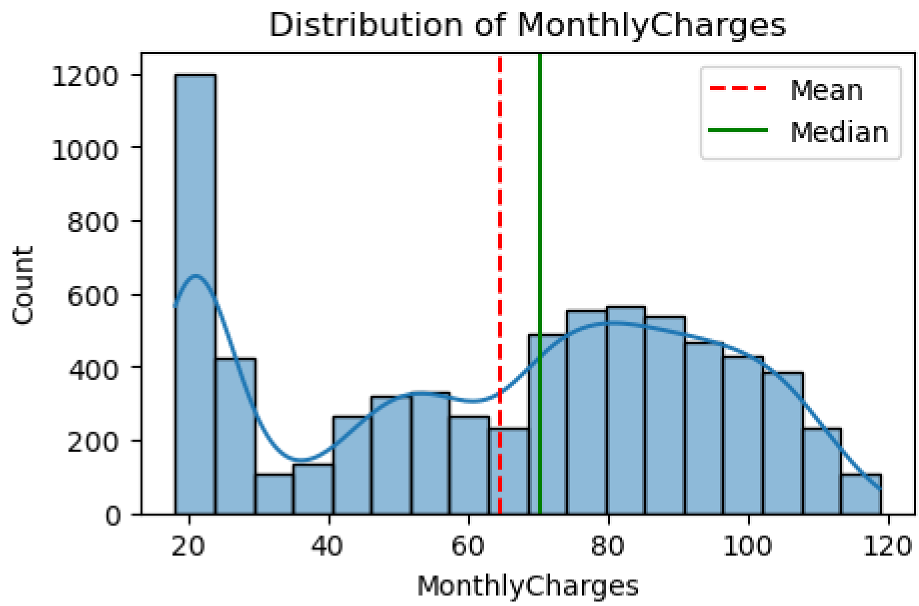
In [18]:

```
plot_histogram(df, "tenure")
```



In [19]:

```
plot_histogram(df, "MonthlyCharges")
```



In [20]:

```
df[df["TotalCharges"]==" "]
```

Out[20]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
488	4472-LVYGI	Female	0	Yes	Yes	0	No	No phone service	
753	3115-CZMZD	Male	0	No	Yes	0	Yes	No	
936	5709-LVOEQ	Female	0	Yes	Yes	0	Yes	No	
1082	4367-NUYAO	Male	0	Yes	Yes	0	Yes	Yes	
1340	1371-	Female	0	Yes	Yes	0	No	No phone	

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	Int
	DWPAZ							service	
3331	7644-OMVMY	Male	0	Yes	Yes	0	Yes	No	
3826	3213-VVOLG	Male	0	Yes	Yes	0	Yes	Yes	
4380	2520-SGTTA	Female	0	Yes	Yes	0	Yes	No	
5218	2923-ARZLG	Male	0	Yes	Yes	0	Yes	No	
6670	4075-WKNIU	Female	0	Yes	Yes	0	Yes	Yes	
6754	2775-SEFEE	Male	0	No	Yes	0	Yes	Yes	

In [21]:

```
len(df[df["TotalCharges"]==" "])
```

Out[21]:

11

In [22]:

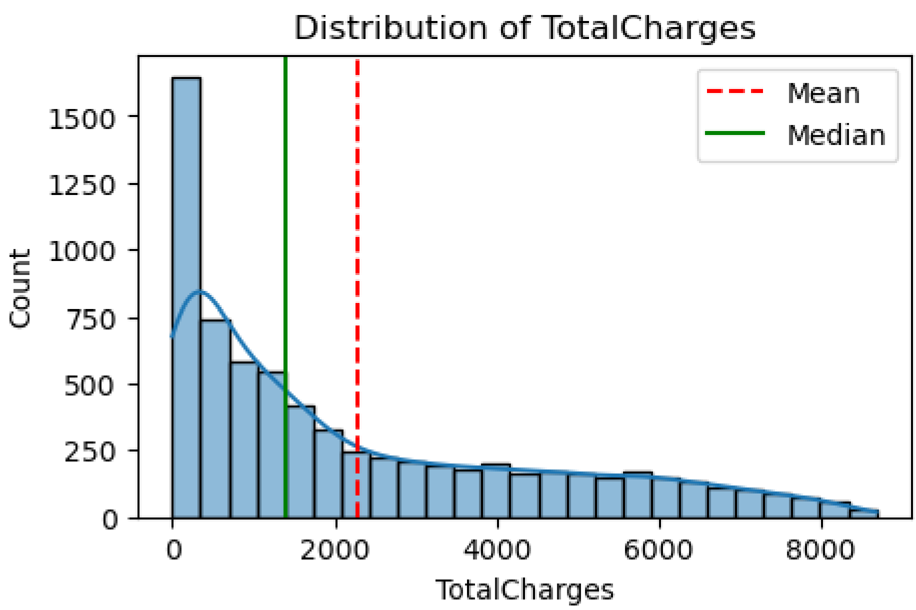
```
df["TotalCharges"] = df["TotalCharges"].replace({" ": "0.0"})
```

In [23]:

```
df["TotalCharges"] = df["TotalCharges"].astype(float)
```

In [24]:

```
plot_histogram(df, "TotalCharges")
```



Box plot for numerical features

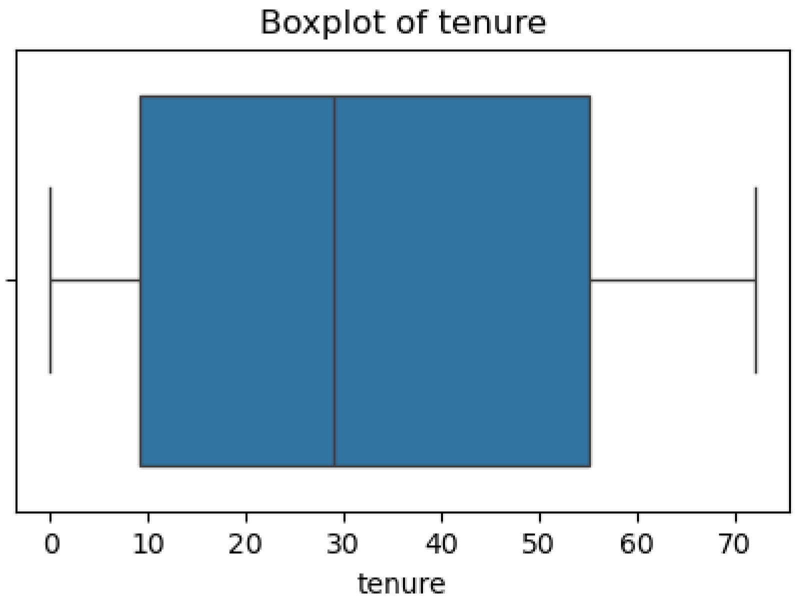
In [26]:

```
def plot_boxplot(df, columns_name):
```

```
    plt.figure(figsize=(5,3))
    sns.boxplot(x=df[columns_name])
    plt.title(f"Boxplot of {columns_name}")
    plt.xlabel(columns_name)
    plt.show()
```

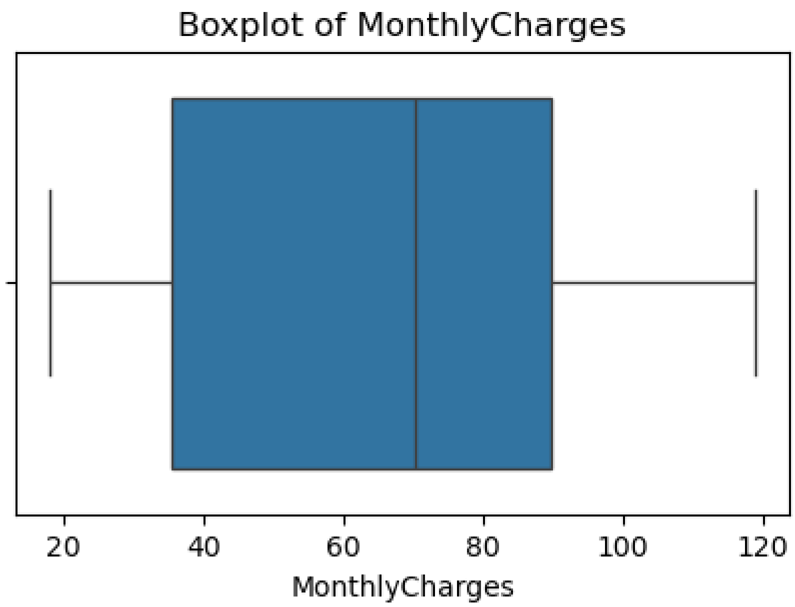
In [27]:

```
plot_boxplot(df, "tenure")
```



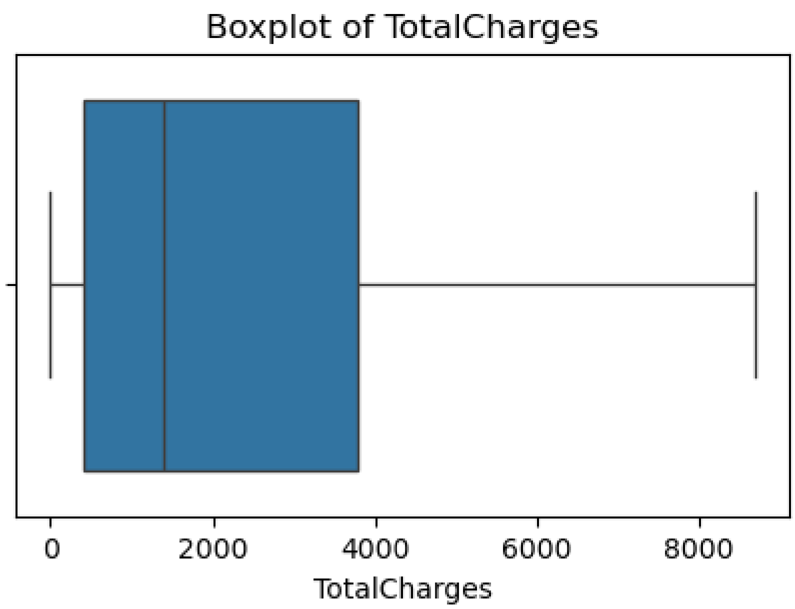
In [28]:

```
plot_boxplot(df, "MonthlyCharges")
```



In [29]:

