📝 Telco Customer Churn Analysis

✅ Author: Muhammad Tahir

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📊 What I did here:

In this notebook, I explored the Telco Customer Churn dataset, broke down key trends and factors causing churn.

1️⃣ Importing Libraries and Dataset

1.1 Load necessary libraries

In [4]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

1.2 Import dataset

In [6]:

```
df = pd.read_csv('Telco_Customer_Churn.csv')
```

1.3 Quick dataset overview

In [8]:

```
df.sample(5)
```

Out[8]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	Phon
3785	8337-UPOAQ	Male	1	Yes	No	10	
4082	0112-QWPNC	Male	0	Yes	No	49	
2679	7341-LXCAF	Male	0	Yes	No	4	
6760	5295-PCJOO	Male	0	No	Yes	4	
1163	0135-NMXAP	Female	0	No	No	12	

5 rows × 21 columns

2️⃣ Data Understanding & Basic Checks

2.1 Dataset shape

In [11]:
```
df.shape
```

Out[11]: (7043, 21)

2.2 Check columns names and dtypes

In [13]:
```
df.info(verbose=True)
```

```
<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
```

2.3 Check for missing values

In [15]:
```
df.isnull().sum()
```

Out[15]:
```
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
```

2.4 Quick statistical summary

In [17]:
```
df.describe()
```

Out[17]:

	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

- The **SeniorCitizen** column represents a categorical variable (0 = No, 1 = Yes), meaning percentile-based distribution (25%-50%-75%) isn’t meaningful for analysis. Only **16.2%** of the customers fall into this category.
- Regarding **tenure**, 75% of customers have been subscribed for **less than 55 months**, with an average tenure of **32 months**. However, some customers have remained for as long as **72 months** (6 years), showing significant variability.
- For monthly charges, the average bill stands at $64.76, butpricingvarieswidely. Whilehalfofthecustomerspay$70.35 or less, the top 25% are billed over $89.85permonth. Thehighestmonthlychargereaches$118.75, which is significantly above the average.

2.5 Check Duplicates

In [20]:
```
df.duplicated().sum()
```

Out[20]: 0

3️⃣ Data Cleaning & Preprocessing

In [22]:
```
# TotalCharges is stored as an object; it needs conversion
df['TotalCharges'] =  pd.to_numeric(df['TotalCharges'], errors='coerce')
```

In [23]:
```
df.isnull().sum()
```

Out[23]:
```
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        11
Churn                0
dtype: int64
```

In [24]:
```
df.dropna(how='any', inplace=True)
```

In [25]:
```
# convert 'SeniorCitizen' to categorical
df['SeniorCitizen'] = df['SeniorCitizen'].map({1:'Yes', 0:'No'})
```

In [26]:
```
df.info(verbose=True)
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 7032 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   customerID        7032 non-null   object 
 1   gender            7032 non-null   object 
 2   SeniorCitizen     7032 non-null   object 
 3   Partner           7032 non-null   object 
 4   Dependents        7032 non-null   object 
 5   tenure            7032 non-null   int64  
 6   PhoneService      7032 non-null   object 
 7   MultipleLines     7032 non-null   object 
 8   InternetService   7032 non-null   object 
 9   OnlineSecurity    7032 non-null   object 
 10  OnlineBackup      7032 non-null   object 
 11  DeviceProtection  7032 non-null   object 
 12  TechSupport       7032 non-null   object 
 13  StreamingTV       7032 non-null   object 
 14  StreamingMovies   7032 non-null   object 
 15  Contract          7032 non-null   object 
 16  PaperlessBilling  7032 non-null   object 
 17  PaymentMethod     7032 non-null   object 
 18  MonthlyCharges    7032 non-null   float64
 19  TotalCharges      7032 non-null   float64
 20  Churn             7032 non-null   object 
dtypes: float64(2), int64(1), object(18)
memory usage: 1.2+ MB
```

Categorize customers into groups based on their tenure. For example, assign a tenure group of 1-12 for customers with a tenure of less than 12 months, 13-24 for those with a tenure between 1 and 2 years, and continue grouping in a similar manner.

In [28]:
```
df['tenure'].max()
```

Out[28]:
```
72
```

In [29]:
```
# group tenure into bins of 12 months and assign labels to these groups
labels = [f"{i} - {i+11}" for i in range(1, 72, 12)]

df['tenure_group'] = pd.cut(df['tenure'], range(1, 80, 12), right=False, lab
```

In [30]:
```
df['tenure_group'].value_counts()
```

Out[30]:
```
tenure_group
1 - 12     2175
61 - 72    1407
13 - 24    1024
25 - 36     832
49 - 60     832
37 - 48     762
Name: count, dtype: int64
```

In [31]:
```
# drop unnecessary columns
df.drop(columns=['customerID'], axis=1 ,inplace=True)
df.sample(5)
```

Out[31]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Mu
6974	Female	No	Yes	No	51	Yes	
2331	Female	No	Yes	No	25	Yes	
4162	Female	No	Yes	Yes	72	No	
2192	Male	Yes	Yes	No	56	Yes	
6490	Male	No	No	No	26	Yes	

5 rows × 21 columns

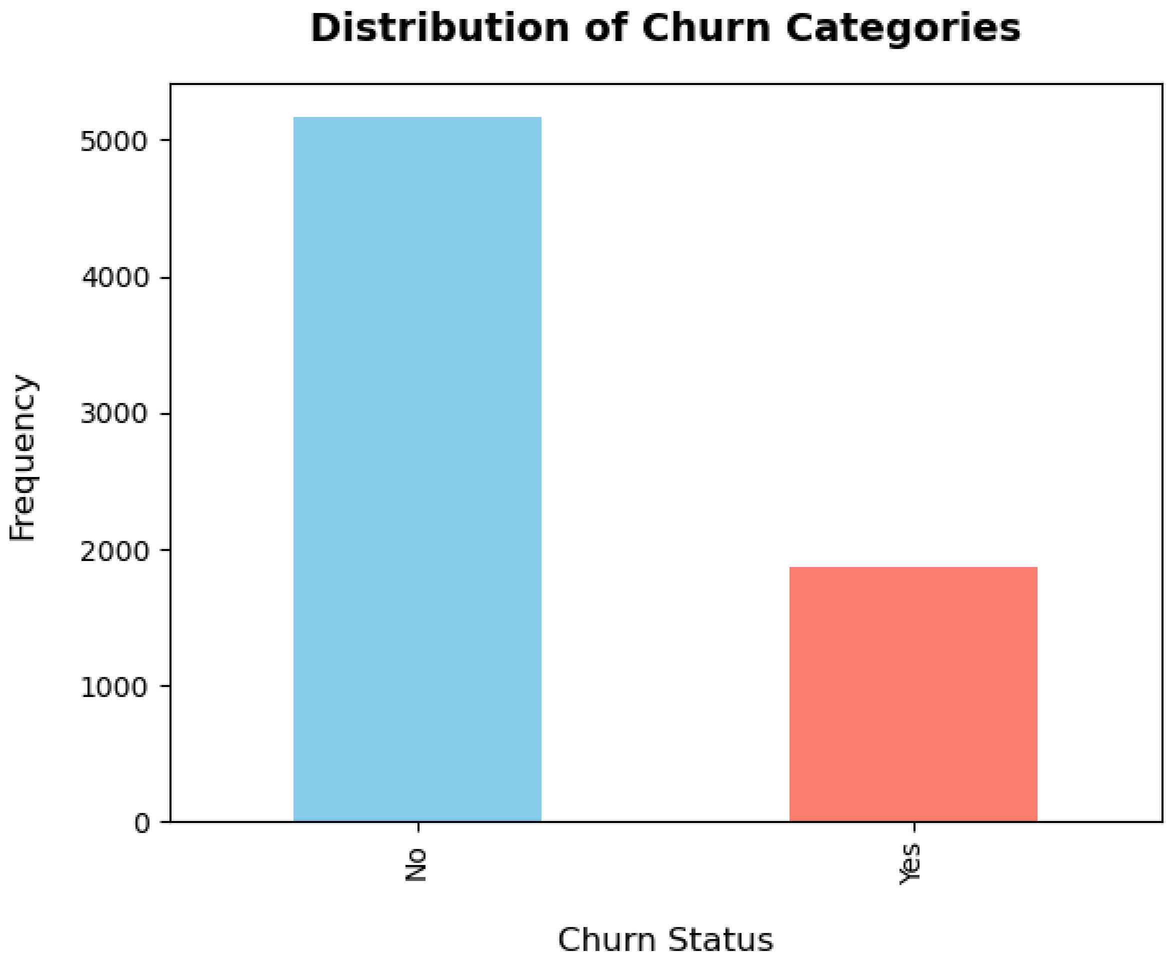
🔎 Data Exploration

4️⃣ Univariate Analysis

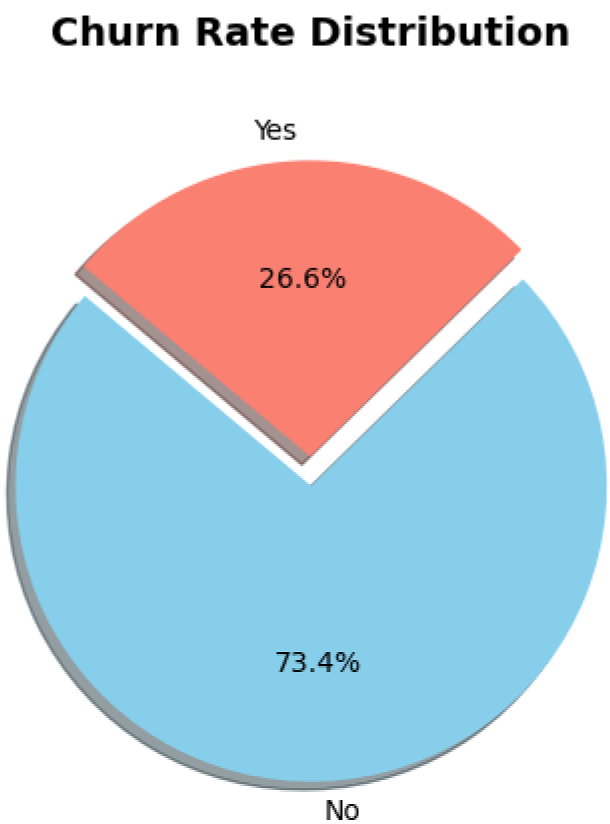
In [34]:
```
df['Churn'].value_counts()
```

Out[34]:
```
Churn
No     5163
Yes    1869
Name: count, dtype: int64
```

In [35]:
```
# visulaizing the distribution of churn variable
df['Churn'].value_counts().plot(kind='bar', color=['skyblue', 'salmon'])
plt.ylabel('Frequency', fontsize=12, labelpad=15)
plt.xlabel('Churn Status', fontsize=12, labelpad=15)
plt.title('Distribution of Churn Categories', fontsize=14, fontweight='bold'
plt.show()
```

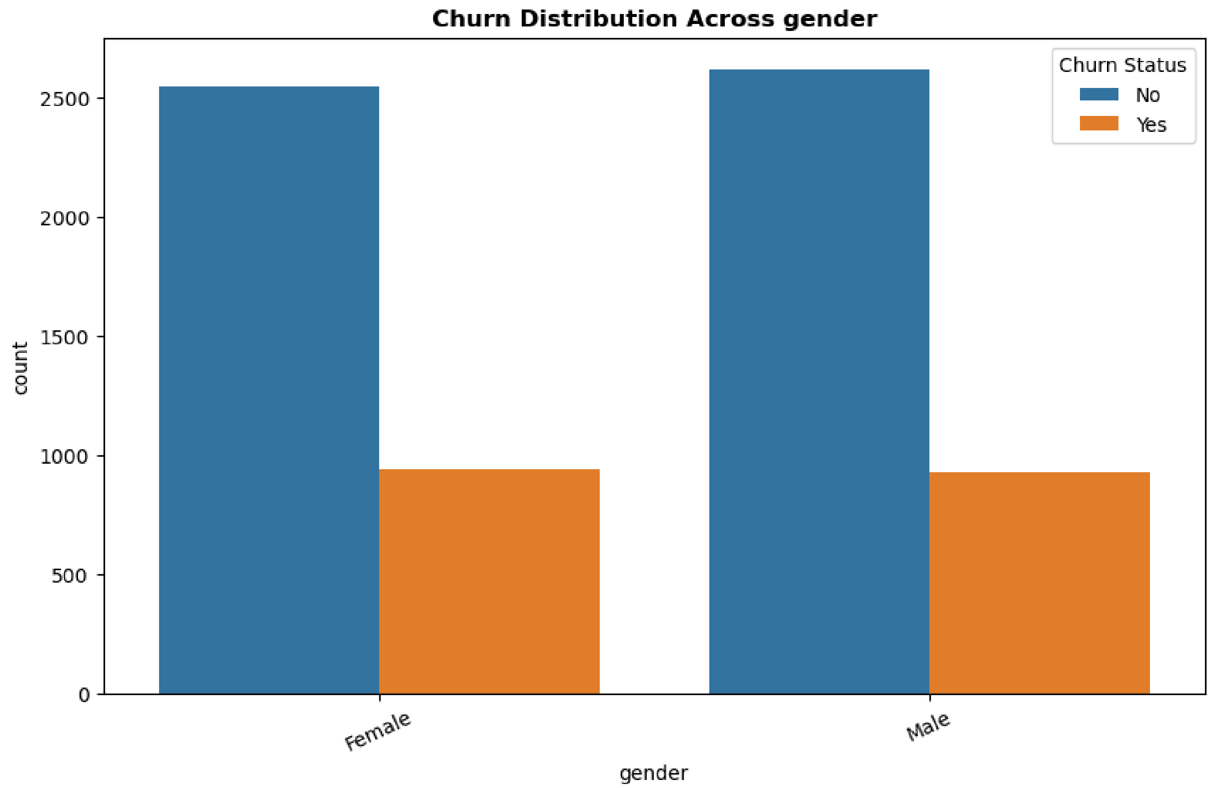


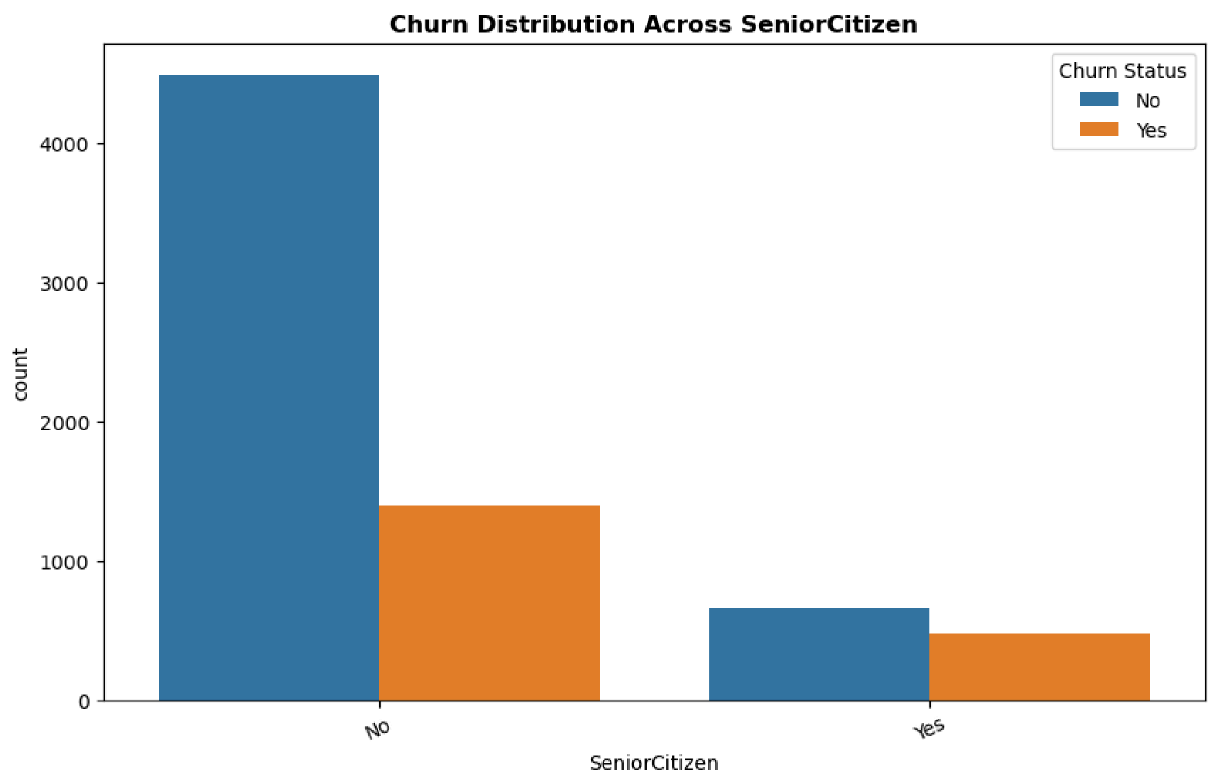
In [36]:
```
df['Churn'].value_counts().plot(kind='pie', autopct='%1.1f%%', startangle=14
plt.ylabel("")
plt.title("Churn Rate Distribution", fontsize=14, fontweight='bold', pad=15)
plt.show()
```