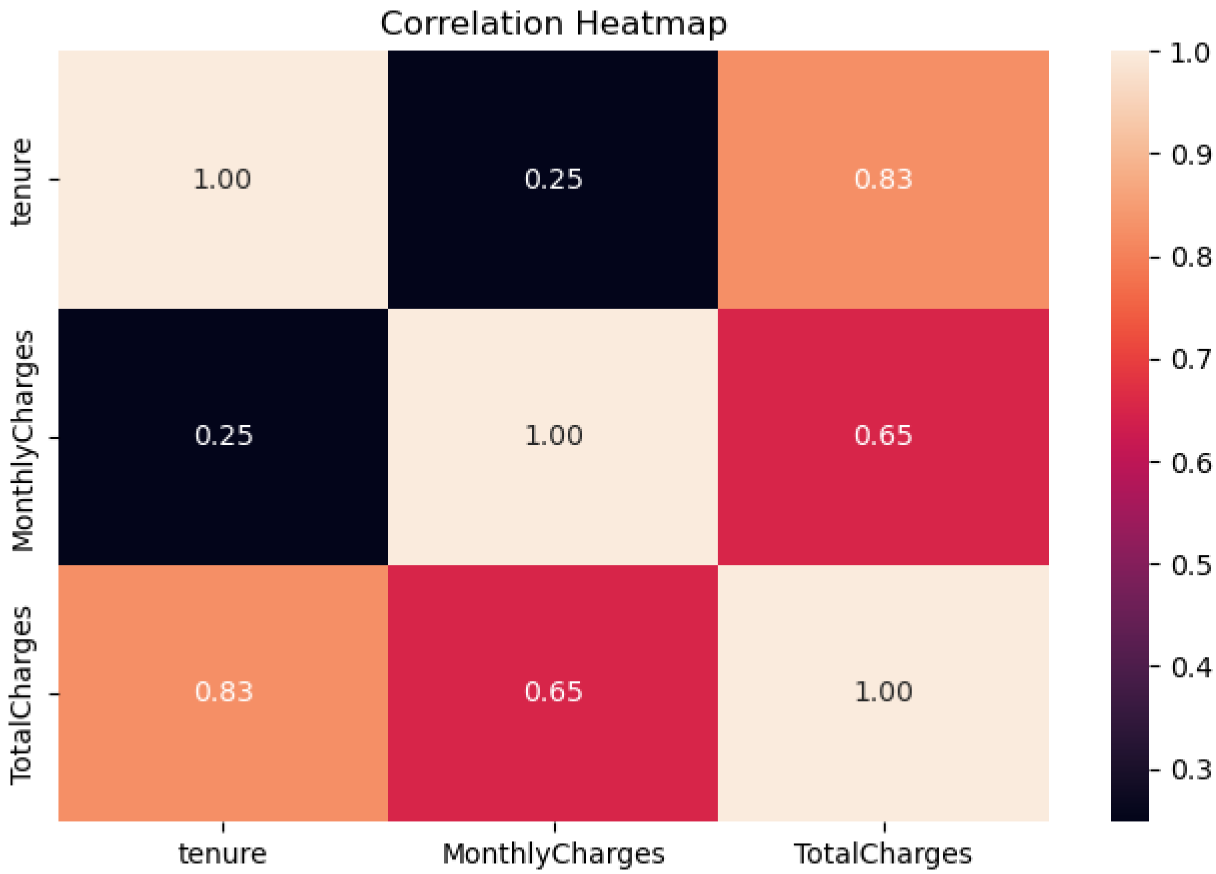
```
plot_boxplot(df, "TotalCharges")
```



Correlation Heatmap for numerical columns

In [31]:

```
# correlation matrix - heatmap
plt.figure(figsize=(8,5))
sns.heatmap(df[["tenure","MonthlyCharges","TotalCharges"]].corr(), annot=True,fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```



Categorical features - Analysis

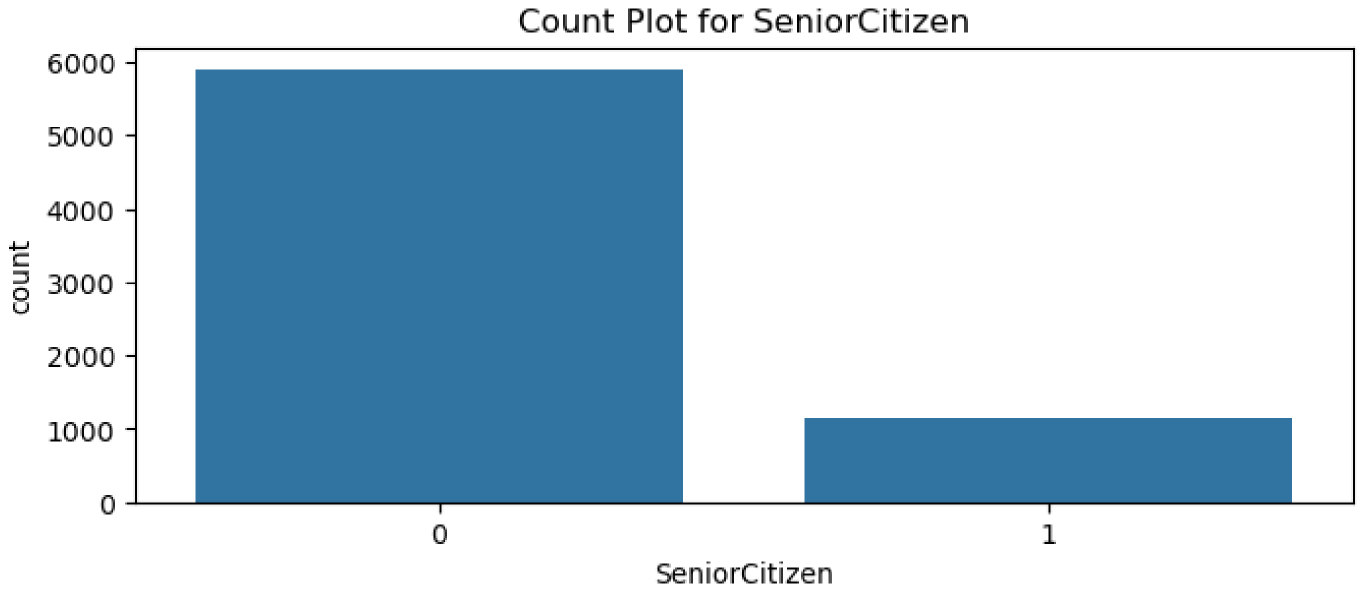
Counplot for categorical columns

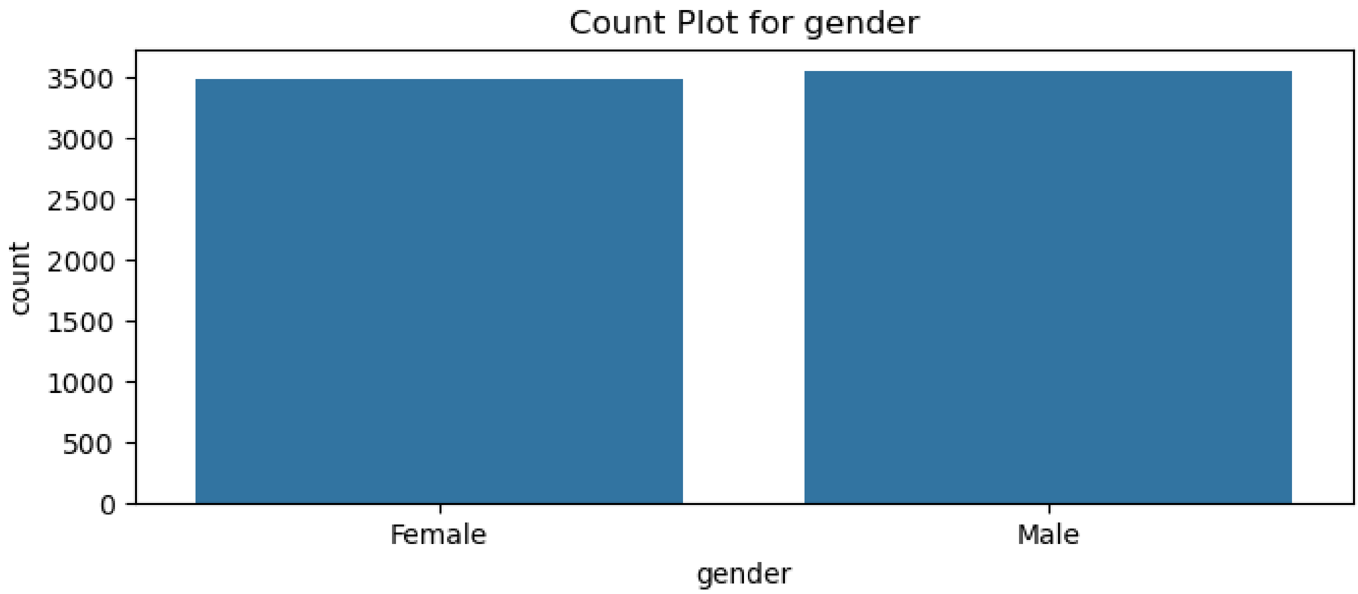
In [33]:

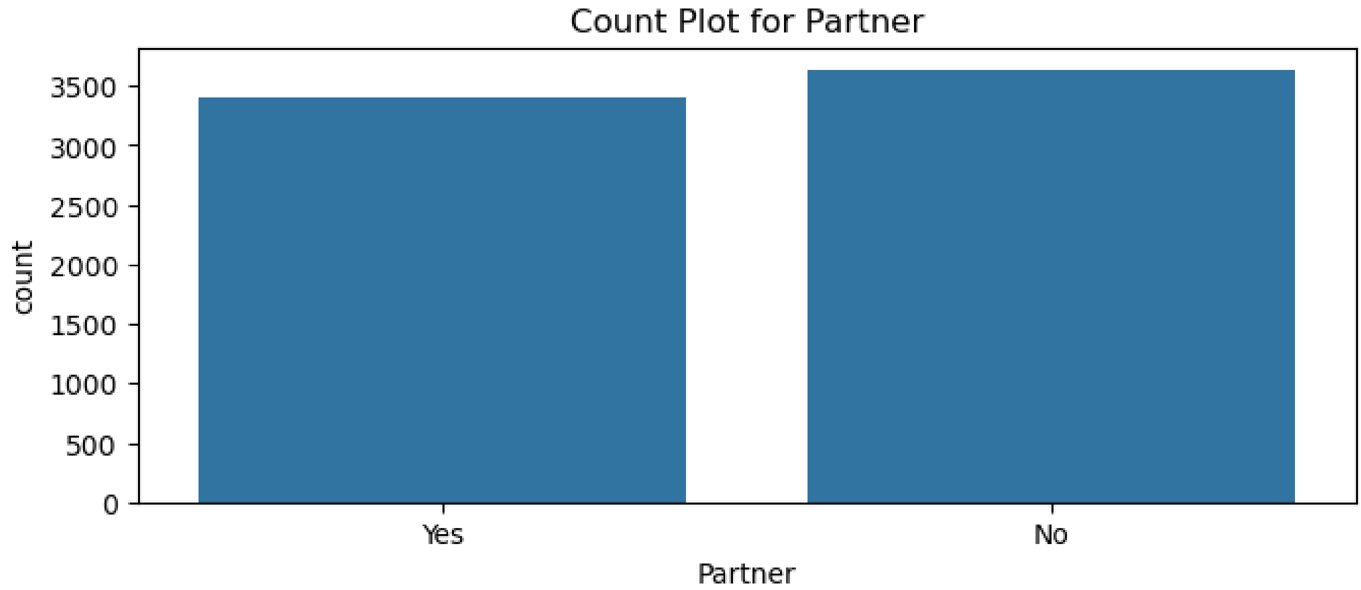
```
# dropping customerID column cause this is not required for modelling
df = df.drop(columns="customerID")
```

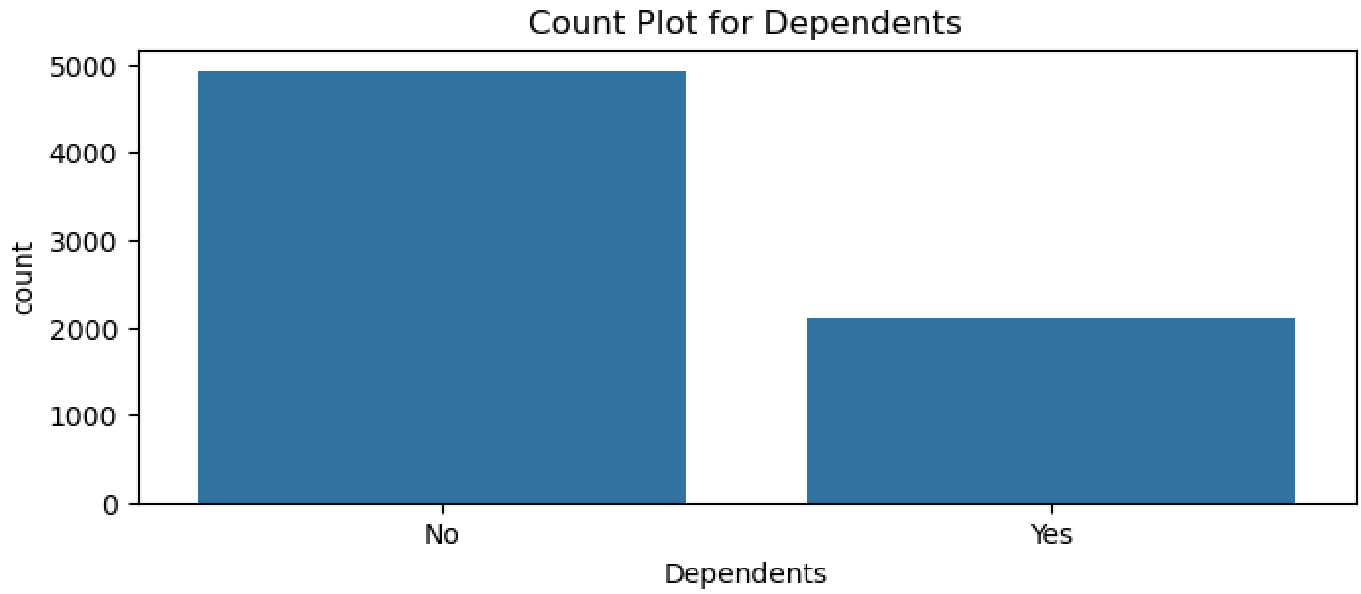
In [34]:

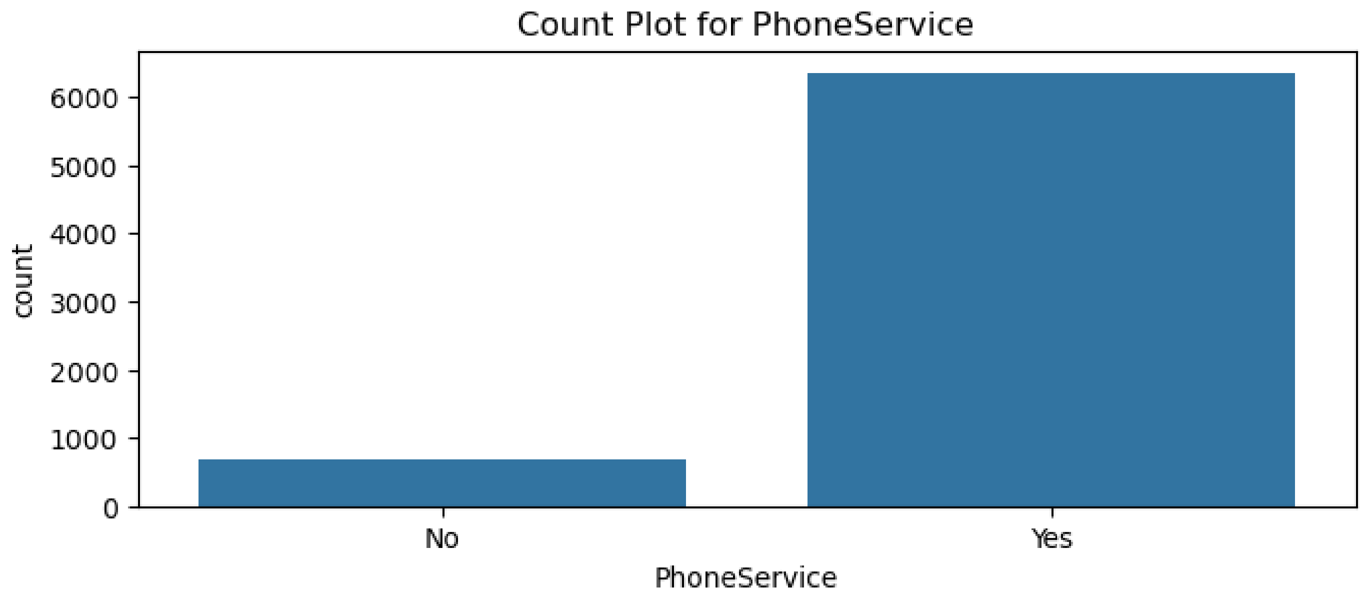
```
object_cols = df.select_dtypes(include="object").columns.to_list()
object_cols= ["SeniorCitizen"] + object_cols

for col in object_cols:
  plt.figure(figsize=(8, 3))
  sns.countplot(x=df[col])
  plt.title(f"Count Plot for {col}")
  plt.show()
```

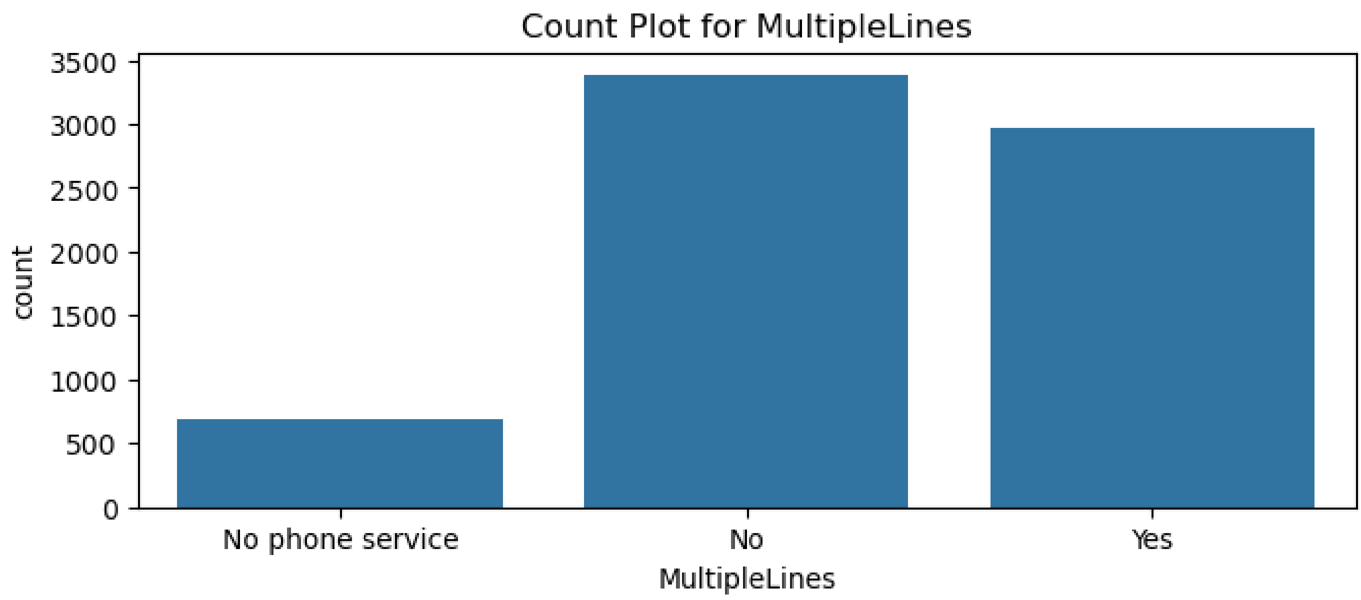


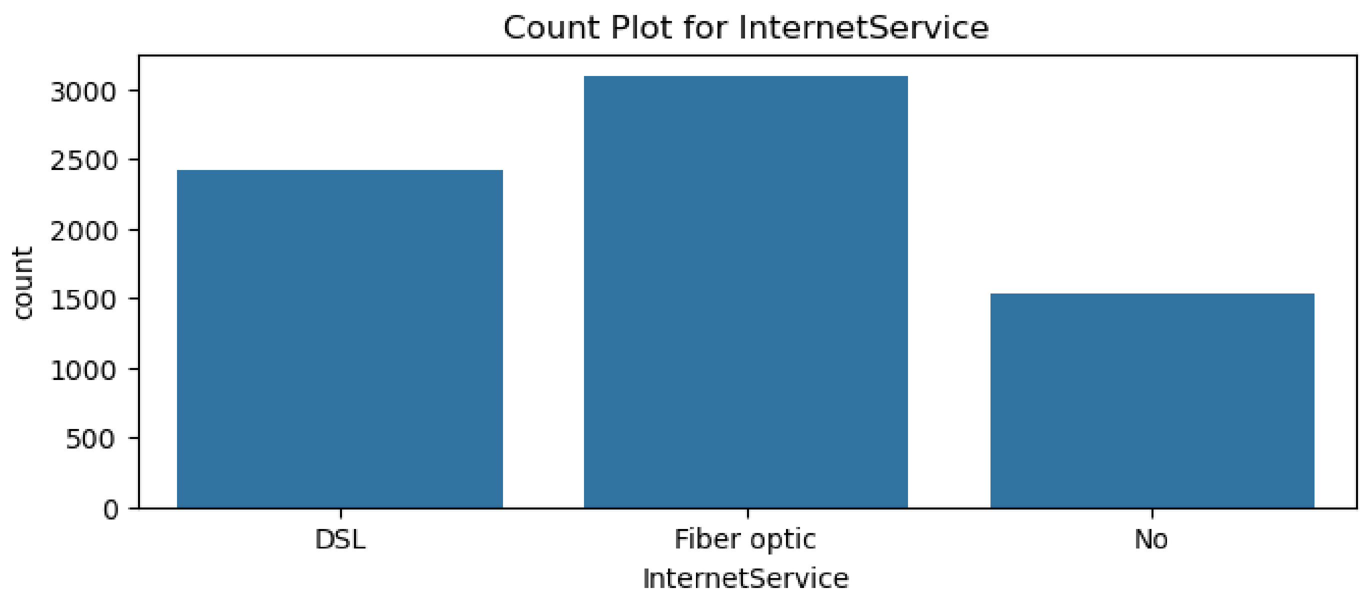


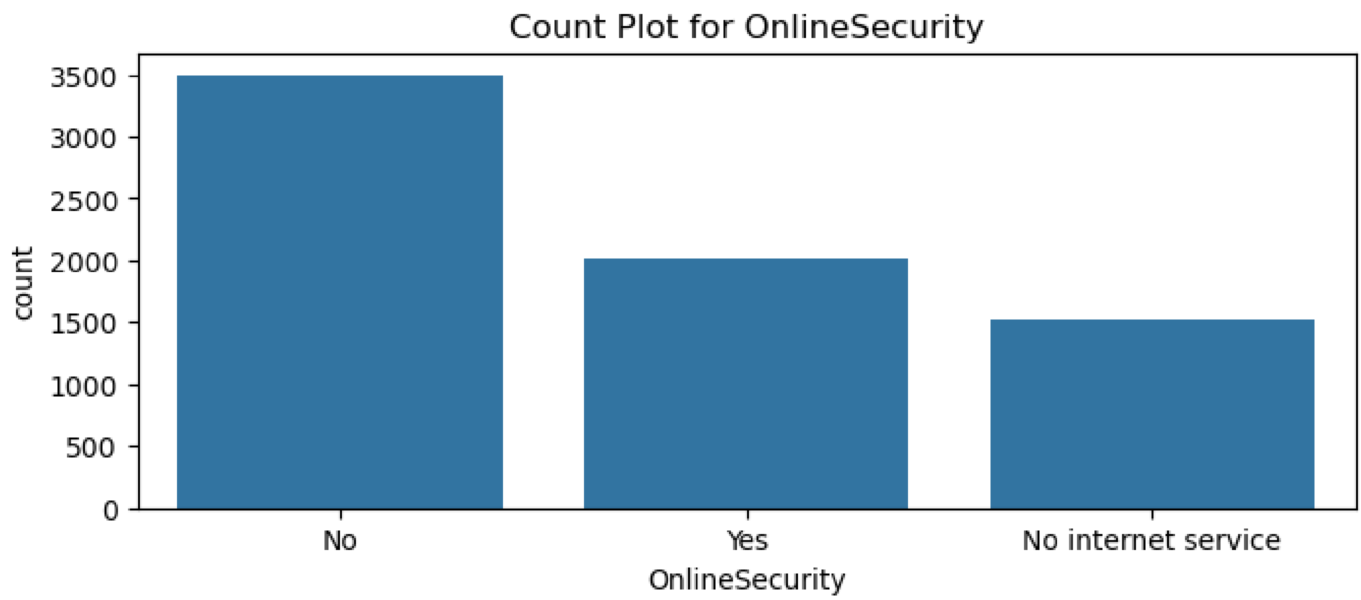

Count Plot for Partner
count
3500
3000
2500
2000
1500
1000
500
0
Yes
No
Partner

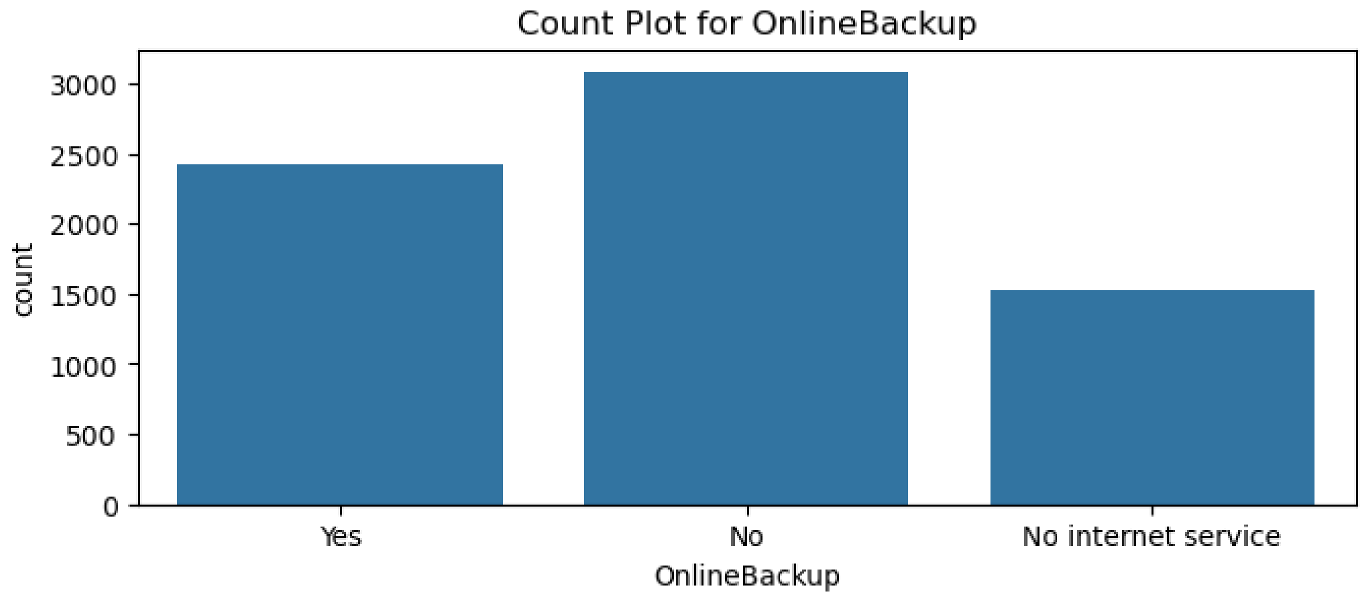

Count Plot for Dependents
count
5000
4000
3000
2000
1000
0
No
Yes
Dependents

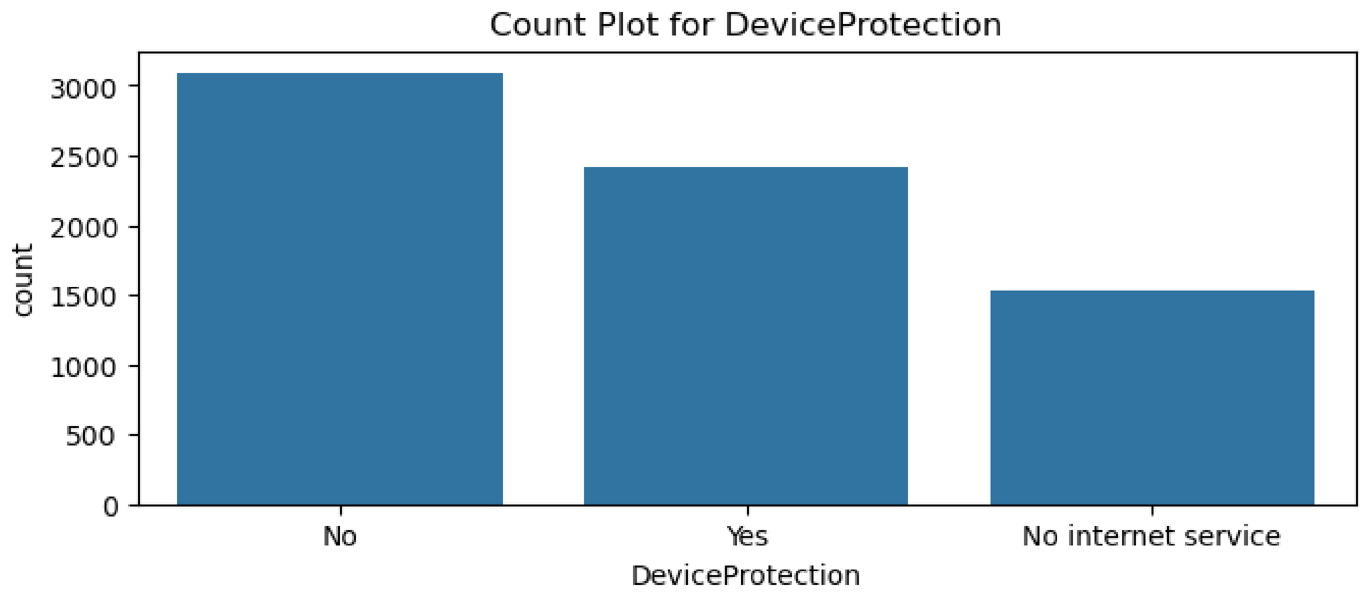

Count Plot for PhoneService
count
6000
5000
4000
3000
2000
1000
0
No
Yes
PhoneService

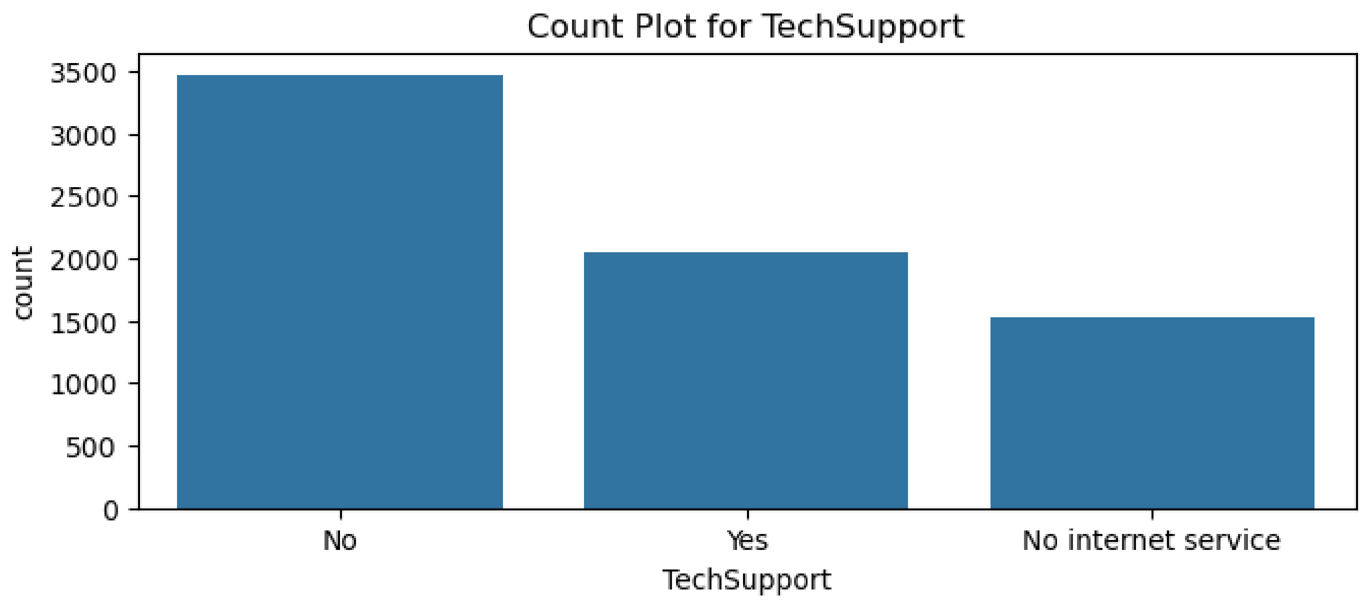