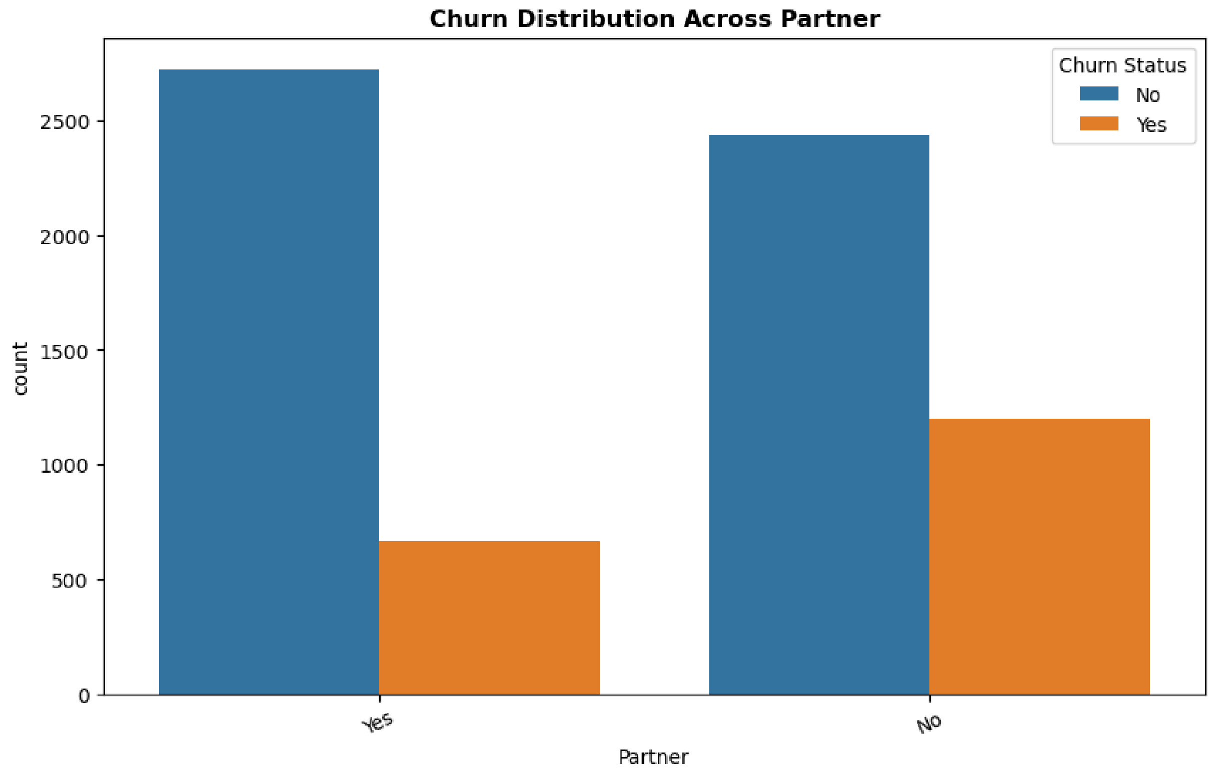


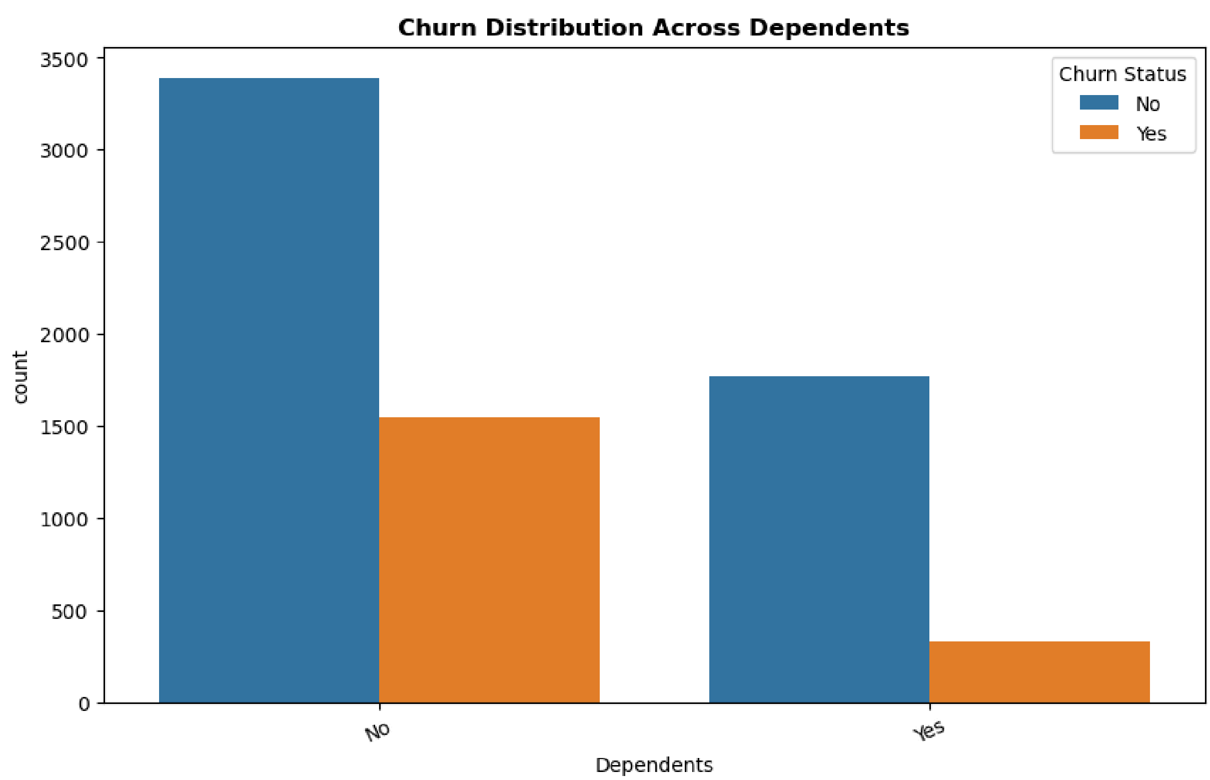
In [37]:
```
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

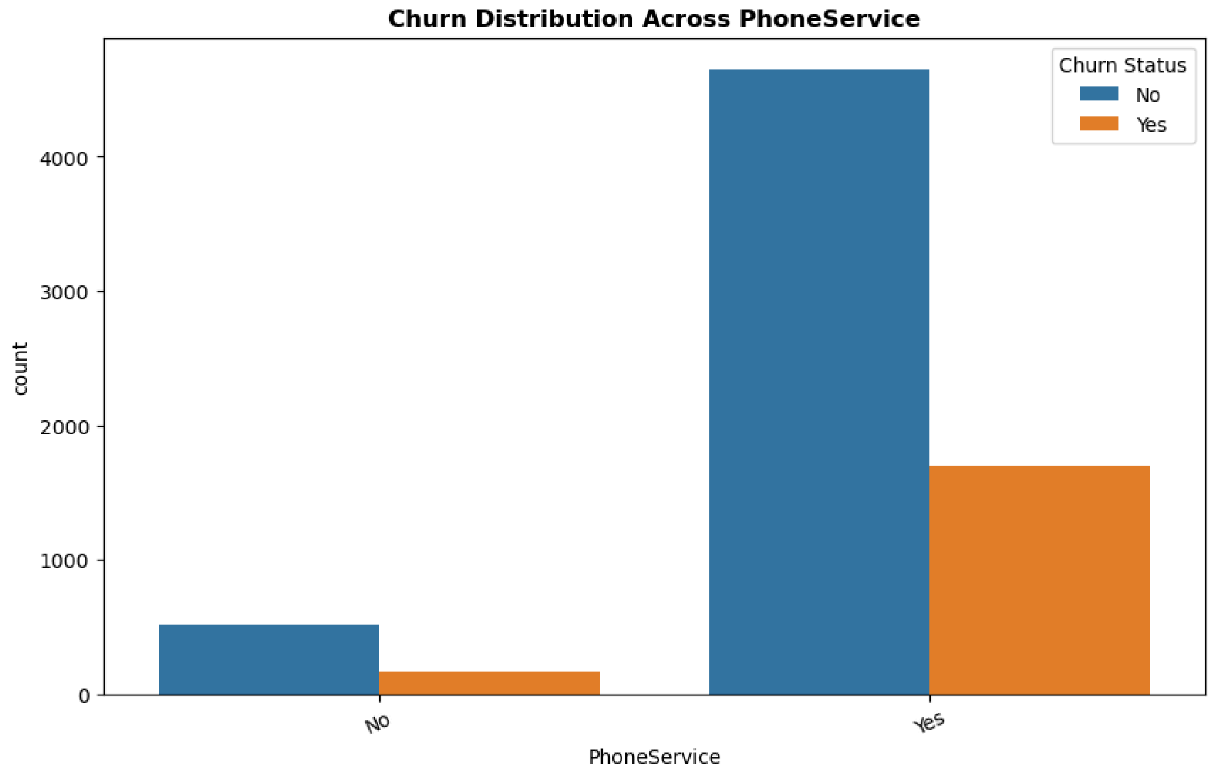
In [38]:
```
# visualizing the distribution of each categorical feature with respect to c
for idx, feature in enumerate(df.drop(columns=['Churn', 'TotalCharges', 'Mor
    plt.figure(idx, figsize=(10,6))
    sns.countplot(data=df, x=feature, hue='Churn')
    plt.title(f"Churn Distribution Across {feature}", fontweight='bold')
    plt.xticks(rotation=25)
    plt.legend(title='Churn Status')
    plt.show()
    print("\n\n")
```


Churn Distribution Across gender
Churn Status
No
Yes
count
2500
2000
1500
1000
500
0
Female
Male
gender

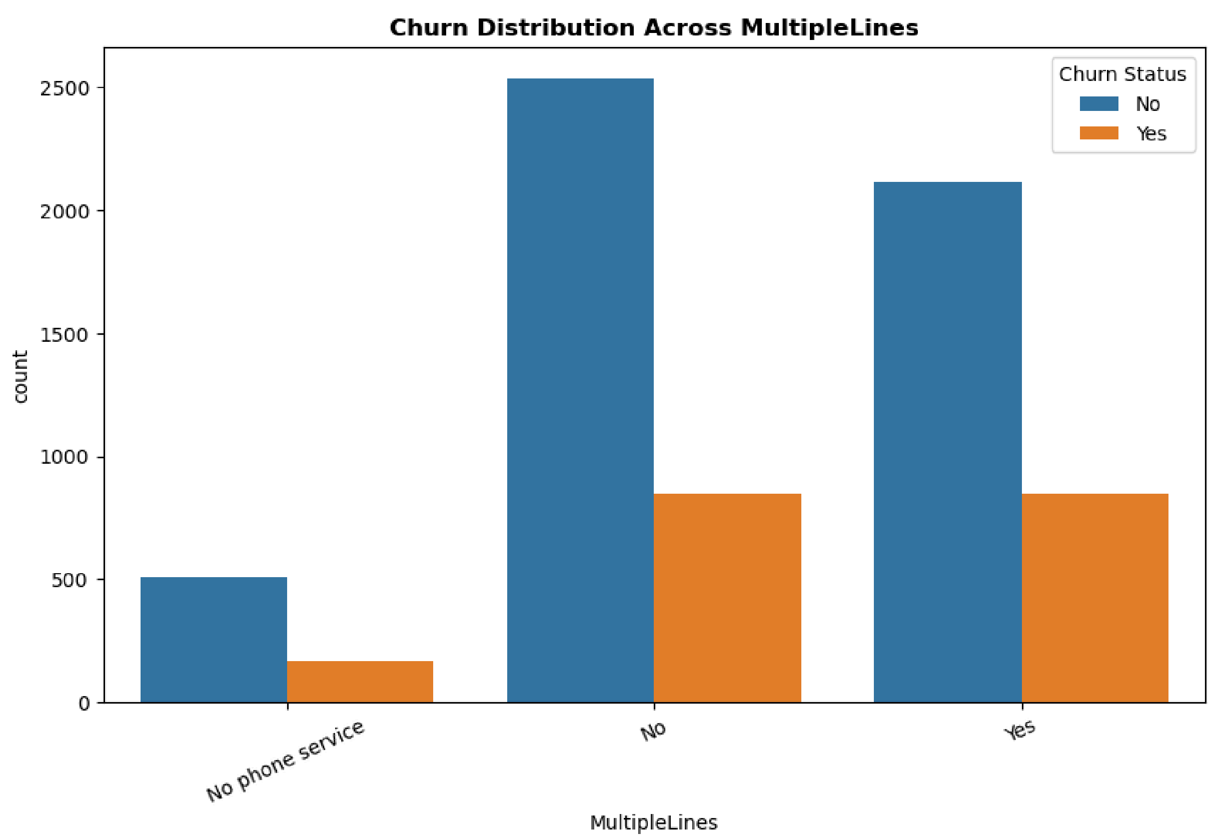

Churn Distribution Across SeniorCitizen
Churn Status
No
Yes
count
4000
3000
2000
1000
0
No
Yes
SeniorCitizen


Churn Distribution Across Partner
Churn Status
No
Yes
count
0
500
1000
1500
2000
2500
Yes
No
Partner

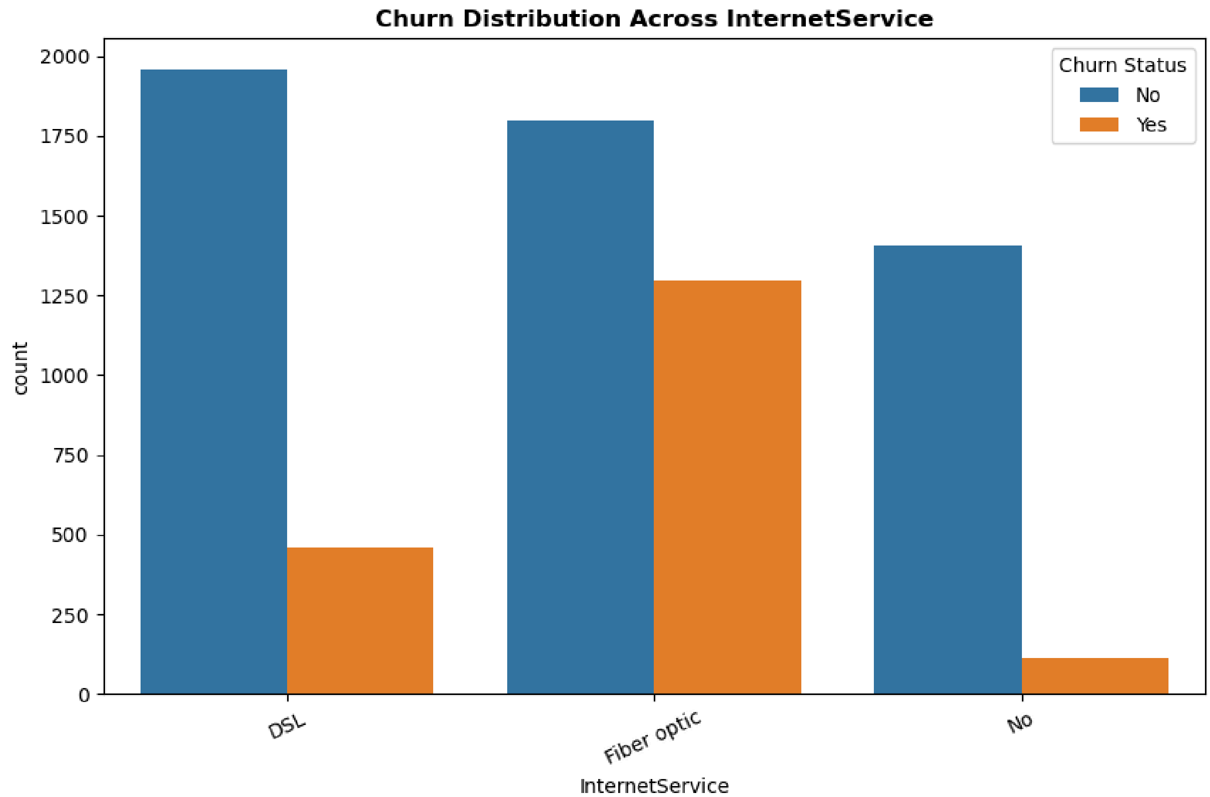

Churn Distribution Across Dependents
Churn Status
No
Yes
count
0
500
1000
1500
2000
2500
3000
3500
No
Yes
Dependents

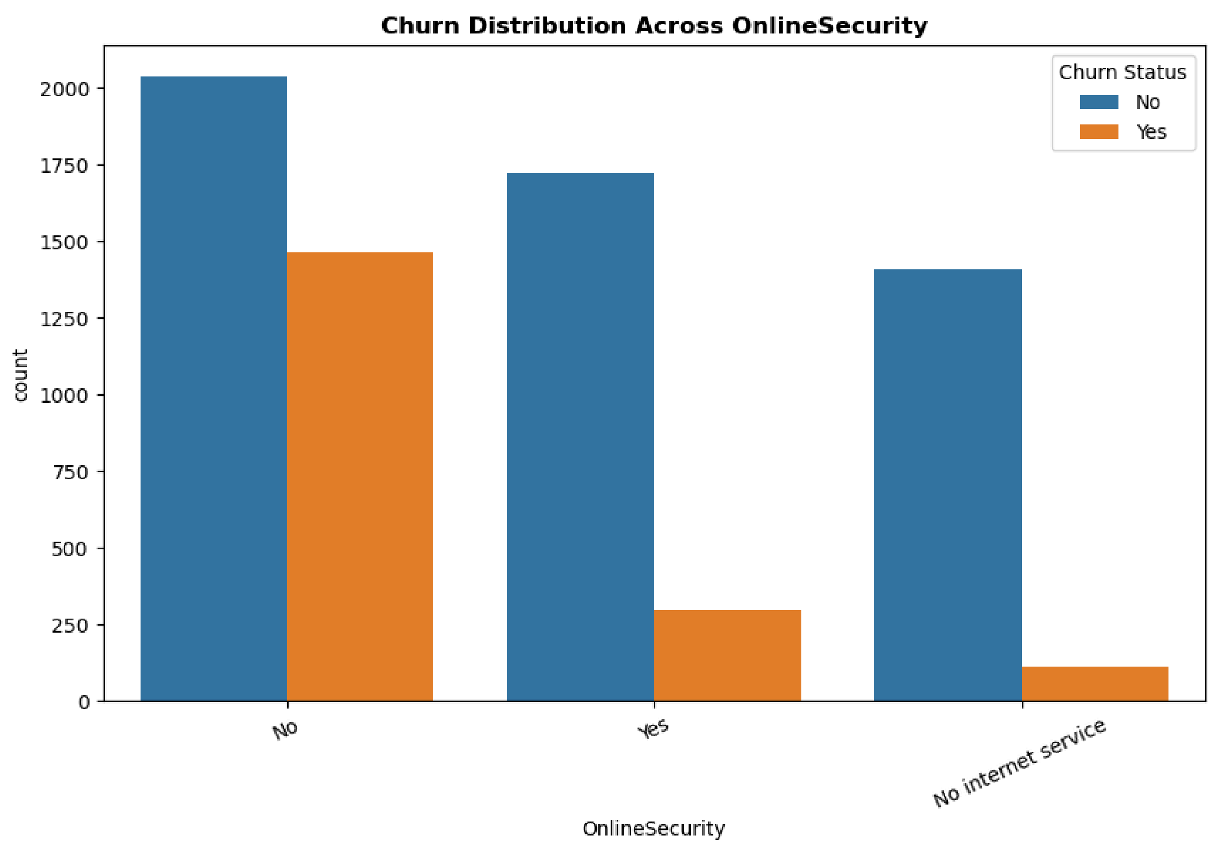


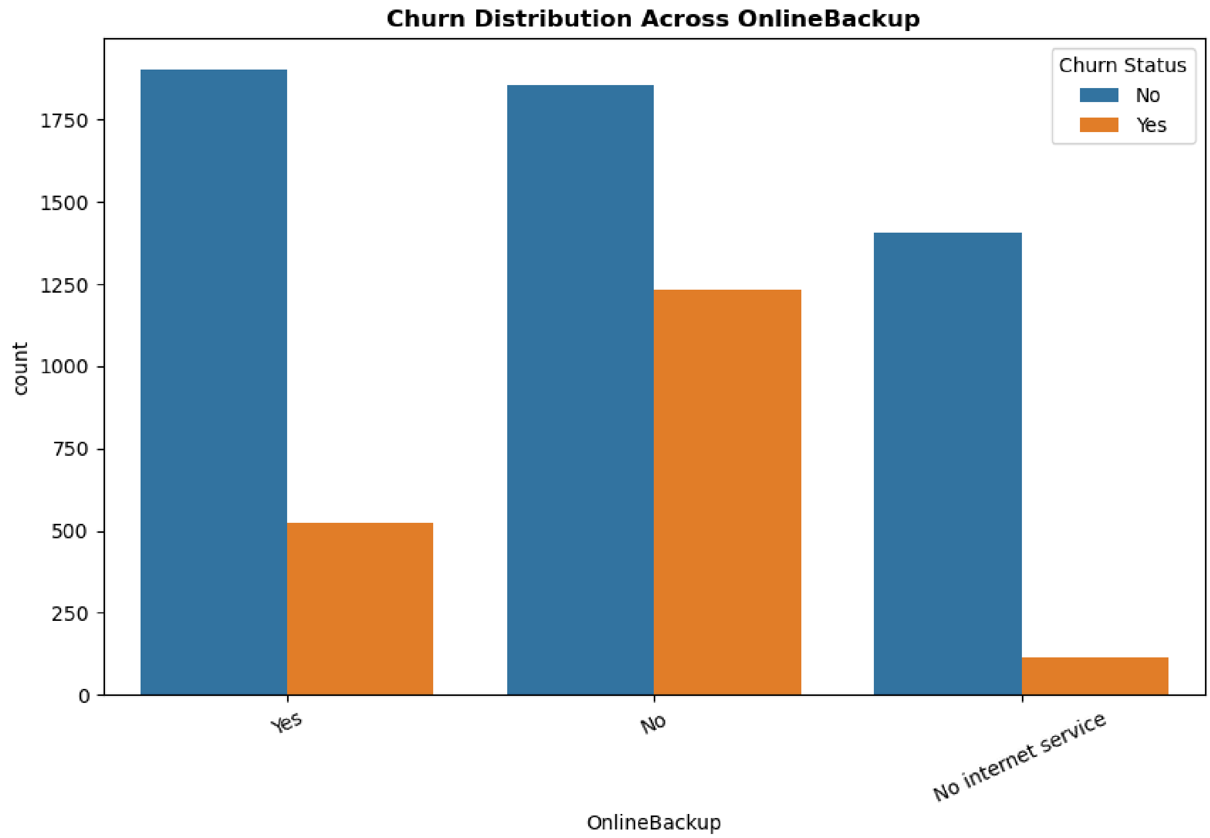
Churn Distribution Across PhoneService
Churn Status
No
Yes
count
0
1000
2000
3000
4000
No
Yes
PhoneService

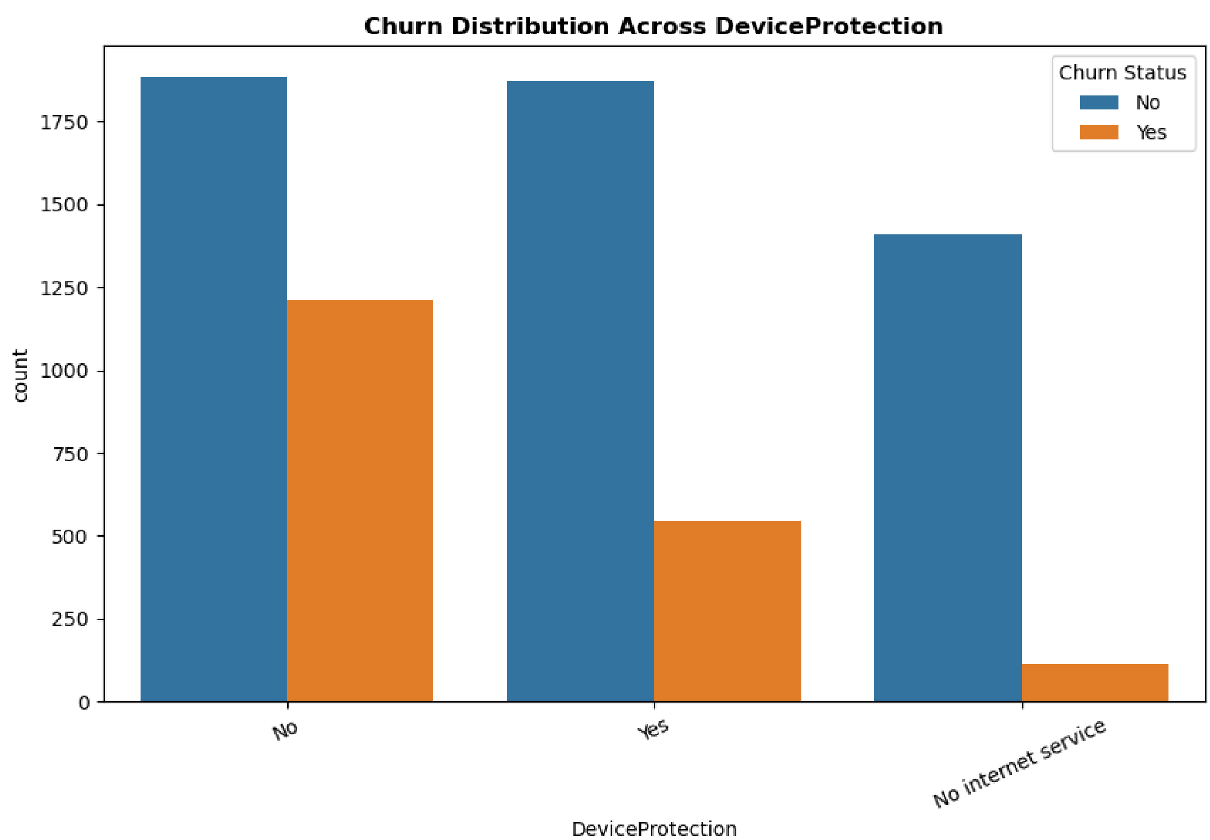