Count Plot for MultipleLines
count
3500
3000
2500
2000
1500
1000
500
0
No phone service
No
Yes
MultipleLines

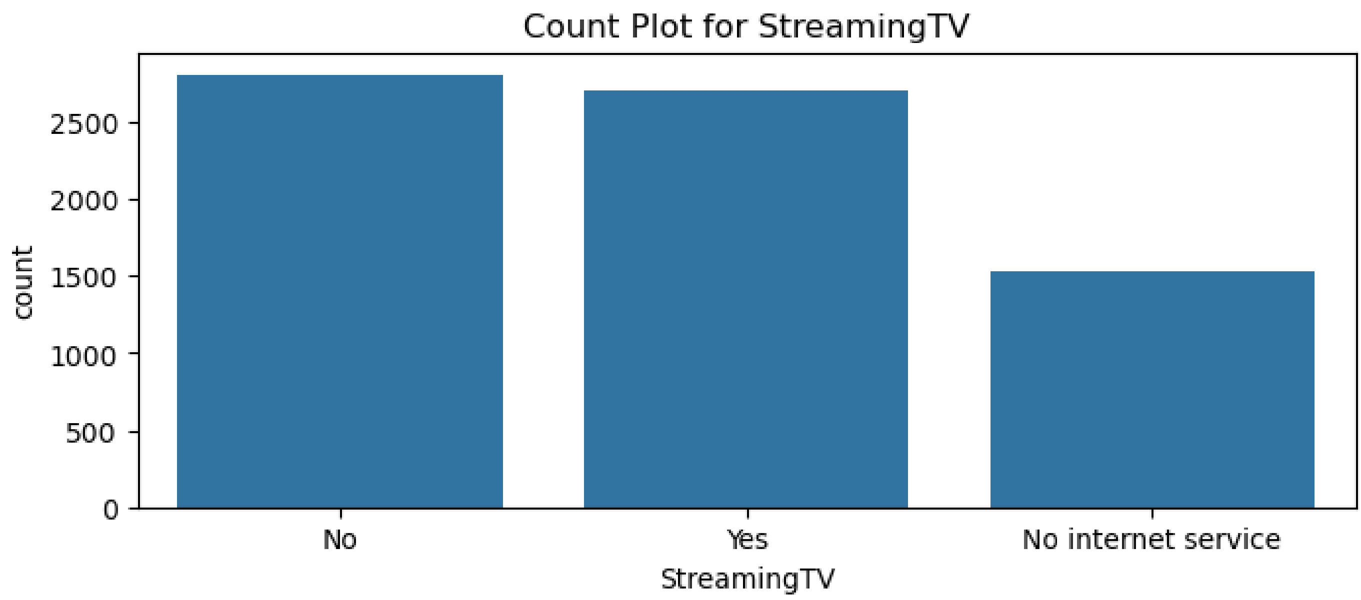

Count Plot for InternetService
count
3000
2500
2000
1500
1000
500
0
DSL
Fiber optic
No
InternetService

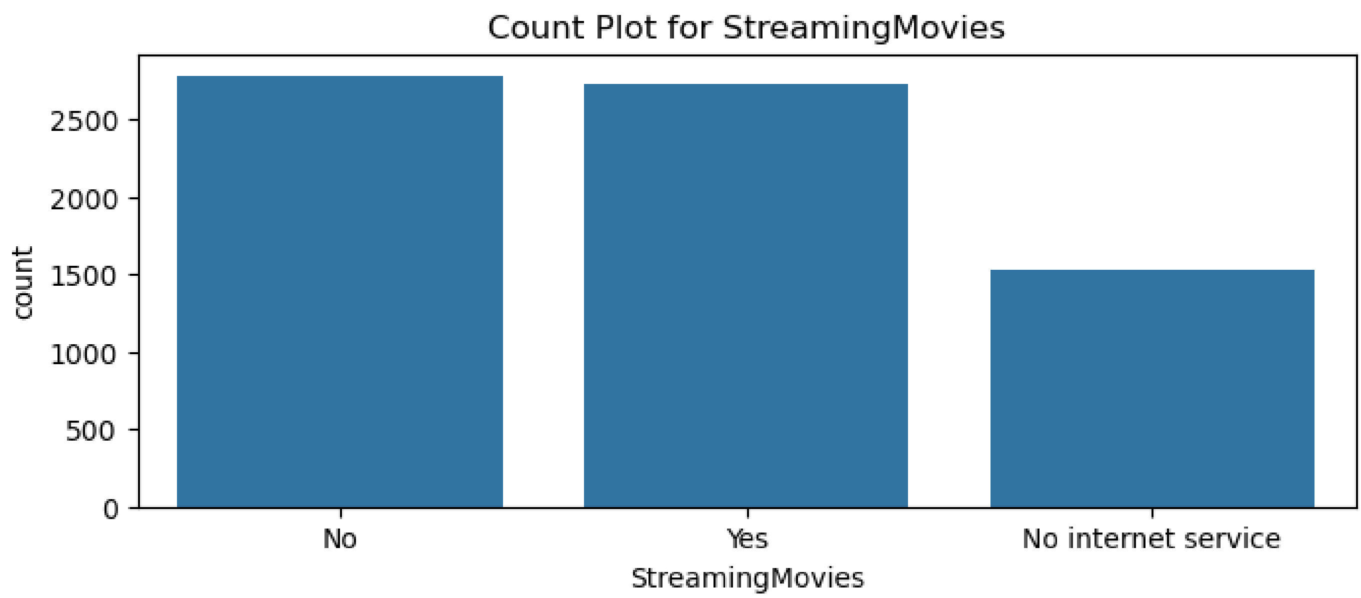

Count Plot for OnlineSecurity
count
3500
3000
2500
2000
1500
1000
500
0
No
Yes
No internet service
OnlineSecurity

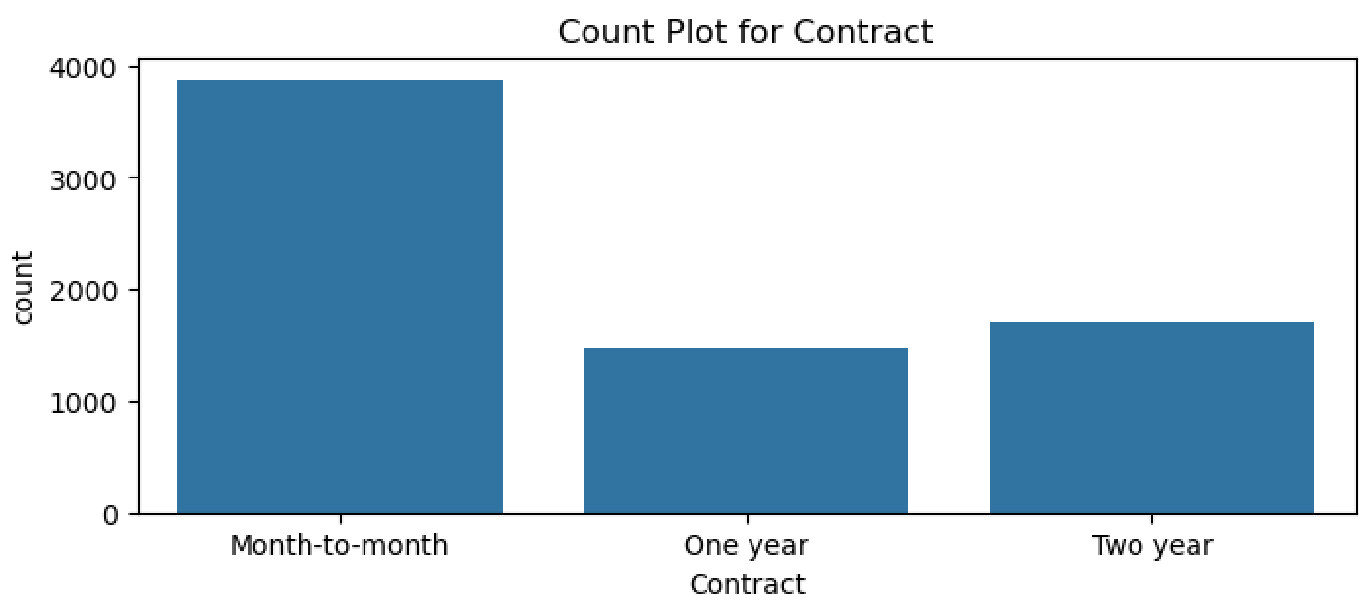

Count Plot for OnlineBackup
count
3000
2500
2000
1500
1000
500
0
Yes
No
No internet service
OnlineBackup

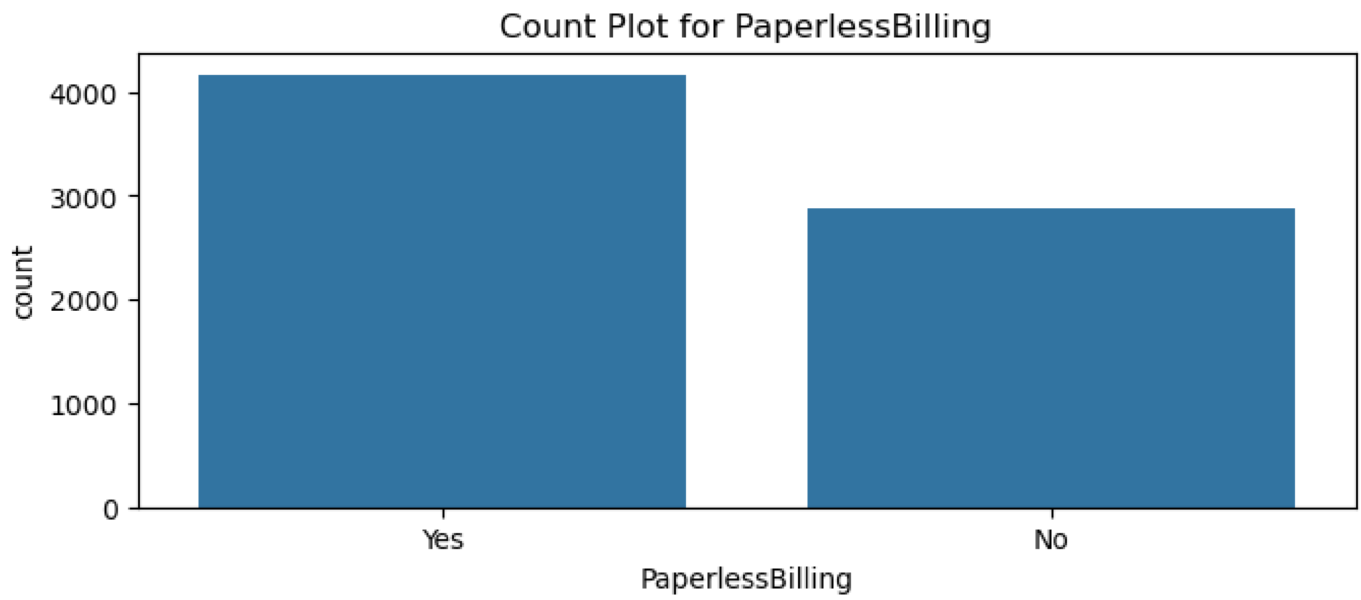

Count Plot for DeviceProtection
count
3000
2500
2000
1500
1000
500
0
No
Yes
No internet service
DeviceProtection

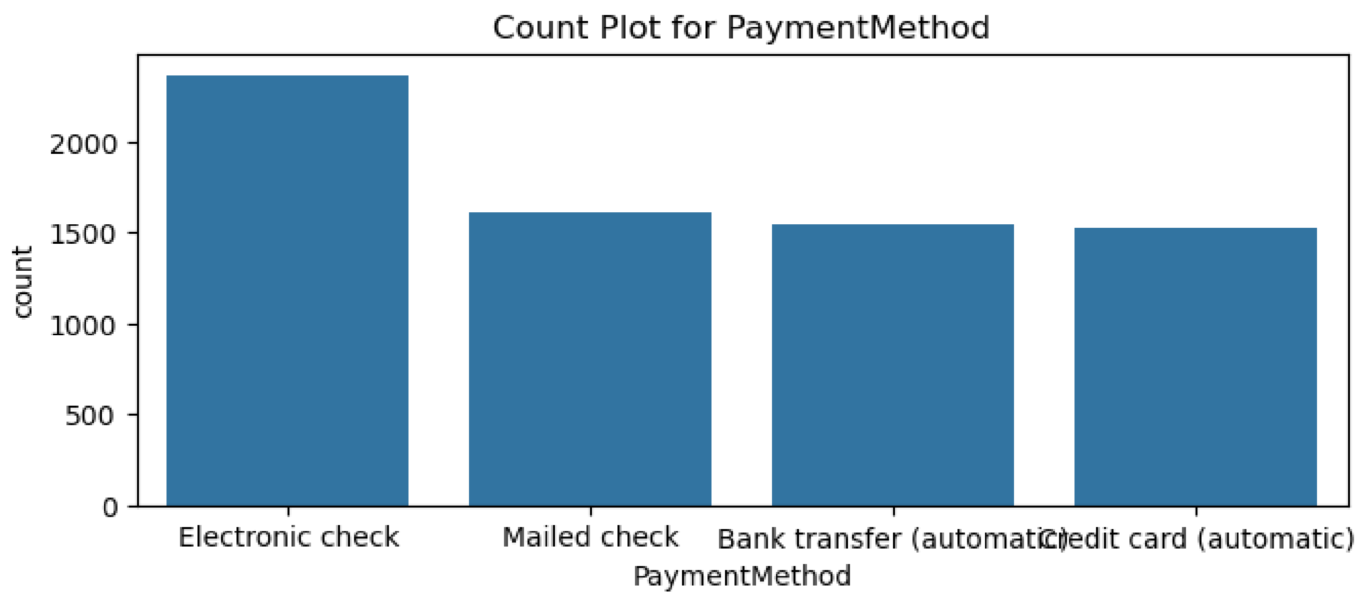

Count Plot for TechSupport
count
3500
3000
2500
2000
1500
1000
500
0
No
Yes
No internet service
TechSupport

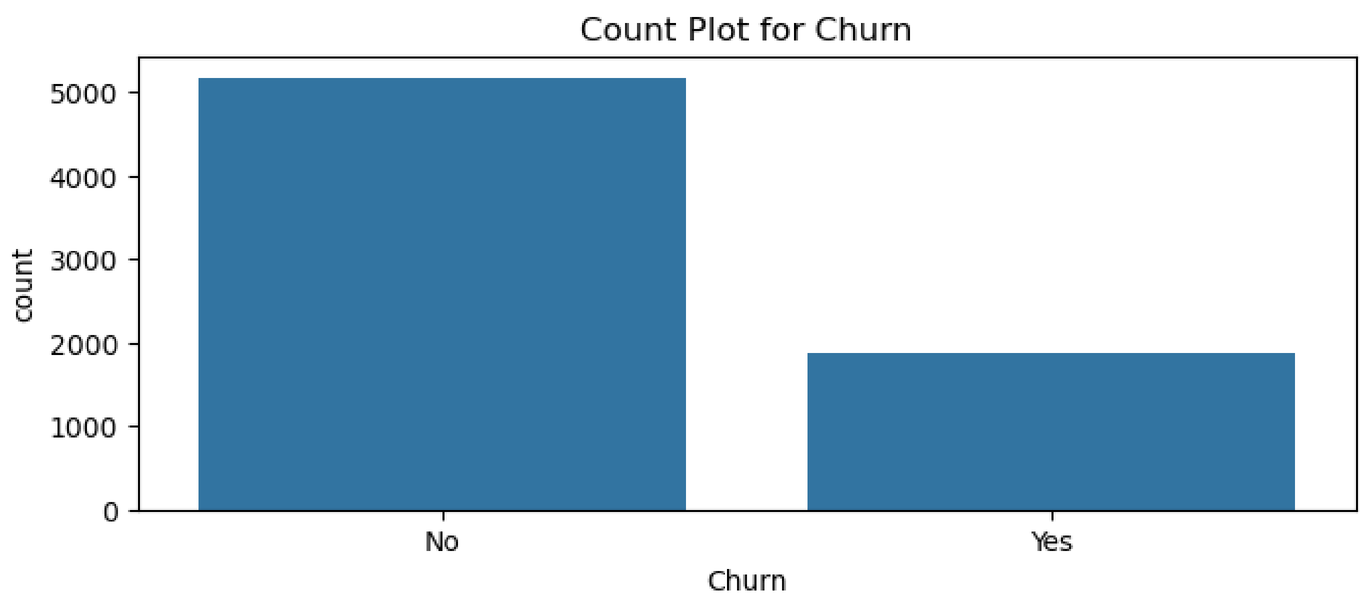

Count Plot for StreamingTV
count
0
500
1000
1500
2000
2500
No
Yes
No internet service
StreamingTV


Count Plot for StreamingMovies
count
0
500
1000
1500
2000
2500
No
Yes
No internet service
StreamingMovies


Count Plot for Contract
count
0
1000
2000
3000
4000
Month-to-month
One year
Two year
Contract







4. Data Cleaning and Preprocessing

In [36]:

```
clean_df = df.copy()
```

In [37]:

```
clean_df.head()
```

Out[37]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	O
0	Female	0	Yes	No	1	No	No phone service	DSL	
1	Male	0	No	No	34	Yes	No	DSL	
2	Male	0	No	No	2	Yes	No	DSL	
3	Male	0	No	No	45	No	No phone service	DSL	
4	Female	0	No	No	2	Yes	No	Fiber optic	

In [38]:

```
clean_df.shape
```

Out[38]:
(7043, 20)

In [39]:

```
clean_df.drop_duplicates(inplace=True)
```

In [40]:

```
clean_df.shape
```

Out[40]:
(7021, 20)

In [41]:

```
clean_df.isnull().sum()
```

Out[41]:

```
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 [42]:

```
clean_df.dtypes
```

Out[42]:

```
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         float64
Churn                 object
dtype: object
```

In [43]:

```
# Printing the unique values in columns
numerical_features_list = ["tenure","MonthlyCharges","TotalCharges"]
for col in clean_df.columns:
  if col not in numerical_features_list:
    print(col,clean_df[col].unique())
    print("-"*50)
```

```
gender ['Female' 'Male']
--------------------------------------------------
SeniorCitizen [0 1]
--------------------------------------------------
Partner ['Yes' 'No']
--------------------------------------------------
Dependents ['No' 'Yes']
--------------------------------------------------
PhoneService ['No' 'Yes']
--------------------------------------------------
MultipleLines ['No phone service' 'No' 'Yes']
--------------------------------------------------
InternetService ['DSL' 'Fiber optic' 'No']
--------------------------------------------------
OnlineSecurity ['No' 'Yes' 'No internet service']
--------------------------------------------------
OnlineBackup ['Yes' 'No' 'No internet service']
--------------------------------------------------
DeviceProtection ['No' 'Yes' 'No internet service']
--------------------------------------------------
TechSupport ['No' 'Yes' 'No internet service']
--------------------------------------------------
StreamingTV ['No' 'Yes' 'No internet service']
```

```
------------------------------------------------
StreamingMovies ['No' 'Yes' 'No internet service']
------------------------------------------------
Contract ['Month-to-month' 'One year' 'Two year']
------------------------------------------------
PaperlessBilling ['Yes' 'No']
------------------------------------------------
PaymentMethod ['Electronic check' 'Mailed check' 'Bank transfer (automatic)'
 'Credit card (automatic)']
------------------------------------------------
Churn ['No' 'Yes']
------------------------------------------------
```

Target Label Encoding (Churn)

1 = Yes &

2 = No

In [45]:

```
clean_df["Churn"] = clean_df["Churn"].replace({"Yes":1, "No":0})
```

Features Encoding

Label Encoding

In [47]:

```
binary_cols_label_encode = [
    'gender', 'Partner', 'Dependents', 'PhoneService', 'PaperlessBilling'
]
```

In [48]:

```
# Initialize a dictionary to save encoders
binary_encoders = {}

# Apply label encoding and store the encoders
for column in binary_cols_label_encode:
  le = LabelEncoder()
  clean_df[column] = le.fit_transform(clean_df[column])
  binary_encoders[column] = le

  # save the encoders to a pickle file
  with open("binary_encoders.pkl","wb") as f:
    pickle.dump(binary_encoders, f)
```

In [49]:

```
binary_encoders
```

Out[49]:

```
{'gender': LabelEncoder(),
 'Partner': LabelEncoder(),
 'Dependents': LabelEncoder(),
 'PhoneService': LabelEncoder(),
 'PaperlessBilling': LabelEncoder()}
```

Ordinal Encoding

In [51]:

```
clean_df["Contract"] = clean_df["Contract"].replace({'Month-to-month': 0, 'One year':1,
```

In [52]:

```
clean_df.head(2)
```

Out[52]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	O
0	0	0	1	0	1	0	No phone service	DSL	
1	1	0	0	0	34	1	No	DSL	

OneHotEncoding

In [54]:

```
nominal_encoders = [
    'MultipleLines',
    'InternetService',
    'OnlineSecurity',
    'OnlineBackup',
    'DeviceProtection',
    'TechSupport',
    'StreamingTV',
    'StreamingMovies',
    'PaymentMethod'
]
```

In [55]:

```
# Dictionary to save encoders
onehot_encoders = {}

for col in nominal_encoders:
    # Updated parameter name for scikit-learn >= 1.6
    ohe = OneHotEncoder(drop='first', sparse_output=False, dtype=int)
    encoded = ohe.fit_transform(clean_df[[col]])

    # Create column names
    encoded_df = pd.DataFrame(
        encoded,
        columns=[f"{col}_{cat}" for cat in ohe.categories_[0][1:]],
        index=clean_df.index
    )

    # Update dataframe
    clean_df = pd.concat([clean_df.drop(columns=[col]), encoded_df], axis=1)
    onehot_encoders[col] = ohe

# Save encoders
with open("onehot_encoders.pkl", "wb") as f:
    pickle.dump(onehot_encoders, f)
```

In [56]:

```
clean_df
```

Out[56]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Contract	PaperlessBilling	M
0	0	0	1	0	1	0	0	1	

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Contract	PaperlessBilling	M
1	1	0	0	0	34	1	1	0	
2	1	0	0	0	2	1	0	1	
3	1	0	0	0	45	0	1	0	
4	0	0	0	0	2	1	0	1	
...	...	...	...	...	...	...	...	...	
7038	1	0	1	1	24	1	1	1	
7039	0	0	1	1	72	1	1	1	
7040	0	0	1	1	11	0	0	1	
7041	1	1	1	0	4	1	0	1	
7042	1	0	0	0	66	1	2	1	

7021 rows × 30 columns

In [57]:

```
clean_df.shape
```

Out[57]:

```
(7021, 30)
```

In [58]:

```
clean_df.dtypes
```

Out[58]:

```
gender                                    int32
SeniorCitizen                             int64
Partner                                   int32
Dependents                                int32
tenure                                    int64
PhoneService                              int32
Contract                                  int64
PaperlessBilling                          int32
MonthlyCharges                          float64
TotalCharges                            float64
Churn                                     int64
MultipleLines_No phone service            int32
MultipleLines_Yes                         int32
InternetService_Fiber optic               int32
InternetService_No                        int32
OnlineSecurity_No internet service        int32
OnlineSecurity_Yes                        int32
OnlineBackup_No internet service          int32
OnlineBackup_Yes                          int32
DeviceProtection_No internet service      int32
DeviceProtection_Yes                      int32
TechSupport_No internet service           int32
TechSupport_Yes                           int32
StreamingTV_No internet service           int32
StreamingTV_Yes                           int32
StreamingMovies_No internet service       int32
StreamingMovies_Yes                       int32
```

```
PaymentMethod_Credit card (automatic)      int32
PaymentMethod_Electronic check             int32
PaymentMethod_Mailed check                 int32
dtype: object
```

In [59]:

```
clean_df=clean_df.astype(int)
```

In [60]:

```
clean_df.head(3)
```

Out[60]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Contract	PaperlessBilling	Montl
0	0	0	1	0	1	0	0	1	
1	1	0	0	0	34	1	1	0	
2	1	0	0	0	2	1	0	1	

5. Feature Engineering and Extraction

In [62]:

```
clean_df.columns
```

Out[62]:

```
Index(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'Contract', 'PaperlessBilling', 'MonthlyCharges',
       'TotalCharges', 'Churn', 'MultipleLines_No phone service',
       'MultipleLines_Yes', 'InternetService_Fiber optic',
       'InternetService_No', 'OnlineSecurity_No internet service',
       'OnlineSecurity_Yes', 'OnlineBackup_No internet service',
       'OnlineBackup_Yes', 'DeviceProtection_No internet service',
       'DeviceProtection_Yes', 'TechSupport_No internet service',
       'TechSupport_Yes', 'StreamingTV_No internet service', 'StreamingTV_Yes',
       'StreamingMovies_No internet service', 'StreamingMovies_Yes',
       'PaymentMethod_Credit card (automatic)',
       'PaymentMethod_Electronic check', 'PaymentMethod_Mailed check'],
      dtype='object')
```

In [63]:

```
cols = ["tenure","MonthlyCharges","TotalCharges"]
ss = StandardScaler()

clean_df[cols]=ss.fit_transform(clean_df[cols])

with open("scaler.pkl","wb") as f:
  pickle.dump(ss,f)
```

In [64]:

```
clean_df.head(3)
```

Out[64]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Contract	PaperlessBilling	Mo
0	0	0	1	0	-1.282728	0	0	1	
1	1	0	0	0	0.062387	1	1	0	

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Contract	PaperlessBilling	Mo
2	1	0	0	0	-1.241967	1	0	1	

In [65]:

```
slected_features = ['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'Contract', 'PaperlessBilling', 'MonthlyCharges',
       'TotalCharges', 'MultipleLines_No phone service',
       'MultipleLines_Yes', 'InternetService_Fiber optic',
       'InternetService_No', 'OnlineSecurity_No internet service',
       'OnlineSecurity_Yes', 'OnlineBackup_No internet service',
       'OnlineBackup_Yes', 'DeviceProtection_No internet service',
       'DeviceProtection_Yes', 'TechSupport_No internet service',
       'TechSupport_Yes', 'StreamingTV_No internet service', 'StreamingTV_Yes',
       'StreamingMovies_No internet service', 'StreamingMovies_Yes',
       'PaymentMethod_Credit card (automatic)',
       'PaymentMethod_Electronic check', 'PaymentMethod_Mailed check'
]

correlation = {
    feature: pearsonr(clean_df[feature], clean_df['Churn'])[0]
    for feature in slected_features
}

correlation_df = pd.DataFrame(list(correlation.items()), columns=['Feature', 'Pearson Co
correlation_df.sort_values(by='Pearson Correlation', ascending=False)
```