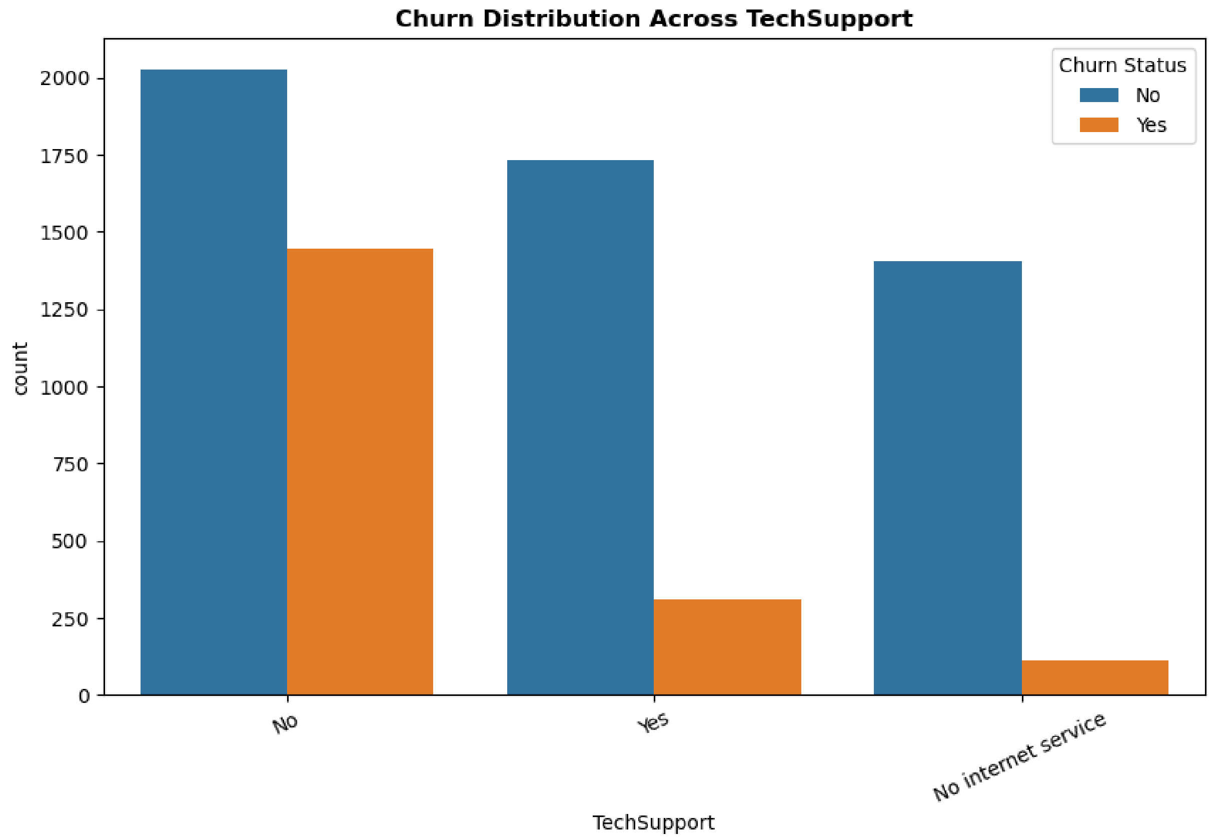
Churn Distribution Across MultipleLines
Churn Status
No
Yes
count
0
500
1000
1500
2000
2500
No phone service
No
Yes
MultipleLines


Churn Distribution Across InternetService
Churn Status
No
Yes
count
2000
1750
1500
1250
1000
750
500
250
0
DSL
Fiber optic
No
InternetService

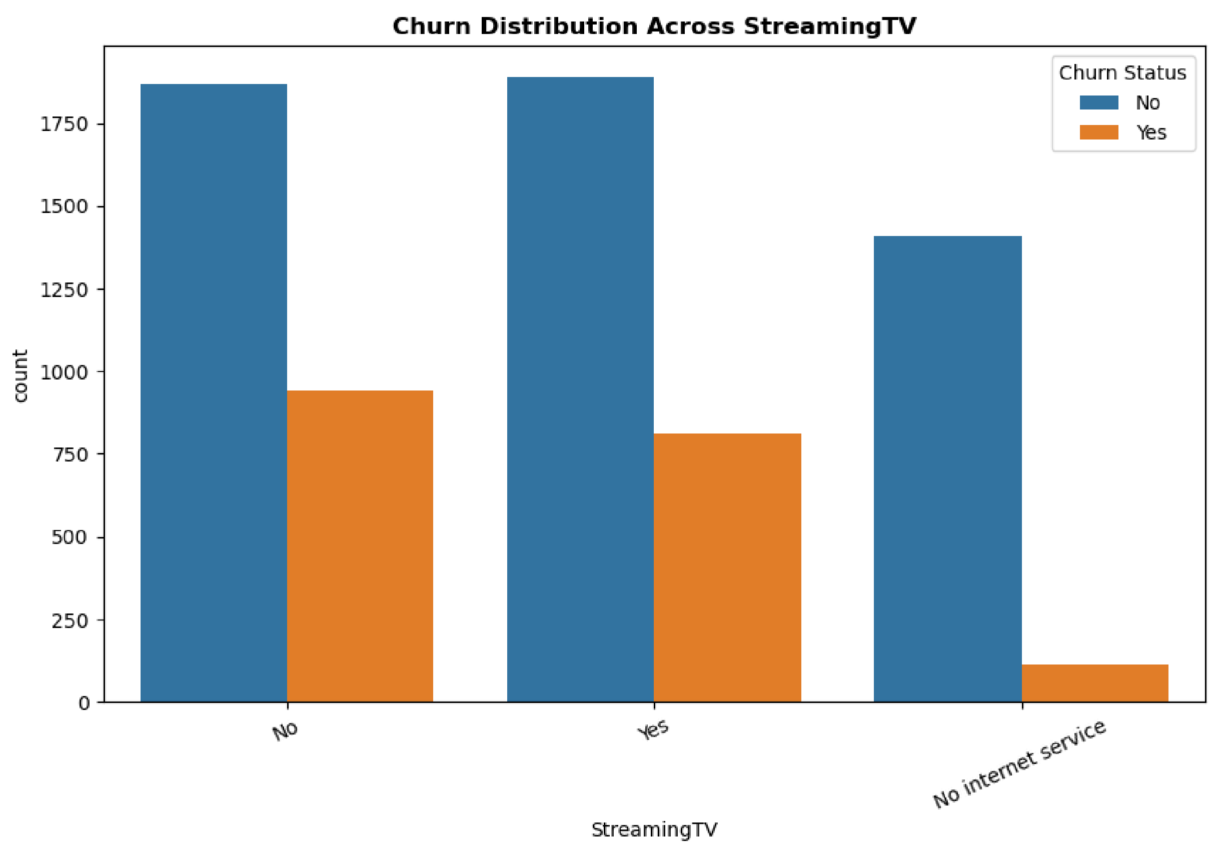

Churn Distribution Across OnlineSecurity
Churn Status
No
Yes
count
2000
1750
1500
1250
1000
750
500
250
0
No
Yes
No internet service
OnlineSecurity


Churn Distribution Across OnlineBackup
Churn Status
No
Yes
count
0
250
500
750
1000
1250
1500
1750
Yes
No
No internet service
OnlineBackup

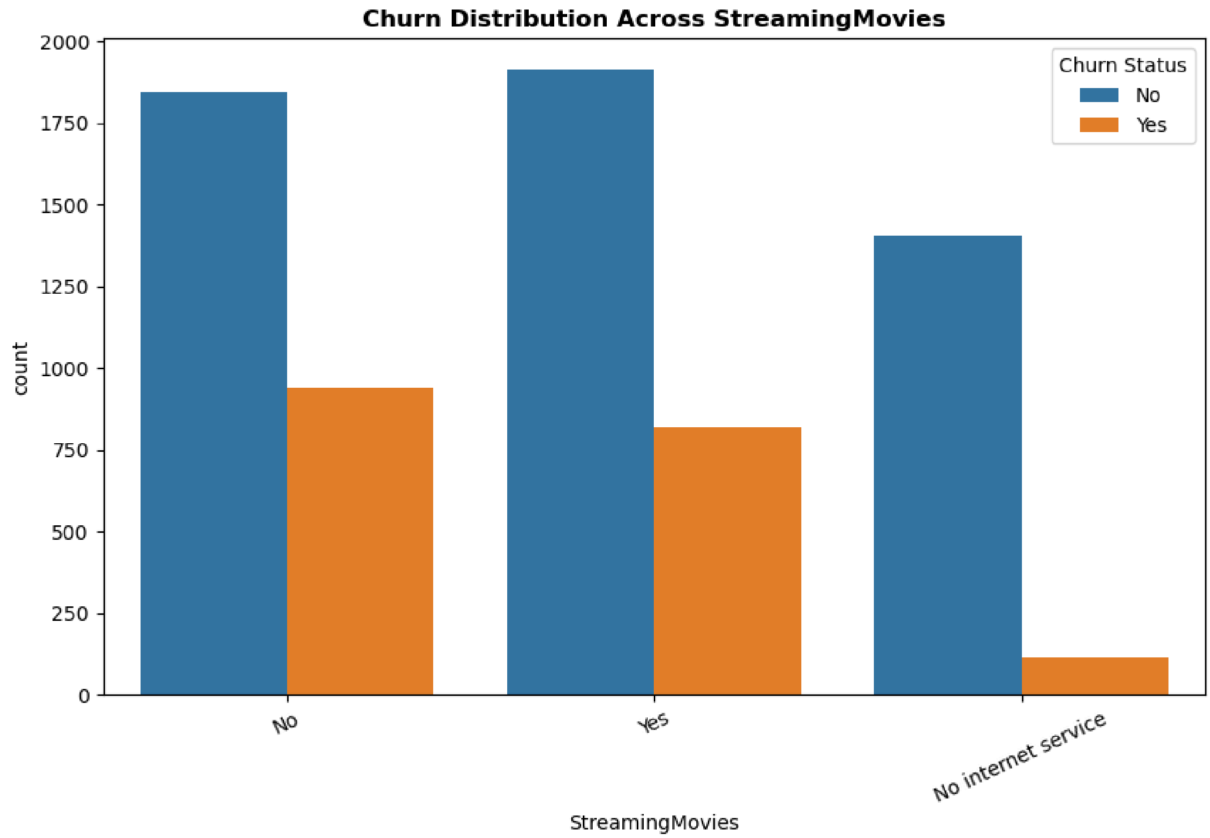

Churn Distribution Across DeviceProtection
Churn Status
No
Yes
count
0
250
500
750
1000
1250
1500
1750
No
Yes
No internet service
DeviceProtection

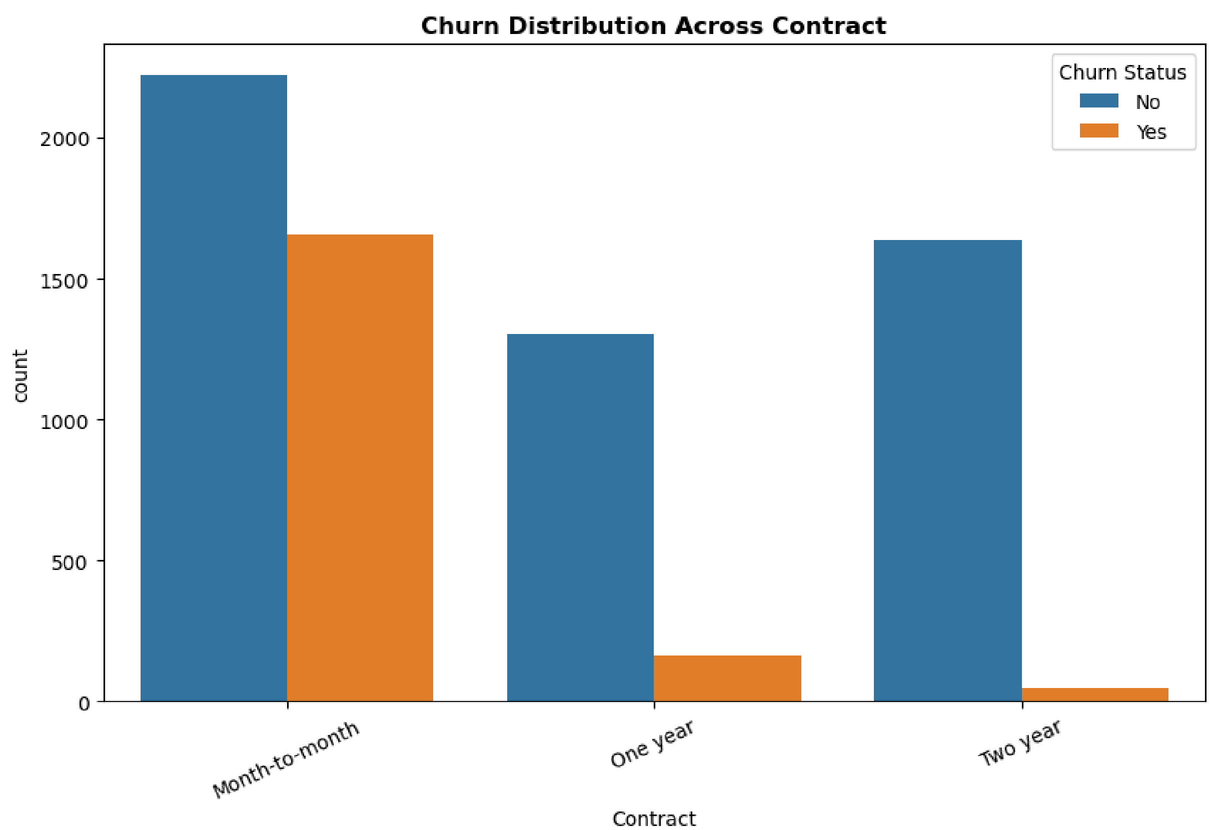


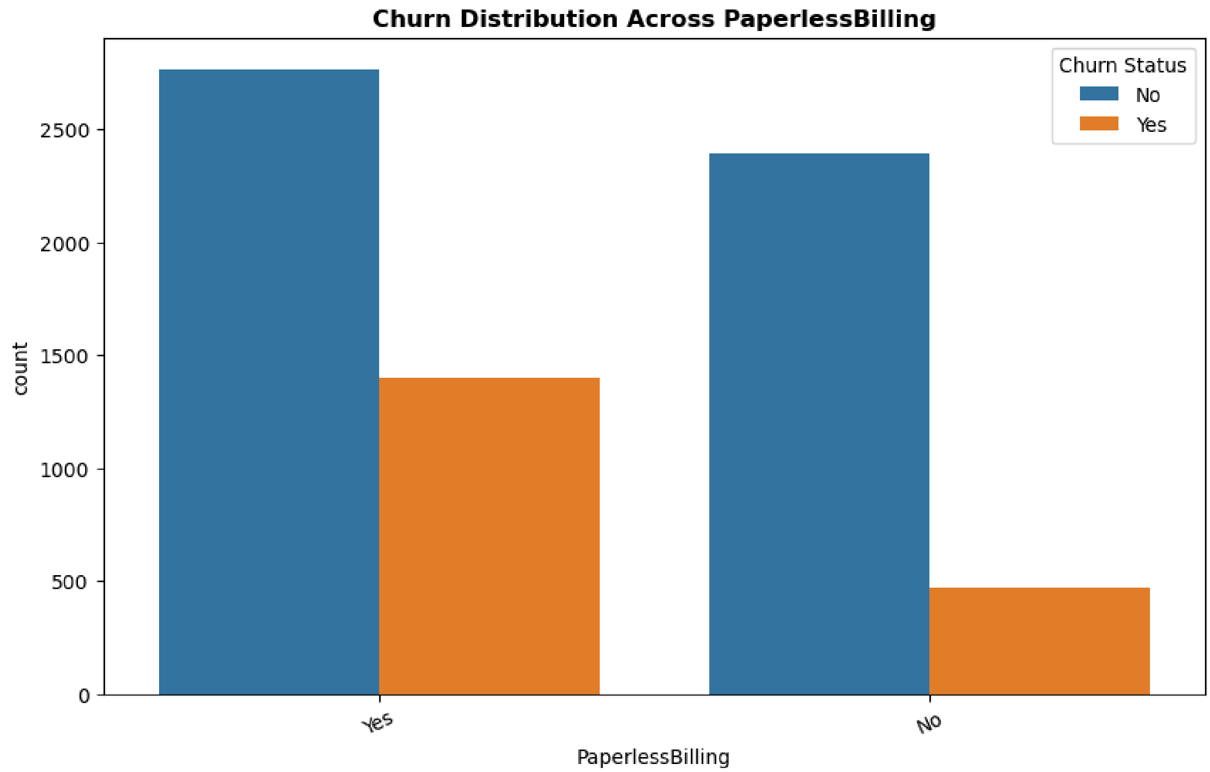
Churn Distribution Across TechSupport
Churn Status
No
Yes
count
2000
1750
1500
1250
1000
750
500
250
0
No
Yes
No internet service
TechSupport

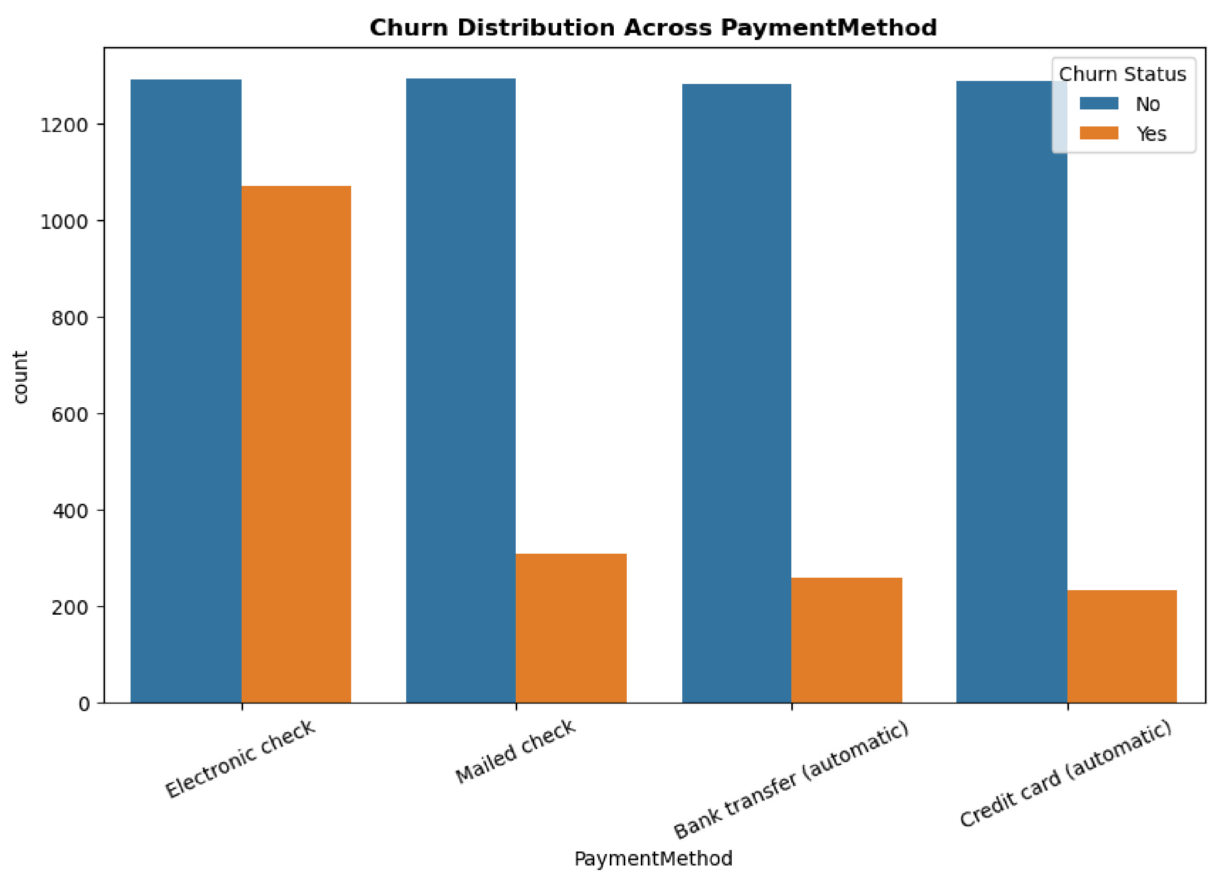


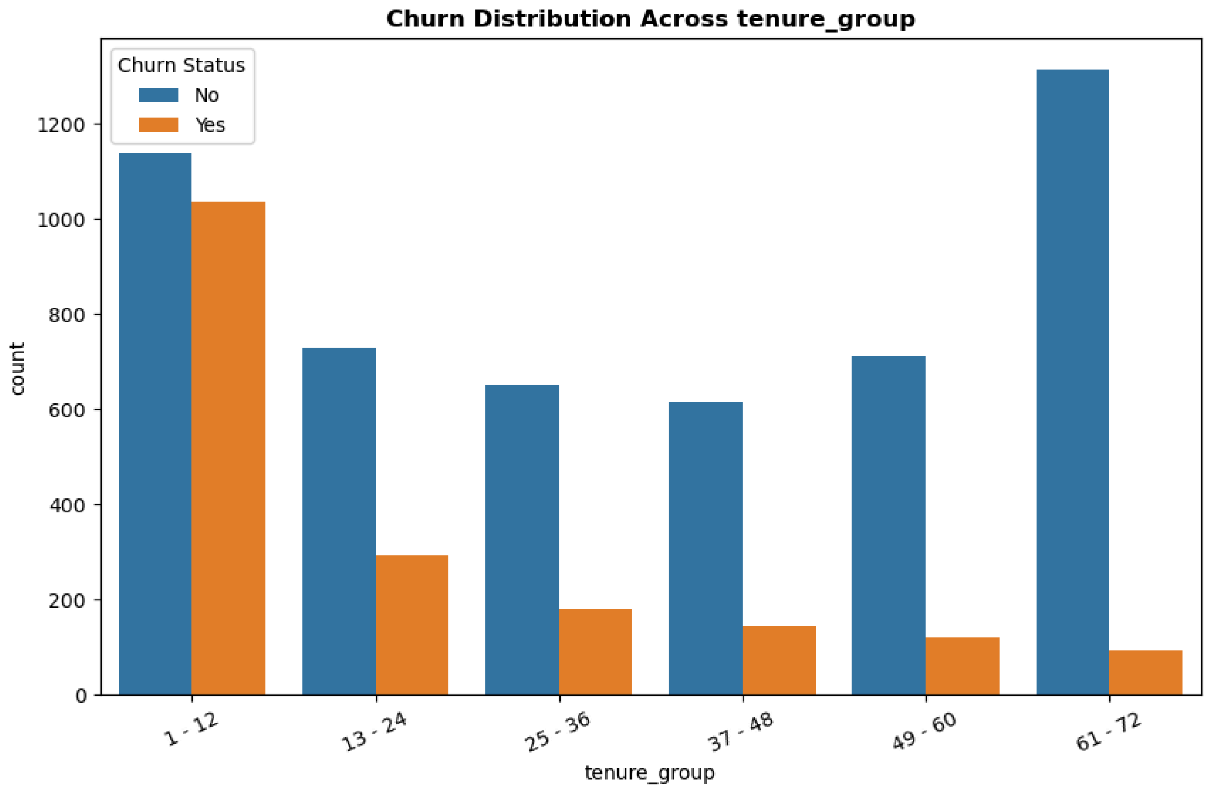
Churn Distribution Across StreamingTV
Churn Status
No
Yes
count
1750
1500
1250
1000
750
500
250
0
No
Yes
No internet service
StreamingTV


Churn Distribution Across StreamingMovies
count
2000
1750
1500
1250
1000
750
500
250
0
Churn Status
No
Yes
No
Yes
No internet service
StreamingMovies


Churn Distribution Across Contract
count
2000
1500
1000
500
0
Churn Status
No
Yes
Month-to-month
One year
Two year
Contract


Churn Distribution Across PaperlessBilling
Churn Status
No
Yes
count
0
500
1000
1500
2000
2500
Yes
No
PaperlessBilling


Churn Distribution Across PaymentMethod
Churn Status
No
Yes
count
0
200
400
600
800
1000
1200
Electronic check
Mailed check
Bank transfer (automatic)
Credit card (automatic)
PaymentMethod



Univariate Analysis:

- Customers who use streaming movies are less likely to churn.
- Month-to-month contracts have the highest churn.
- One-year and two-year contracts show very low churn rates.
- Churn is much higher for Fiber optic users compared to DSL users.
- Paperless billing users churn more compared to those who receive paper bills.
- Customers paying through electronic checks tend to churn the most.
- Automatic payments (bank transfer or credit card) users are more stable.
- New customers with less than a year of tenure churn the most.
- Customers with higher tenure rarely churn.

In [40]:
```
df.head()
```

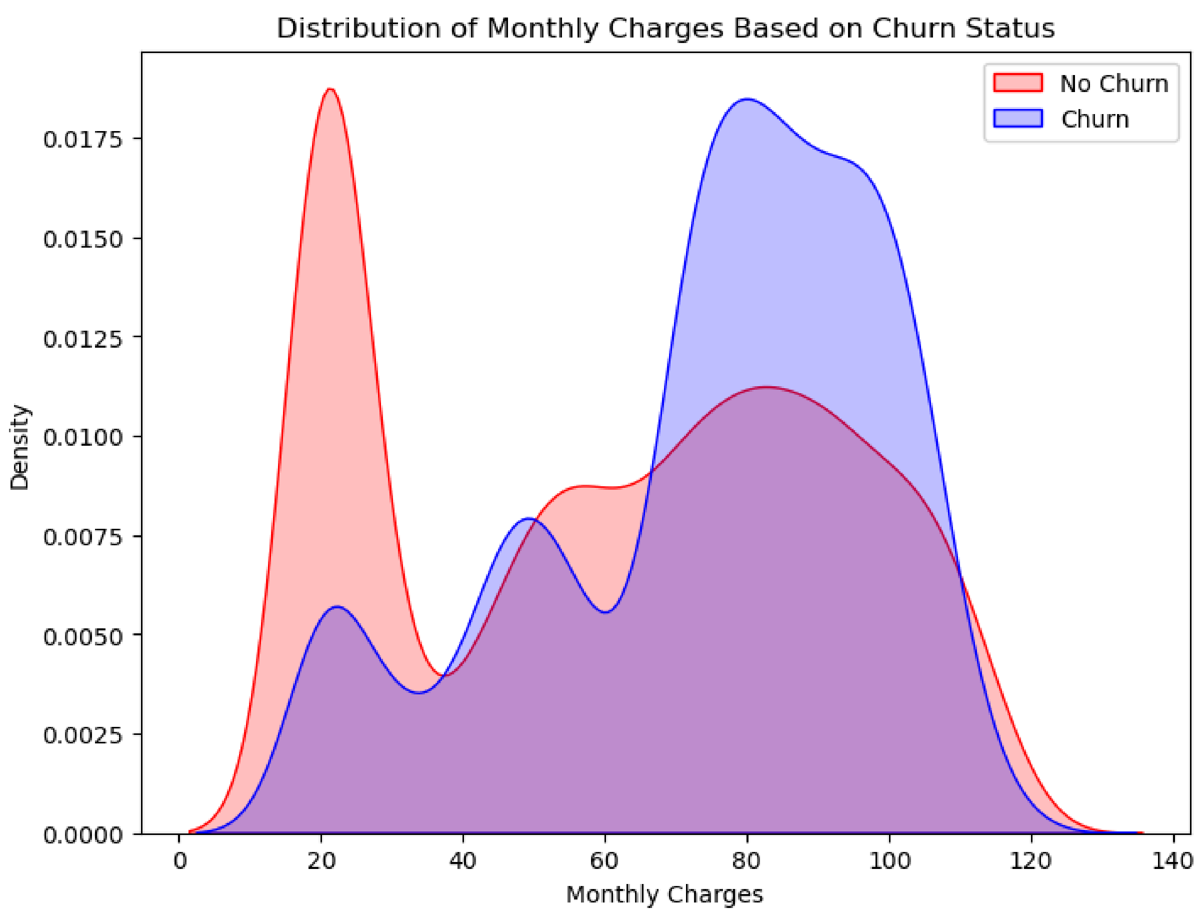
Out[40]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	Multipl
0	Female	No	Yes	No	1	No	Nc
1	Male	No	No	No	34	Yes	
2	Male	No	No	No	2	Yes	
3	Male	No	No	No	45	No	Nc
4	Female	No	No	No	2	Yes	

5 rows × 21 columns

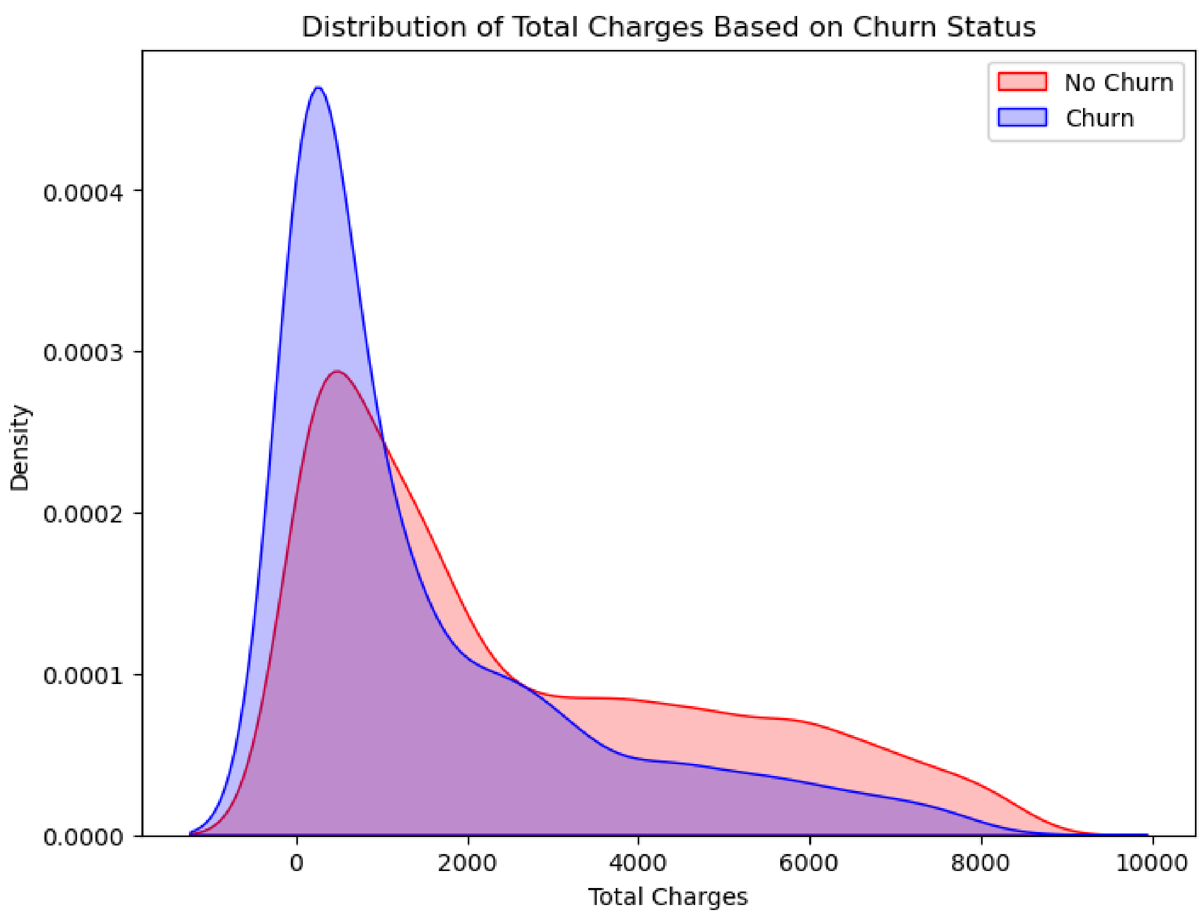
In [41]:

```
# visualizing the distribution of Monthly Charges for churned and non-churne
plt.figure(figsize=(8,6))
sns.kdeplot(df[df["Churn"]=='No']['MonthlyCharges'], shade=True, color='red'
sns.kdeplot(df[df['Churn']=='Yes']['MonthlyCharges'], shade=True, color='blu
plt.legend(loc='upper right')
plt.xlabel("Monthly Charges")
plt.title('Distribution of Monthly Charges Based on Churn Status')
plt.show()
```



Insight: Customers with higher monthly charges tend to have a higher churn rate.

In [43]:
```
# visualizing the distribution of Total Charges for churned and non-churned
plt.figure(figsize=(8,6))
sns.kdeplot(df[df['Churn']=='No']['TotalCharges'], shade=True, color='red',
sns.kdeplot(df[df['Churn']=='Yes']['TotalCharges'], shade=True, color='blue'
plt.legend(loc='upper right')
plt.xlabel('Total Charges')
plt.title("Distribution of Total Charges Based on Churn Status")
plt.show()
```

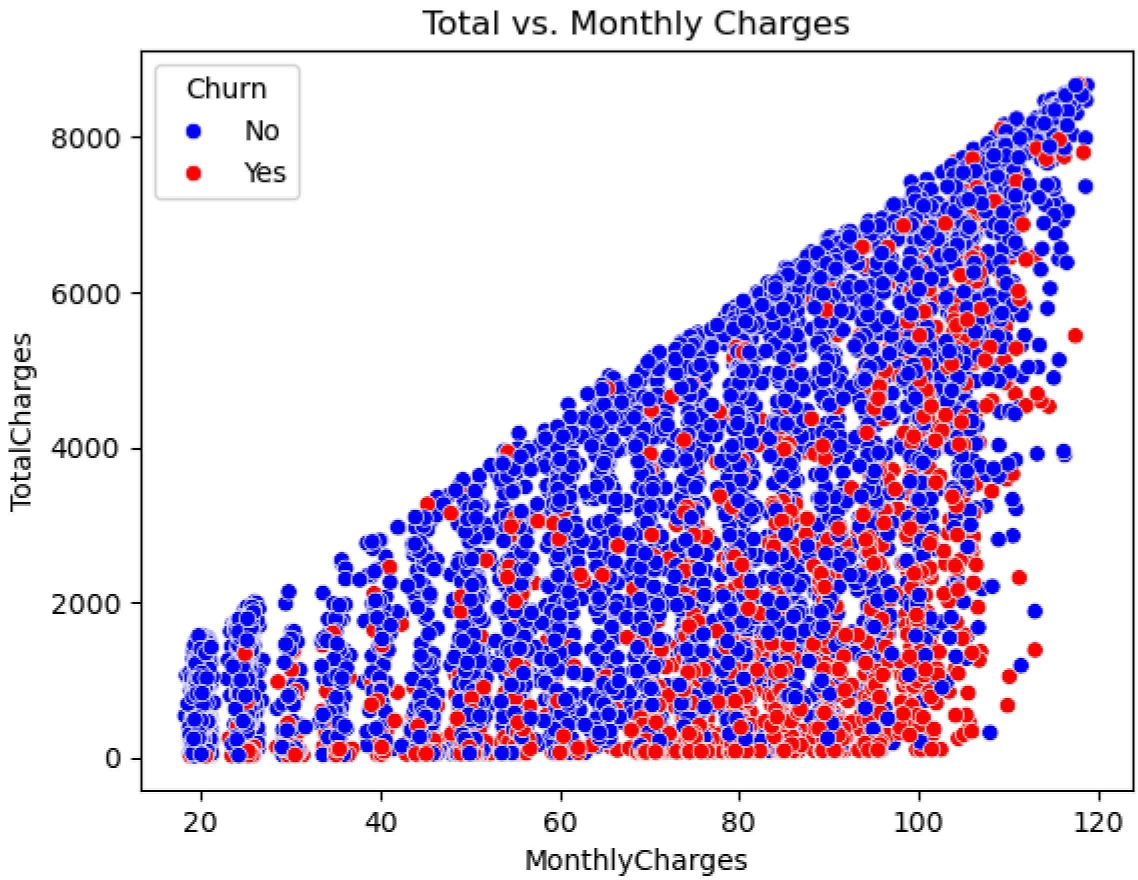


Key Insight:
Churn tends to be higher when **Total Charges** are lower.

However, when analyzing **Tenure, Monthly Charges, and Total Charges** together, a clearer pattern emerges—**higher Monthly Charges with shorter Tenure lead to lower Total Charges**. This suggests that customers with **high Monthly Charges, low Tenure, and low Total Charges** are more likely to churn.

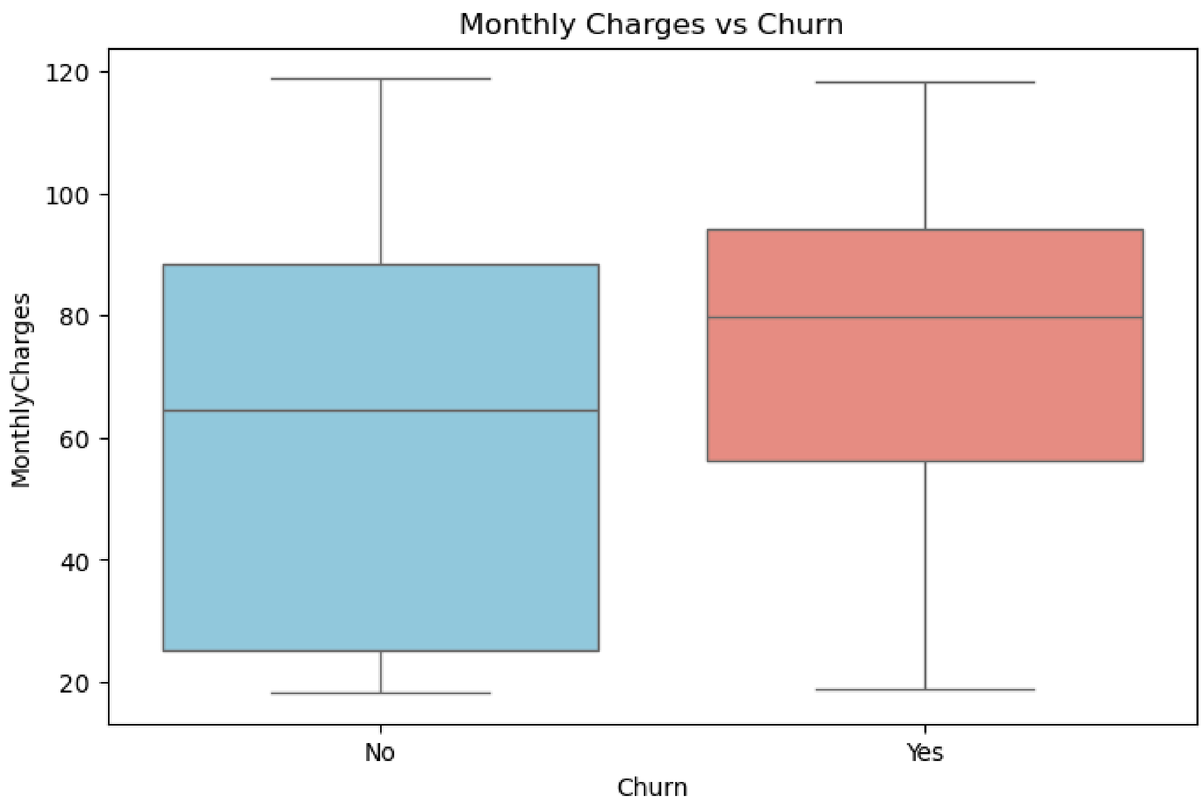
5️⃣ Bivariate Analysis

In [46]:
```
# Relation berween Monthly Charges and Total Charges
sns.scatterplot(df, x='MonthlyCharges', y='TotalCharges', hue='Churn', palet
plt.title("Total vs. Monthly Charges")
plt.show()
```

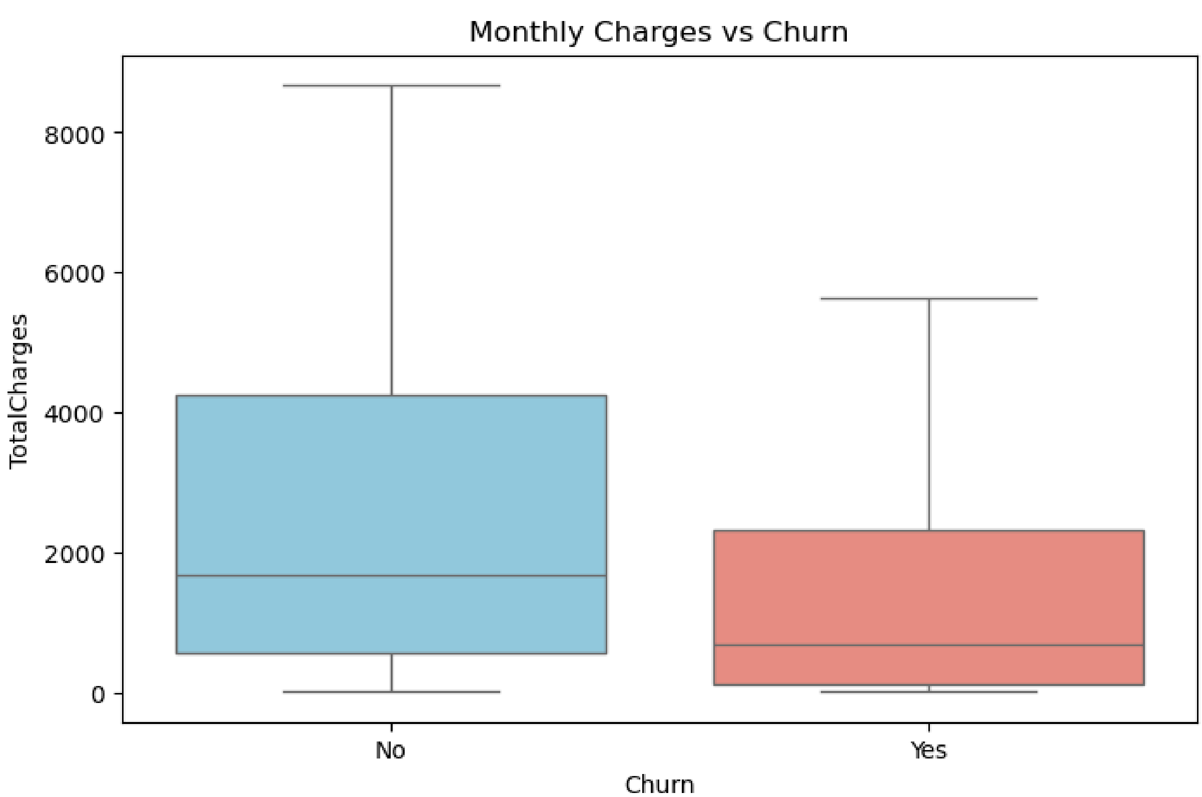


Total Charges increase as **Monthly Charges** increase.

In [48]:
```
plt.figure(figsize=(8,5))
sns.boxplot(df,x="Churn", y='MonthlyCharges', palette=["skyblue", "salmon"])
plt.title('Monthly Charges vs Churn')
plt.show()
```



In [49]:
```
plt.figure(figsize=(8,5))
sns.boxplot(df,x="Churn", y='TotalCharges', showfliers=False, palette=["skyb
plt.title('Monthly Charges vs Churn')
plt.show()
```



In [50]:
```
# spliting data based on churn status
churn_yes = df[df["Churn"]=='Yes']
churn_no = df[df["Churn"]=='No']
```

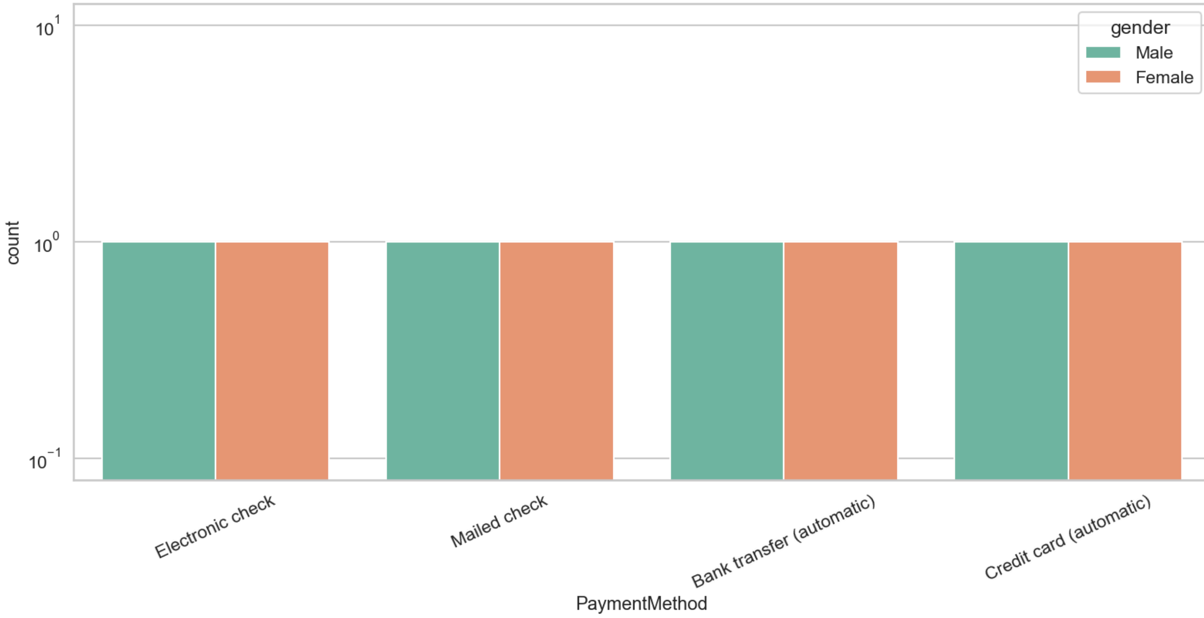
In [51]:
```
# custom plotng fucntion for categorical variables
def custom_plot(data, feature, title, hue=None):
    sns.set_style('whitegrid')
    sns.set_context('talk')
    plt.rcParams.update({'axes.labelsize':17, 'axes.titlesize':19, 'axes.tit