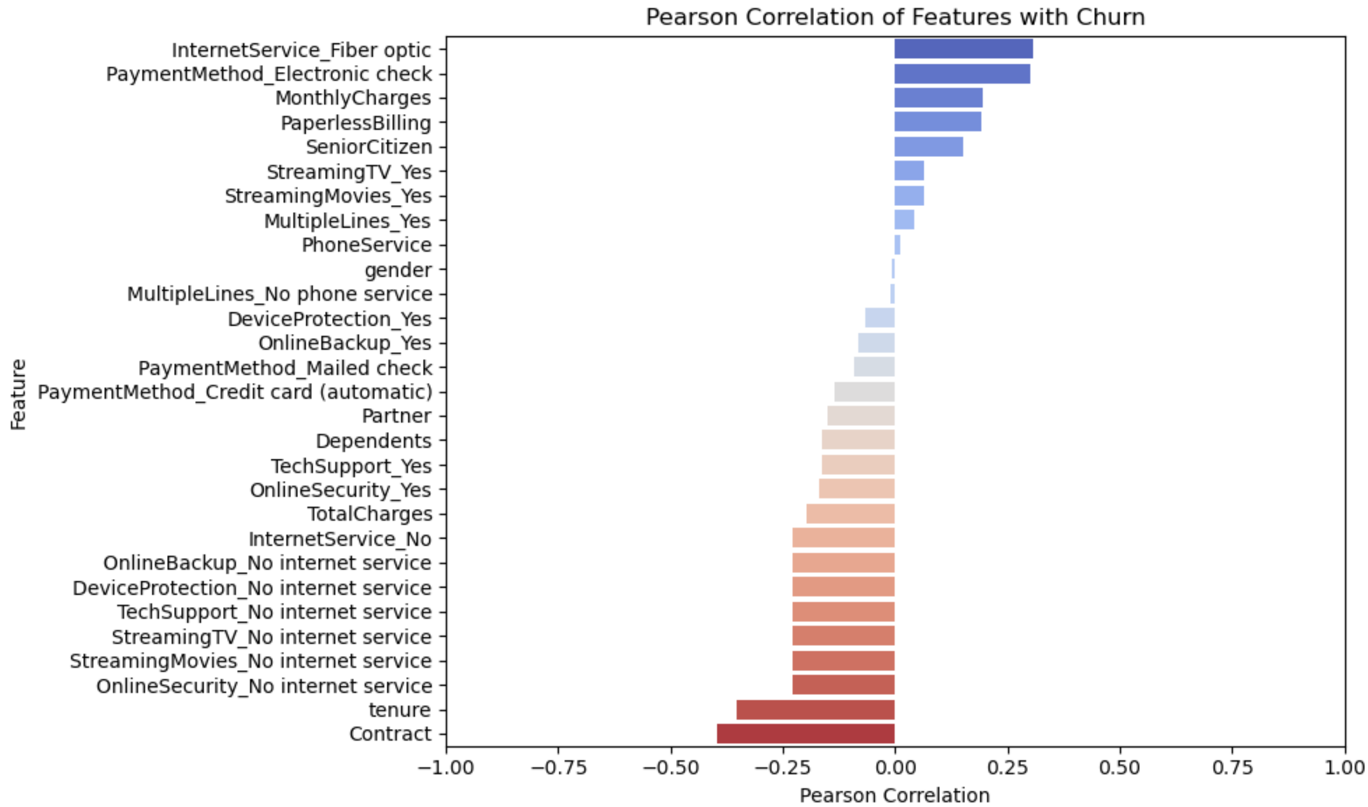
Out[65]:

	Feature	Pearson Correlation
12	InternetService_Fiber optic	0.308170
27	PaymentMethod_Electronic check	0.301544
8	MonthlyCharges	0.194567
7	PaperlessBilling	0.190891
1	SeniorCitizen	0.151619
23	StreamingTV_Yes	0.065032
25	StreamingMovies_Yes	0.063192
11	MultipleLines_Yes	0.041958
5	PhoneService	0.011323
0	gender	-0.008763
10	MultipleLines_No phone service	-0.011323
19	DeviceProtection_Yes	-0.064944
17	OnlineBackup_Yes	-0.081092
28	PaymentMethod_Mailed check	-0.092562
26	PaymentMethod_Credit card (automatic)	-0.133666
2	Partner	-0.149135
3	Dependents	-0.163459

	Feature	Pearson Correlation
21	TechSupport_Yes	-0.163937
15	OnlineSecurity_Yes	-0.170520
9	TotalCharges	-0.197199
13	InternetService_No	-0.228533
16	OnlineBackup_No internet service	-0.228533
18	DeviceProtection_No internet service	-0.228533
20	TechSupport_No internet service	-0.228533
22	StreamingTV_No internet service	-0.228533
24	StreamingMovies_No internet service	-0.228533
14	OnlineSecurity_No internet service	-0.228533
4	tenure	-0.351508
6	Contract	-0.396531

In [66]:

```
# Sort the dataframe by correlation values
correlation_df = correlation_df.sort_values(by='Pearson Correlation', ascending=False)

plt.figure(figsize=(10, 6))
sns.barplot(x='Pearson Correlation', y='Feature', data=correlation_df, palette='coolwarm

plt.title('Pearson Correlation of Features with Churn')
plt.xlabel('Pearson Correlation')
plt.ylabel('Feature')
plt.xlim(-1, 1)  # Correlation values range from -1 to 1
plt.tight_layout()
plt.show()
```



In [67]:

```
categorical_cols = [
    'gender',
    'SeniorCitizen',
    'Partner',
    'Dependents',
    'PhoneService',
    'Contract',
    'PaperlessBilling',
    'MultipleLines_No phone service',
    'MultipleLines_Yes',
    'InternetService_Fiber optic',
    'InternetService_No',
    'OnlineSecurity_No internet service',
    'OnlineSecurity_Yes',
    'OnlineBackup_No internet service',
    'OnlineBackup_Yes',
    'DeviceProtection_No internet service',
    'DeviceProtection_Yes',
    'TechSupport_No internet service',
    'TechSupport_Yes',
    'StreamingTV_No internet service',
    'StreamingTV_Yes',
    'StreamingMovies_No internet service',
    'StreamingMovies_Yes',
    'PaymentMethod_Credit card (automatic)',
    'PaymentMethod_Electronic check',
    'PaymentMethod_Mailed check'
]
```

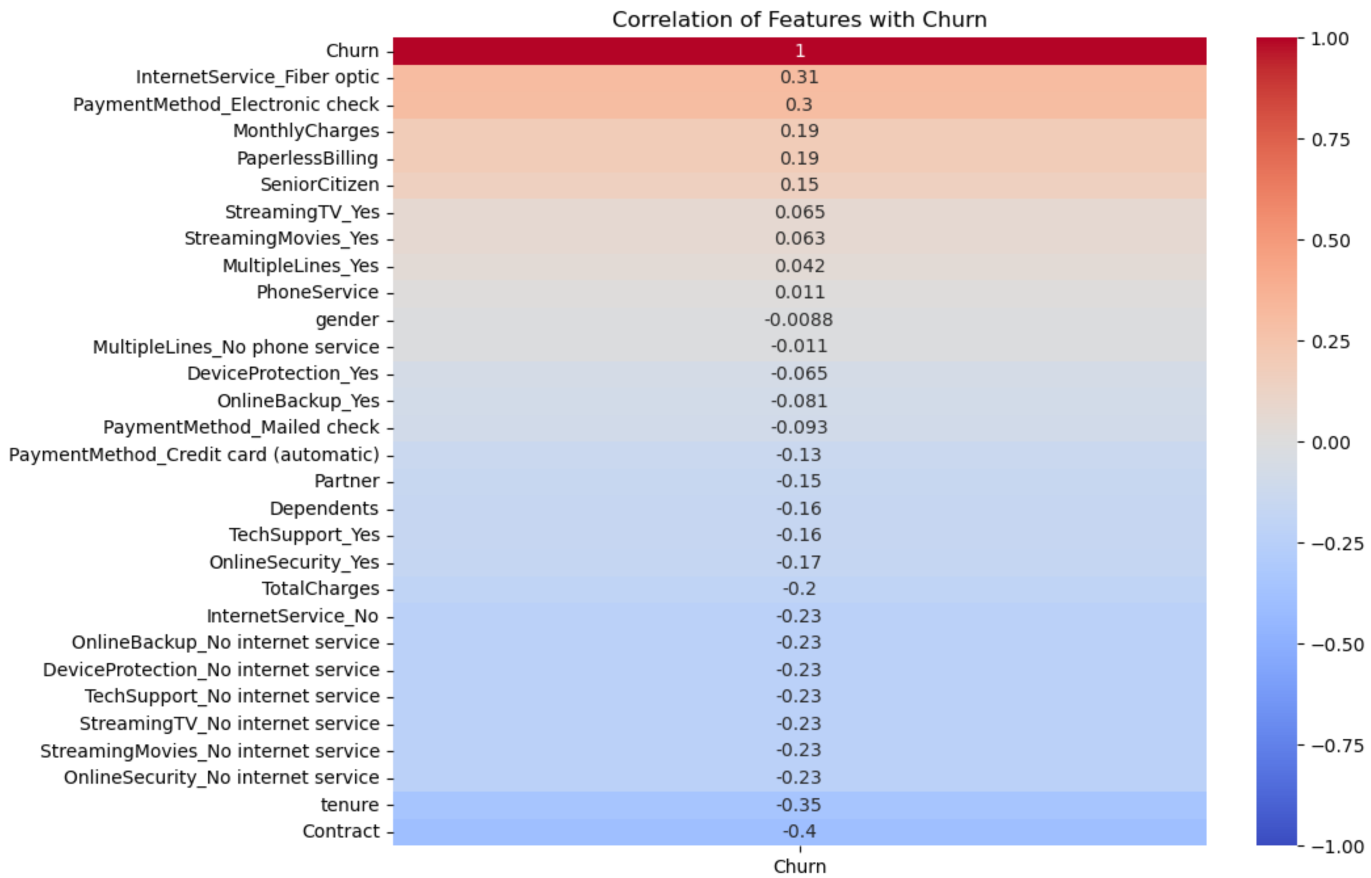
In [68]:

```
# Function to calculate chi-square test
def cramers_v(confusion_matrix):
```

```
    chi2 = chi2_contingency(confusion_matrix)[0]
    n = confusion_matrix.sum().sum()
    phi2 = chi2 / n
    r,k = confusion_matrix.shape
    phi2corr = max(0, phi2 - ((k-1)*(r-1))/(n-1))
    rcorr = r - ((r-1)**2)/(n-1)
    kcorr = k - ((k-1)**2)/(n-1)
    return (phi2corr / min((kcorr-1), (rcorr-1)))**0.5
```

In [69]:

```
# Numeric correlation matrix including Churn_num
corr_matrix = clean_df.corr()

plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix[['Churn']].sort_values(by='Churn', ascending=False),
            annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title('Correlation of Features with Churn')
plt.show()
```