    feature_unique_count = data[feature].nunique()
    hue_unique_count = data[hue].nunique() if hue else 0
    width = feature_unique_count + 7 + 4 * hue_unique_count

    fig, ax = plt.subplots(figsize=(width, 8))

    plt.xticks(rotation=25)
    plt.yscale('log')
    plt.title(title, fontweight='bold')

    sns.countplot(data=data, x=feature, hue=hue, order=data[feature].value_c
    plt.show()
```

In [52]:
```
df.columns.values
```

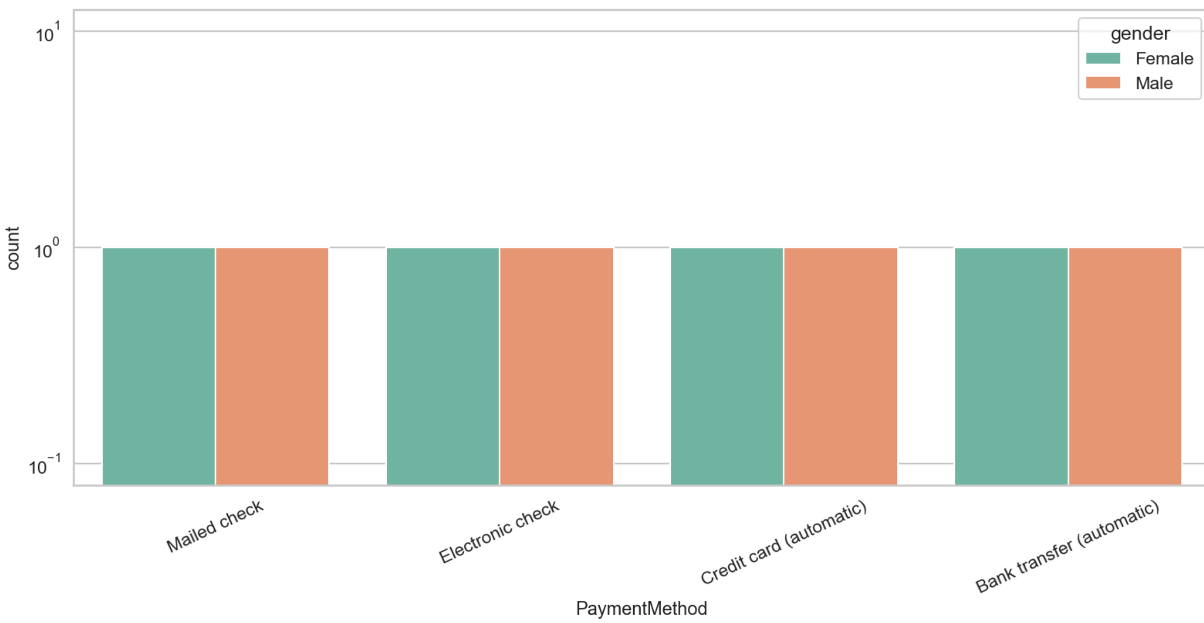
Out[52]:
```
array(['gender', 'SeniorCitizen', 'Partner', 'Dependents', 'tenure',
       'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection',
       'TechSupport', 'StreamingTV', 'StreamingMovies', 'Contract',
       'PaperlessBilling', 'PaymentMethod', 'MonthlyCharges',
       'TotalCharges', 'Churn', 'tenure_group'], dtype=object)
```

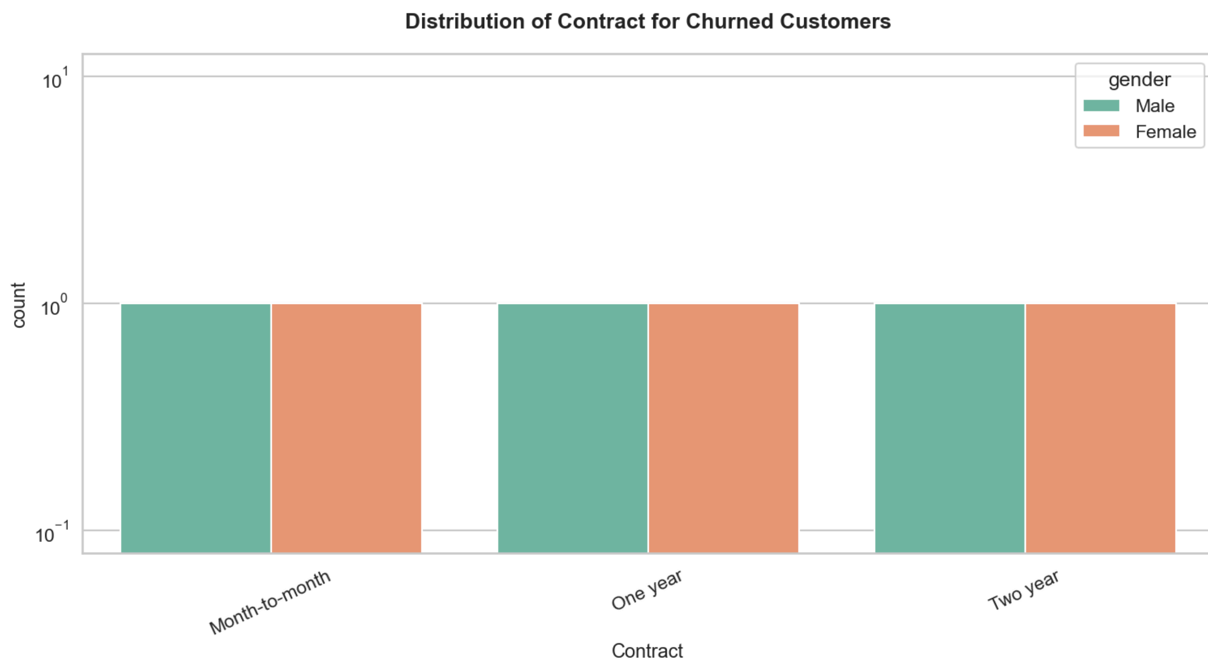
In [53]:
```
cat_features = ['PaymentMethod', 'Contract', 'InternetService', 'Partner', '

for feature in cat_features:
    # plot for churned customers
    custom_plot(churn_yes, feature=feature, title=f'Distribution of {feature
    print("\n")
    # plot for non churned customers
    custom_plot(churn_no, feature=feature, title=f'Distribution of {feature}
    print("\n")
```

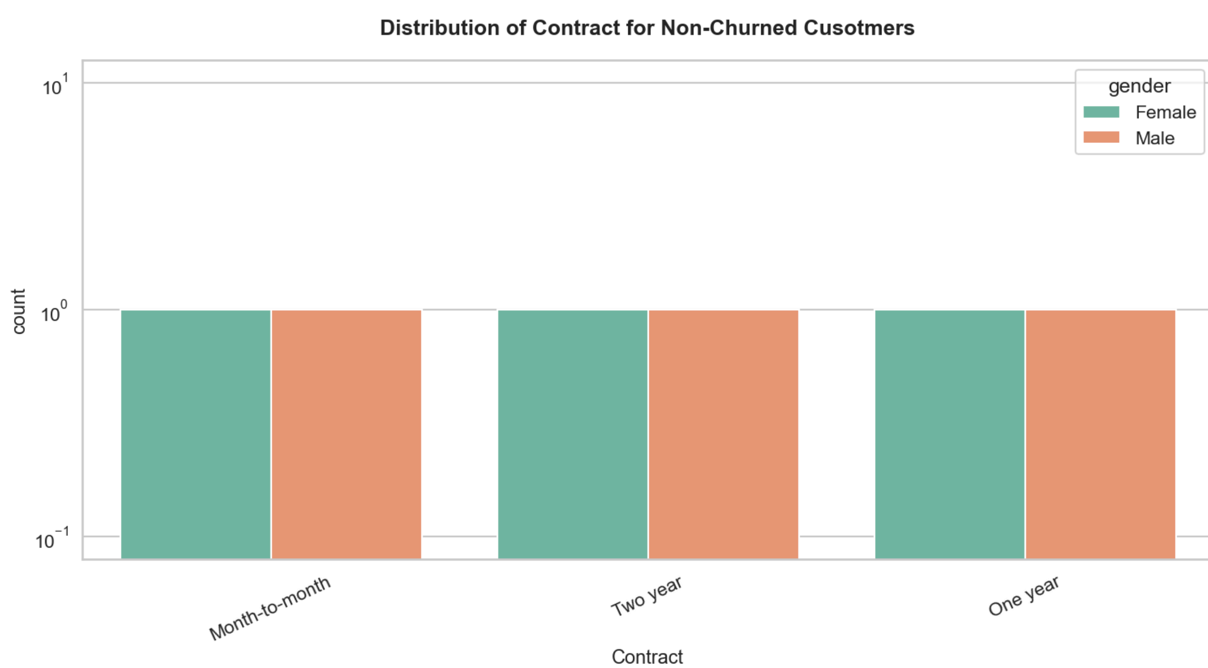
Distribution of PaymentMethod for Churned Customers

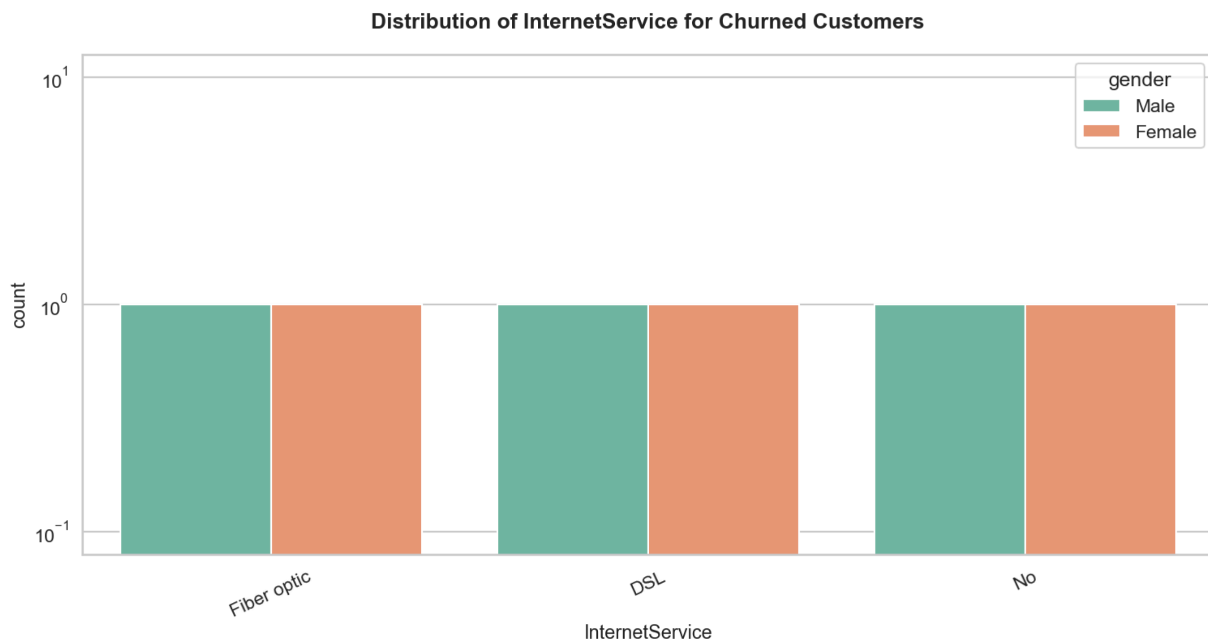


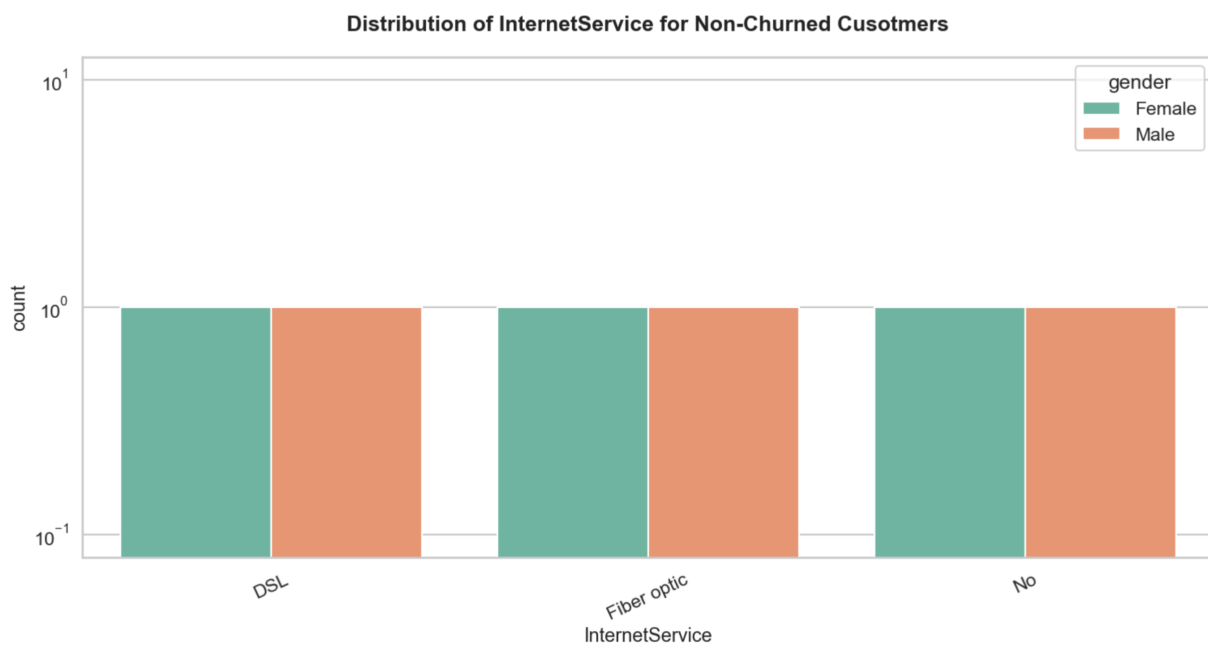
Distribution of PaymentMethod for Non-Churned Cusotmers

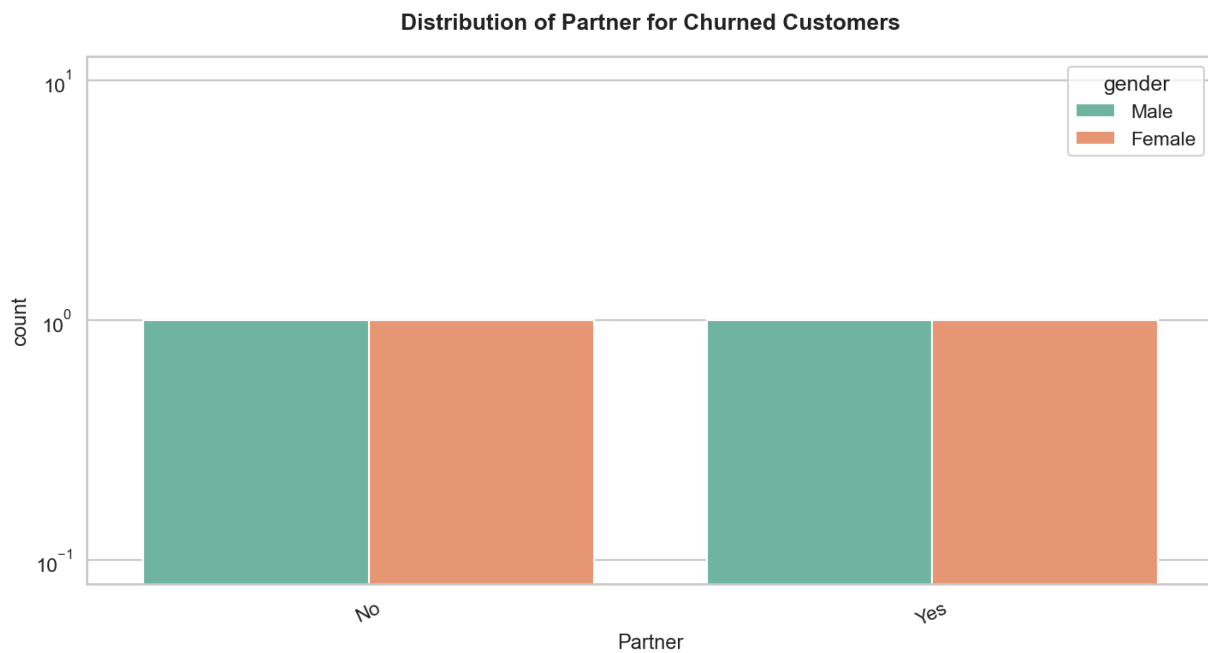


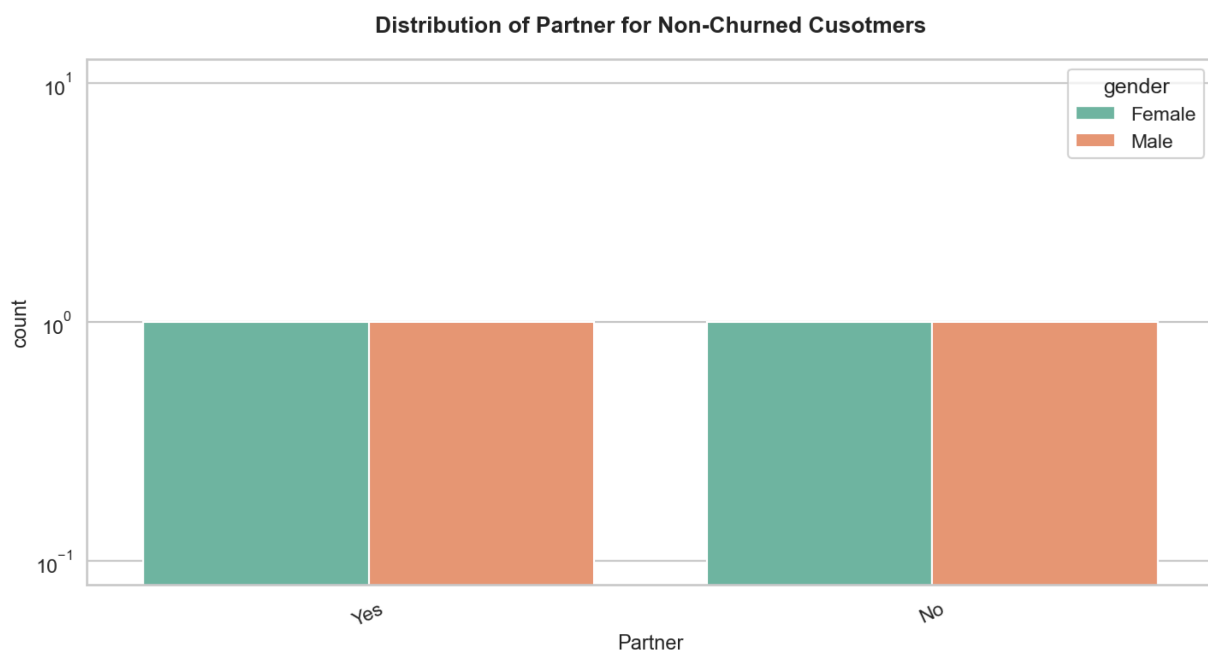

Distribution of Contract for Churned Customers
gender
Male
Female
count
10^1
10^0
10^{-1}
Month-to-month
One year
Two year
Contract

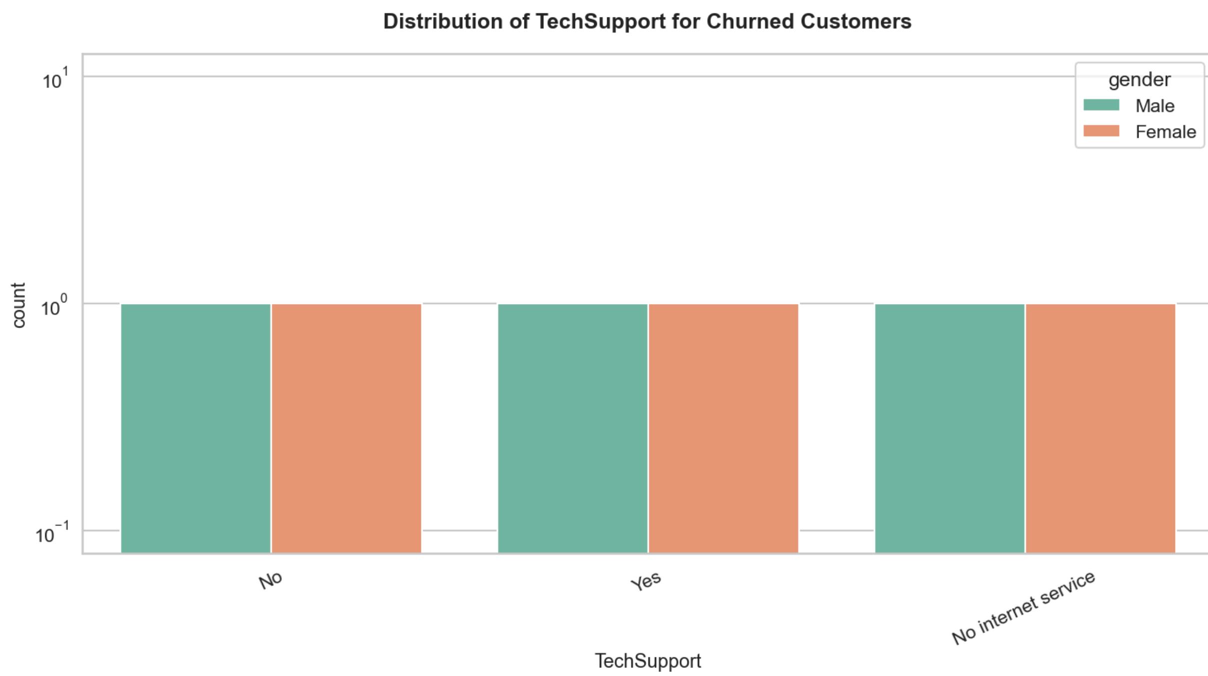

Distribution of Contract for Non-Churned Cusotmers
gender
Female
Male
count
10^1
10^0
10^{-1}
Month-to-month
Two year
One year
Contract


Distribution of InternetService for Churned Customers
gender
Male
Female
count
10^1
10^0
10^{-1}
Fiber optic
DSL
No
InternetService

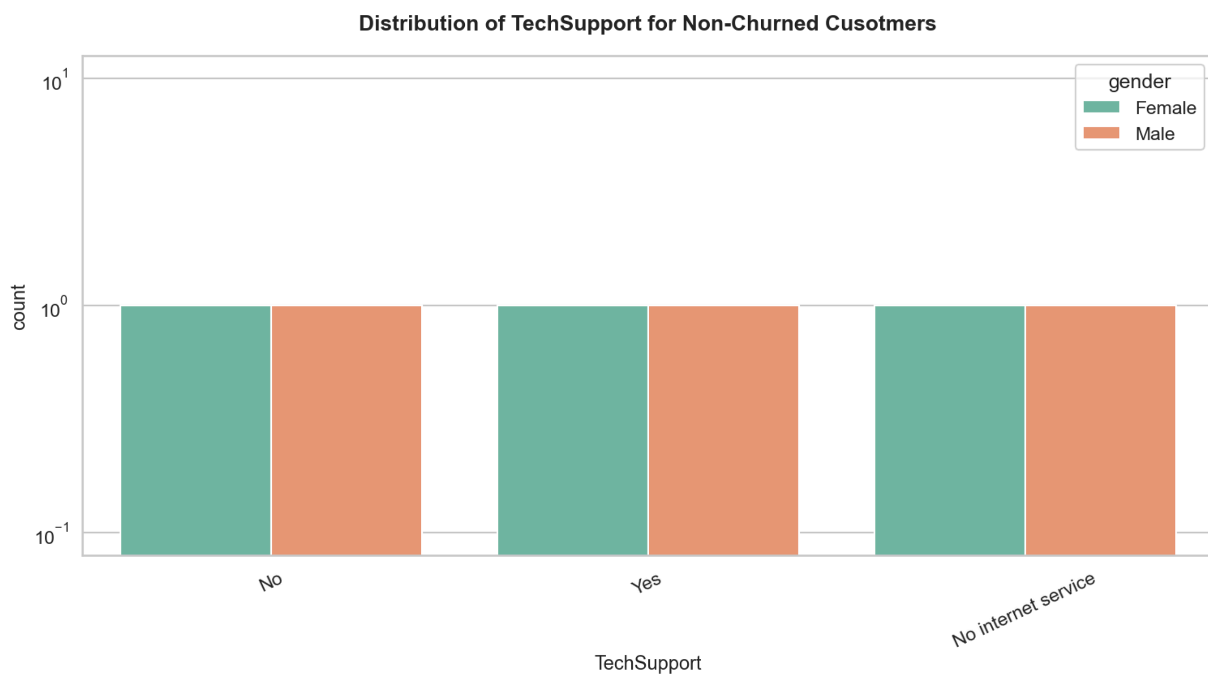

Distribution of InternetService for Non-Churned Cusotmers
gender
Female
Male
count
10^1
10^0
10^{-1}
DSL
Fiber optic
No
InternetService


Distribution of Partner for Churned Customers
gender
Male
Female
count
10^1
10^0
10^{-1}
No
Yes
Partner

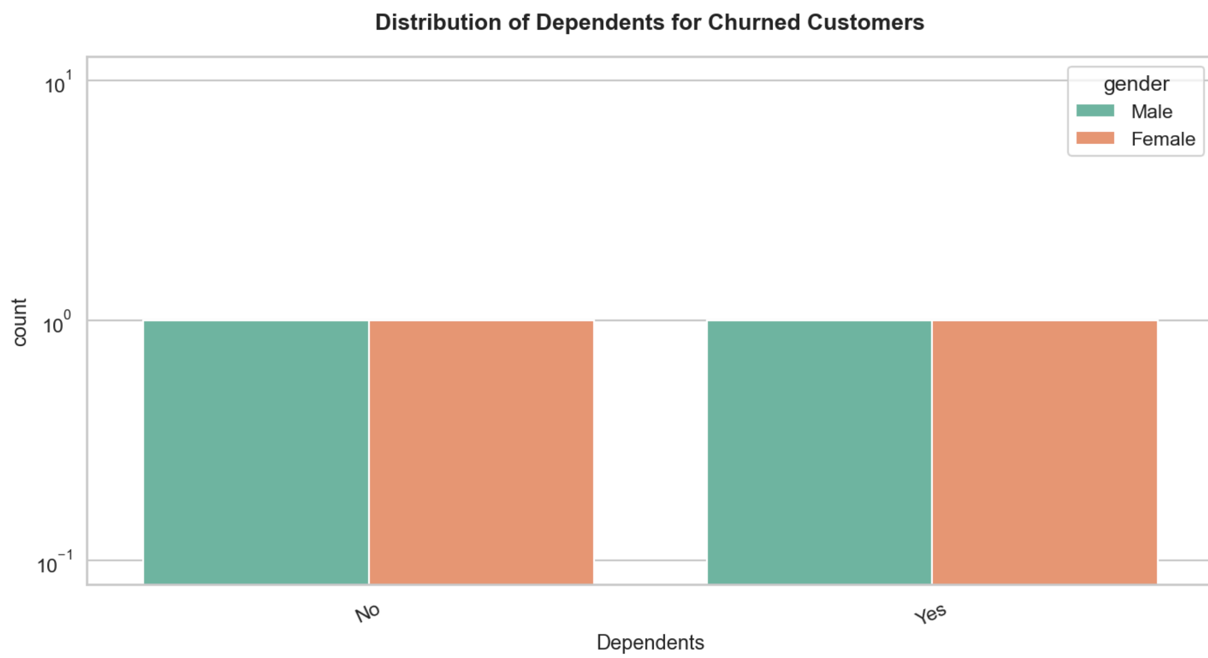

Distribution of Partner for Non-Churned Cusotmers
gender
Female
Male
count
10^1
10^0
10^{-1}
Yes
No
Partner

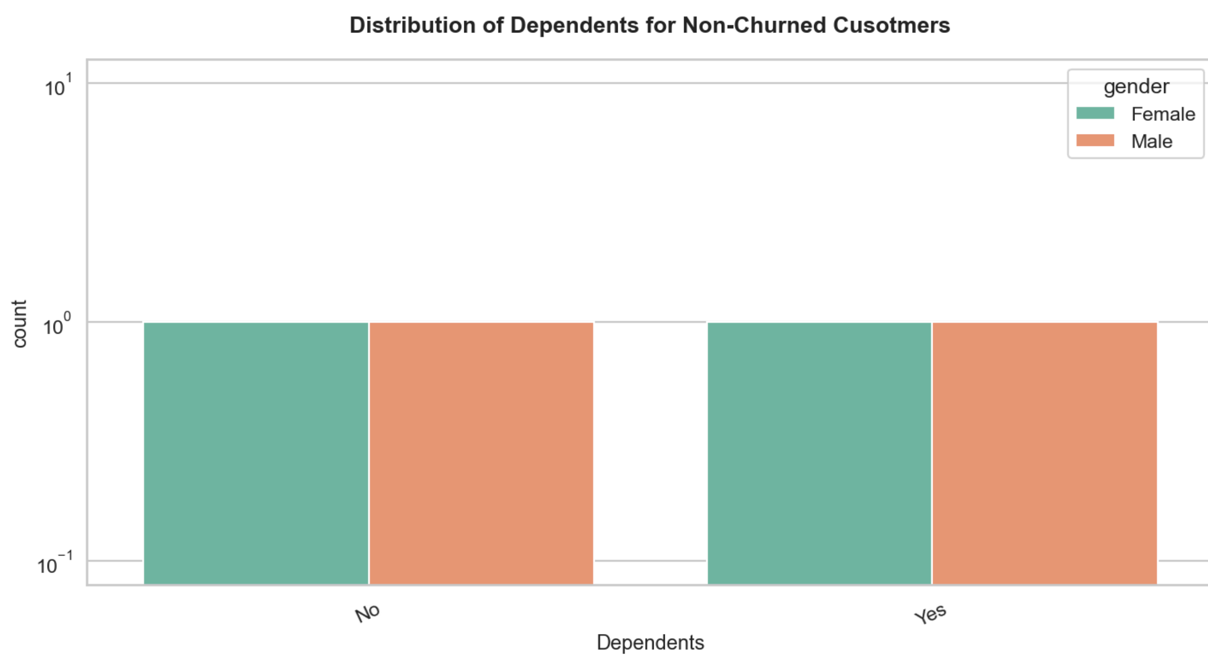


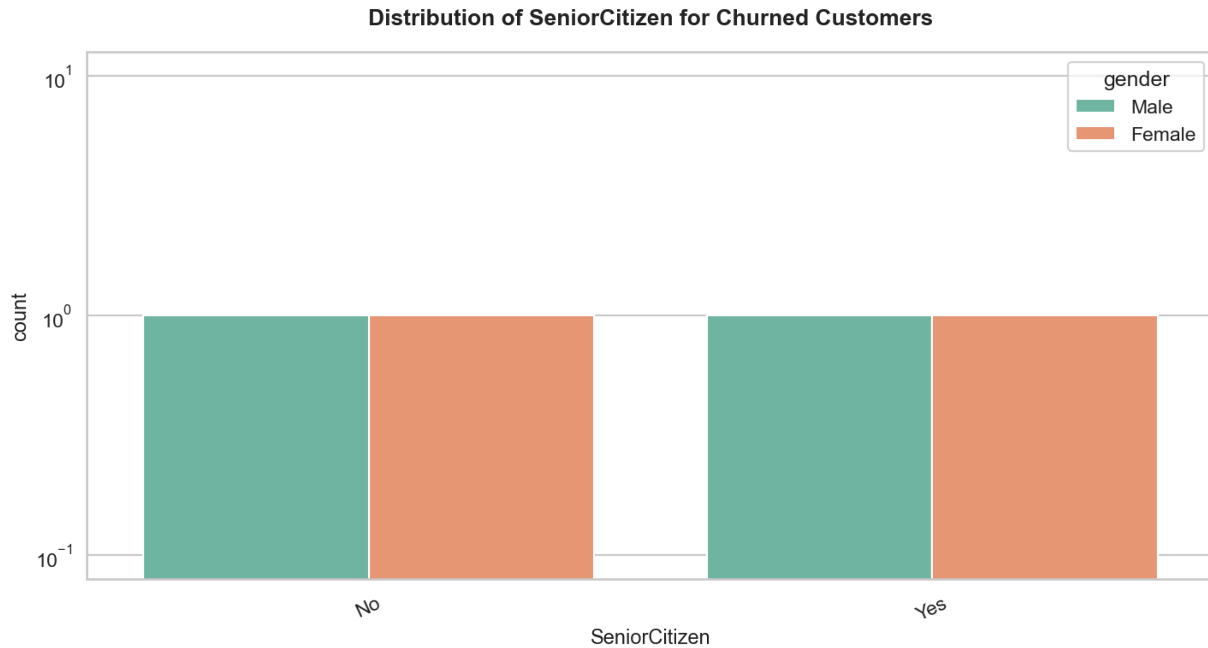
Distribution of TechSupport for Churned Customers
gender
Male
Female
count
10^1
10^0
10^{-1}
No
Yes
No internet service
TechSupport

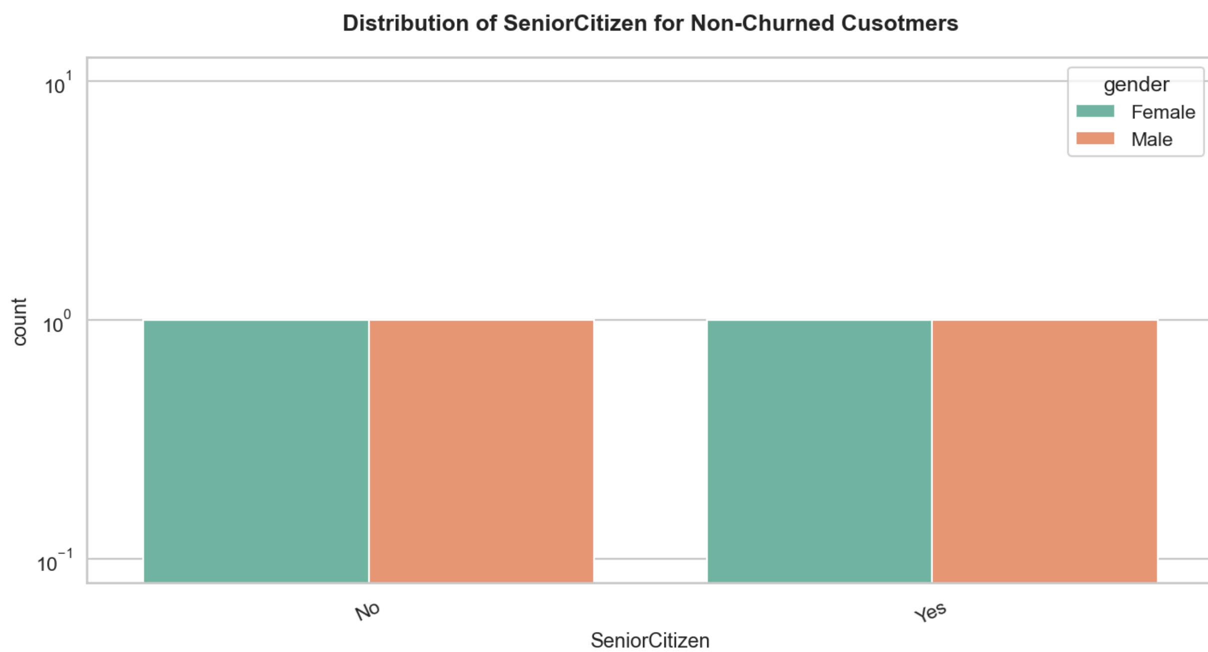


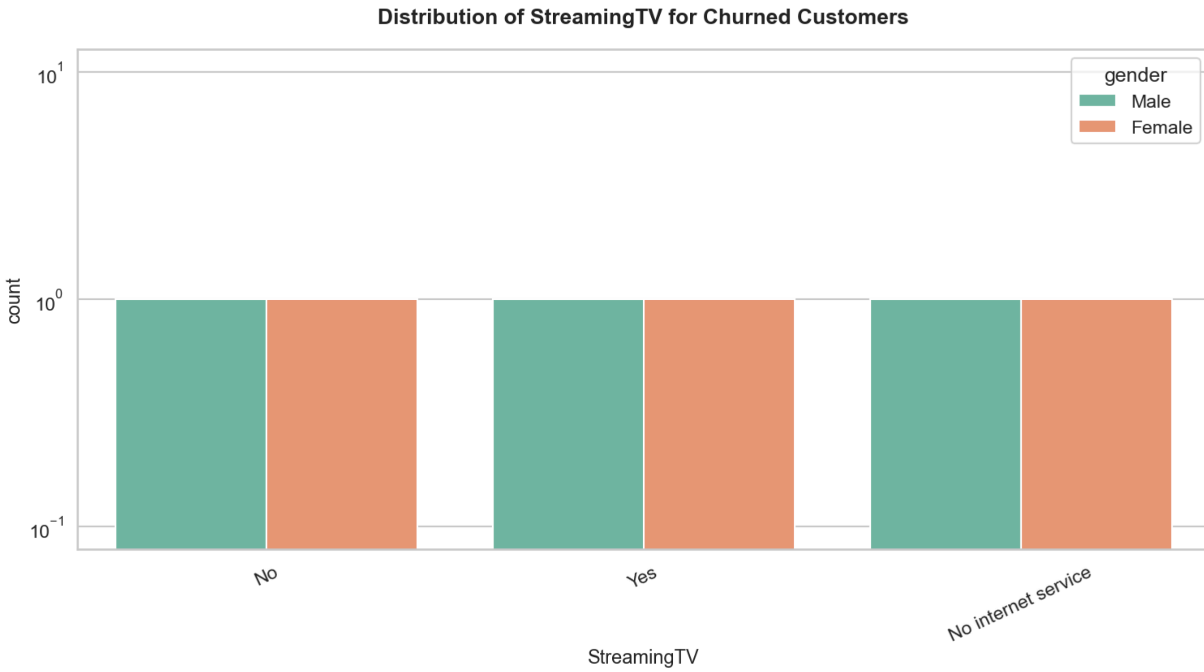
Distribution of TechSupport for Non-Churned Cusotmers
gender
Female
Male
count
10^1
10^0
10^{-1}
No
Yes
No internet service
TechSupport

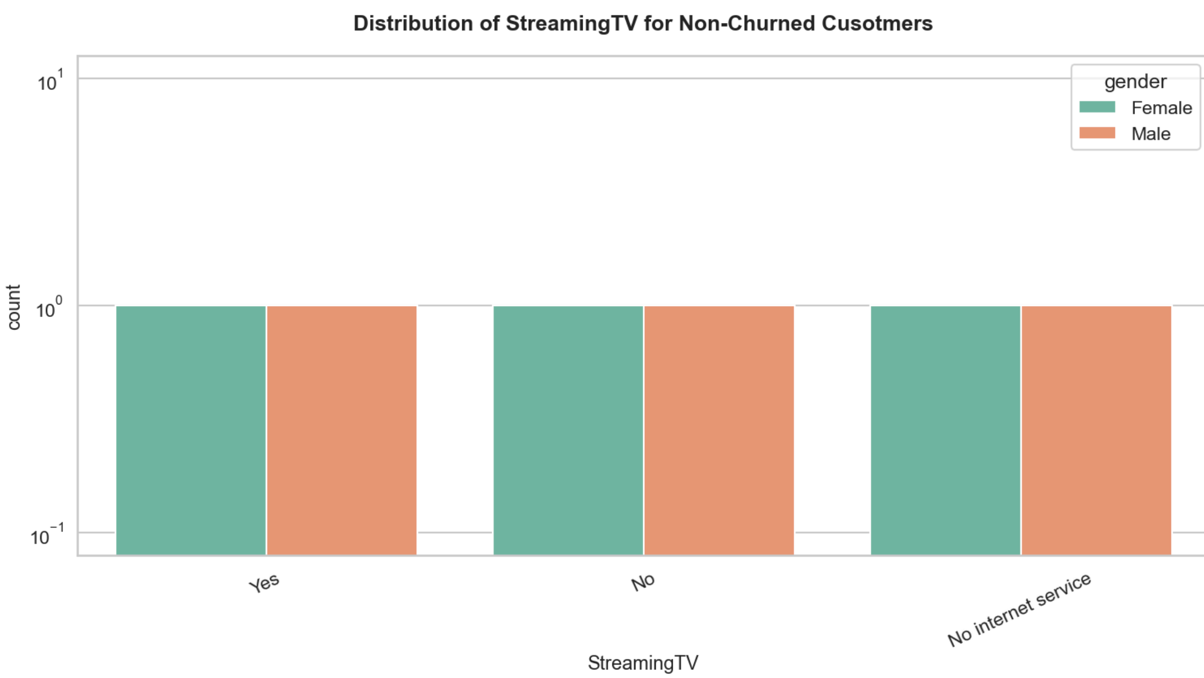

Distribution of Dependents for Churned Customers
gender
Male
Female
10^1
10^0
10^{-1}
count
No
Yes
Dependents

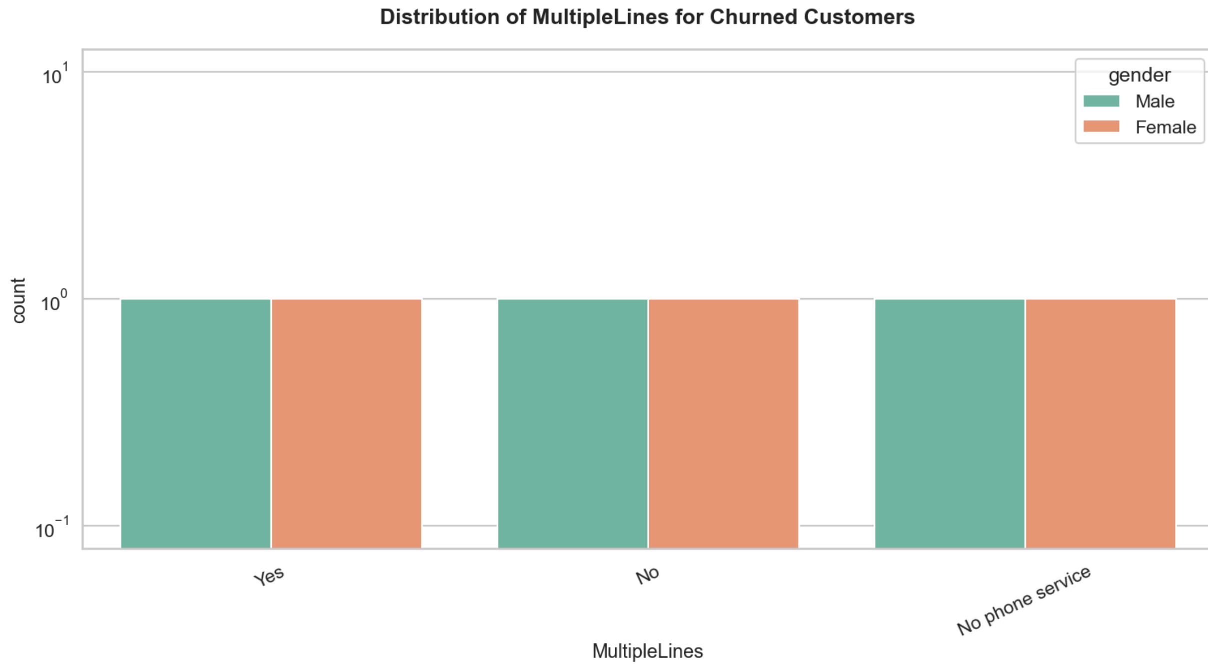

Distribution of Dependents for Non-Churned Cusotmers
gender
Female
Male
10^1
10^0
10^{-1}
count
No
Yes
Dependents