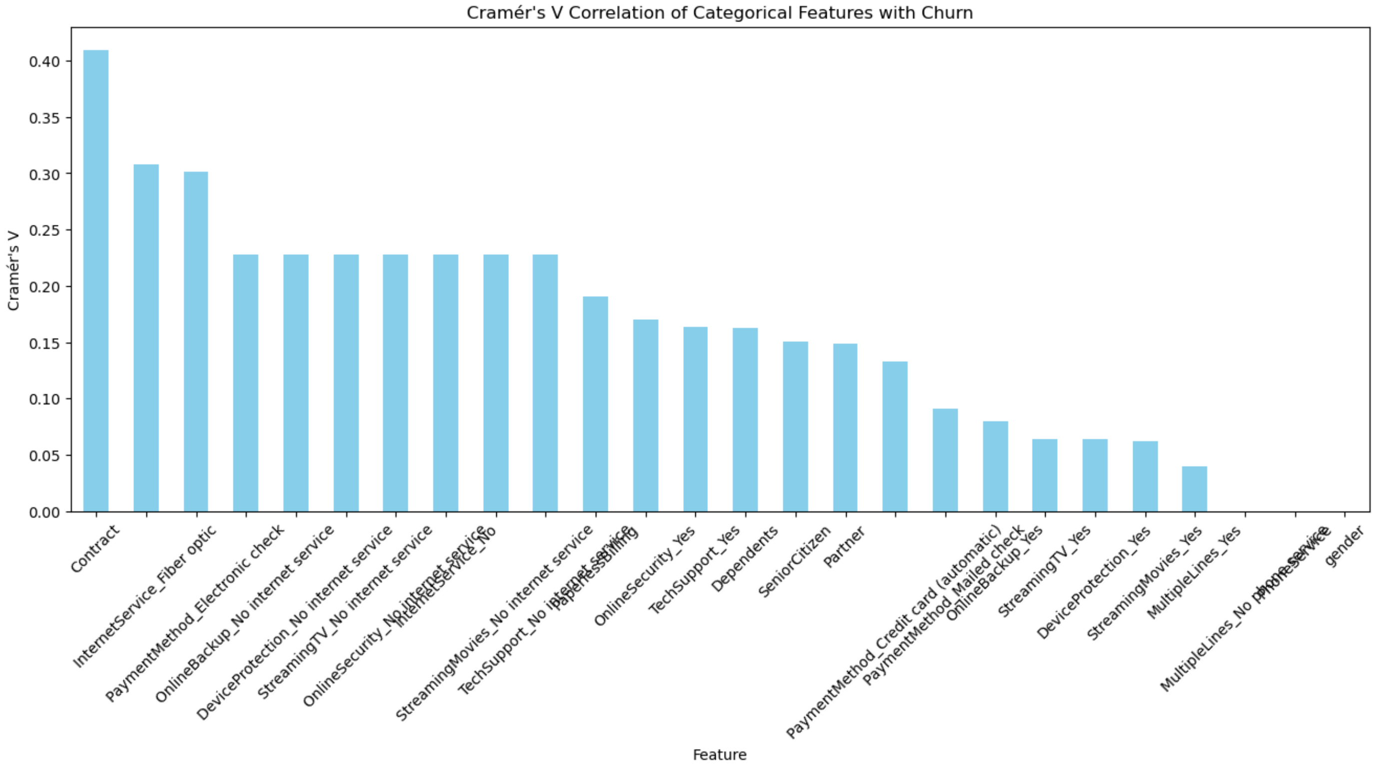
In [70]:

```
# Calculate Cramér's V between Churn and each categorical feature
cramers_results = {}
for col in categorical_cols:
    confusion_mat = pd.crosstab(clean_df[col], clean_df['Churn'])
    cramers_results[col] = cramers_v(confusion_mat)

# Display results sorted by correlation strength
cramers_df = pd.Series(cramers_results).sort_values(ascending=False)
print("Cramér's V correlation with Churn:")
print(cramers_df)
```

```
Cramér's V correlation with Churn:
Contract                                   0.409607
InternetService_Fiber optic                0.307635
PaymentMethod_Electronic check             0.300987
OnlineBackup_No internet service           0.227844
DeviceProtection_No internet service       0.227844
StreamingTV_No internet service            0.227844
OnlineSecurity_No internet service         0.227844
InternetService_No                         0.227844
StreamingMovies_No internet service        0.227844
TechSupport_No internet service            0.227844
PaperlessBilling                           0.190202
OnlineSecurity_Yes                         0.169756
TechSupport_Yes                            0.163157
Dependents                                 0.162681
SeniorCitizen                              0.150720
Partner                                    0.148343
PaymentMethod_Credit card (automatic)      0.132748
PaymentMethod_Mailed check                 0.091407
OnlineBackup_Yes                           0.079871
StreamingTV_Yes                            0.063595
DeviceProtection_Yes                       0.063497
StreamingMovies_Yes                        0.061722
MultipleLines_Yes                          0.039886
MultipleLines_No phone service             0.000000
PhoneService                               0.000000
gender                                     0.000000
dtype: float64
```

In [71]:

```
plt.figure(figsize=(16, 6))
cramers_df.plot(kind='bar', color='skyblue')
plt.title("Cramér's V Correlation of Categorical Features with Churn")
plt.ylabel("Cramér's V")
plt.xlabel("Feature")
plt.xticks(rotation=45)
plt.show()
```



In [72]:

```
'Contract','tenure',
```

Out[72]:

```
('Contract', 'tenure')
```

In [73]:

```
final_df = clean_df[[
    'SeniorCitizen',
    'Partner',
    'Dependents',
    'PaperlessBilling',
    'MonthlyCharges',
    'TotalCharges',
    'tenure',
    'MultipleLines_No phone service',
    'MultipleLines_Yes',
    'InternetService_Fiber optic',
    'InternetService_No',
    'OnlineSecurity_No internet service',
    'OnlineSecurity_Yes',
    'OnlineBackup_No internet service',
    'OnlineBackup_Yes',
    'DeviceProtection_No internet service',
    'DeviceProtection_Yes',
    'TechSupport_No internet service',
    'TechSupport_Yes',
    'StreamingTV_No internet service',
    'StreamingTV_Yes',
    'StreamingMovies_No internet service',
    'StreamingMovies_Yes',
    'PaymentMethod_Credit card (automatic)',
    'PaymentMethod_Electronic check',
    'PaymentMethod_Mailed check',
```

```
    'Churn'
]]
```

In [74]:

```
final_df.shape
```

Out[74]:

```
(7021, 27)
```

In [75]:

```
final_df
```

Out[75]:

	SeniorCitizen	Partner	Dependents	PaperlessBilling	MonthlyCharges	TotalCharges	tenure	M
0	0	1	0	1	-1.176789	-0.995855	-1.282728	
1	0	0	0	0	-0.278879	-0.175276	0.062387	
2	0	0	0	1	-0.378647	-0.961003	-1.241967	
3	0	0	0	0	-0.744462	-0.196893	0.510759	
4	0	0	0	1	0.186704	-0.942032	-1.241967	
...	...	...	...	...	...	...	...	
7038	0	1	1	1	0.652287	-0.130717	-0.345224	
7039	0	1	1	1	1.284150	2.239258	1.611307	
7040	0	1	1	1	-1.176789	-0.856004	-0.875118	
7041	1	1	0	1	0.319728	-0.873651	-1.160445	
7042	0	0	0	1	1.350662	2.010731	1.366741	

7021 rows × 27 columns

6. Training and Test data Split

In [77]:

```
# Splitting the features and target
x = final_df.drop('Churn',axis=1)
y = final_df['Churn']
```

In [78]:

```
# split training and test data
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42
```

In [79]:

```
print(y_train.shape)
```

```
(5616,)
```

In [80]:

```
print(y_train.value_counts())
```

```
Churn
0    4111
```

```
1    1505
Name: count, dtype: int64
```

Synthetic Minority Oversampling Thechnique(SMOTE)

In [82]:

```
smote = SMOTE()
```

In [83]:

```
x_train_smote, y_train_smote = smote.fit_resample(x_train, y_train)
```

In [84]:

```
print(y_train_smote.shape)
```

```
(8222,)
```

In [85]:

```
print(y_train_smote.value_counts())
```

```
Churn
1    4111
0    4111
Name: count, dtype: int64
```

7. Model Training

In [87]:

```
# Dictionary of Model
models = {
    "Decision Tree": DecisionTreeClassifier(random_state=42),
    "Random Forest": RandomForestClassifier(random_state=42),
    "XGBoost": XGBClassifier(random_state=42),
    "Logistic Regression": LogisticRegression(random_state=42, max_iter=1000)
}
```

In [88]:

```
# Dictionary to store the cross validation result
cv_scores = {}

# Perform 3_fold cross validation for each model
for model_name, model in models.items():
  # print(model_name)
  # print(model)
  # print("-"*500)
  print(f"Training {model_name} with default parameters")
  scores = cross_val_score(model, x_train_smote, y_train_smote, cv=5, scoring="accuracy"
  cv_scores[model_name] = scores
  print(f"{model_name} cross-validation accuracy: {np.mean(scores):.2f}")
  print("-"*50)
```

```
Training Decision Tree with default parameters
Decision Tree cross-validation accuracy: 76.76
--------------------------------------------------
Training Random Forest with default parameters
Random Forest cross-validation accuracy: 83.95
--------------------------------------------------
Training XGBoost with default parameters
XGBoost cross-validation accuracy: 81.99
--------------------------------------------------
```

```
Training Logistic Regression with default parameters
Logistic Regression cross-validation accuracy: 78.46
--------------------------------------------------
```

Random Forest gives the highest accuracy compared to other models with default parameters

In [90]:

```
rfc = RandomForestClassifier(random_state=42)
```

In [91]:

```
rfc.fit(x_train_smote, y_train_smote)
```

Out[91]:

```
▾ RandomForestClassifier
RandomForestClassifier(random_state=42)
```

In [92]:

```
print(y_test.value_counts())
```

```
Churn
0    1053
1     352
Name: count, dtype: int64
```

8. Model Evaluation

In [94]:

```
# evaluate on test data
y_test_pred = rfc.predict(x_test)

print("Accuracy Score:\n", accuracy_score(y_test, y_test_pred))
print("Confsuion Matrix:\n", confusion_matrix(y_test, y_test_pred))
print("Classification Report:\n", classification_report(y_test, y_test_pred))
```

```
Accuracy Score:
 0.7651245551601423
Confsuion Matrix:
 [[853 200]
 [130 222]]
Classification Report:
               precision    recall  f1-score   support

           0       0.87      0.81      0.84      1053
           1       0.53      0.63      0.57       352

    accuracy                           0.77      1405
   macro avg       0.70      0.72      0.71      1405
weighted avg       0.78      0.77      0.77      1405
```

In [95]:

```
 # save the trained model as a pickle file
model_data = {"model": rfc, "features_names": x.columns.tolist()}

with open("customer_churn_model.pkl","wb") as f:
  pickle.dump(model_data, f)
loaded_model = model_data["model"]
```

```
feature_names = model_data["features_names"]

with open("onehot_encoders.pkl", "rb") as f:
  encoders = pickle.load(f)

with open("binary_encoders.pkl", "rb") as f:
  binary_encoders = pickle.load(f)

with open("scaler.pkl", "rb") as f:
  scaler = pickle.load(f)
```

9. Load the saved model and build a Predictive System

In [97]:

```
customer_data = {
    'gender': 'Female',
    'SeniorCitizen': 0,
    'Partner': 'Yes',
    'Dependents': 'No',
    'tenure': 1,
    'PhoneService': 'No',
    'MultipleLines': 'No phone service',
    'InternetService': 'DSL',
    'OnlineSecurity': 'No',
    'OnlineBackup': 'Yes',
    'DeviceProtection': 'No',
    'TechSupport': 'No',
    'StreamingTV': 'No',
    'StreamingMovies': 'No',
    'Contract': 'Month-to-month',
    'PaperlessBilling': 'Yes',
    'PaymentMethod': 'Electronic check',
    'MonthlyCharges': 29.85,
    'TotalCharges': 29.85
}

input_df = pd.DataFrame([customer_data])
print(input_df.head())

# encode categorical features using the saved encoders

# Label encode binary columns
binary_encoders_df = ['Partner', 'Dependents', 'PhoneService', 'PaperlessBilling']
for col in binary_encoders_df:
  if col in input_df.columns:
    input_df[col] = binary_encoders[col].transform(input_df[col])

# One-hot encode multi-class columns
multi_class_cols = [
        'MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBackup',
        'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies',
        'Contract', 'PaymentMethod'
]
for col in encoders:
    if col in input_df.columns:
        col_data = input_df[[col]]
        encoded = encoders[col].transform(col_data)
        encoded_df = pd.DataFrame(
```

```
            encoded,
            columns=encoders[col].get_feature_names_out([col]),
            index=input_df.index
        )
        input_df = pd.concat([input_df.drop(columns=[col]), encoded_df], axis=1)

# Scale numerical features
num_cols = ["tenure", "MonthlyCharges", "TotalCharges"]
input_df[num_cols] = scaler.transform(input_df[num_cols])

# Add missing columns with 0
for col in model_data['features_names']:
    if col not in input_df.columns:
        input_df[col] = 0

# Ensure column order matches training
input_df = input_df[model_data['features_names']]
```

```
   gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  Female              0     Yes         No       1           No

      MultipleLines InternetService OnlineSecurity OnlineBackup  \
0  No phone service             DSL             No          Yes

  DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
0               No          No          No              No  Month-to-month

  PaperlessBilling     PaymentMethod  MonthlyCharges  TotalCharges
0              Yes  Electronic check           29.85         29.85
```

In [98]:

```
# Predict class label (0 or 1)
prediction = loaded_model.predict(input_df)

# Predict class probabilities (array of [prob_no_churn, prob_churn])
pred_prob = loaded_model.predict_proba(input_df)

print("Raw prediction output:", prediction)
print("Prediction probabilities:", pred_prob)

# Interpret prediction
print(f"Prediction: {'Churn' if prediction[0] == 1 else 'No Churn'}")

# Show probability of churn (class 1)
print(f"Probability of Churn: {pred_prob[0][1]:.4f}")
```

```
Raw prediction output: [0]
Prediction probabilities: [[0.62 0.38]]
Prediction: No Churn
Probability of Churn: 0.3800
```

In [ ]: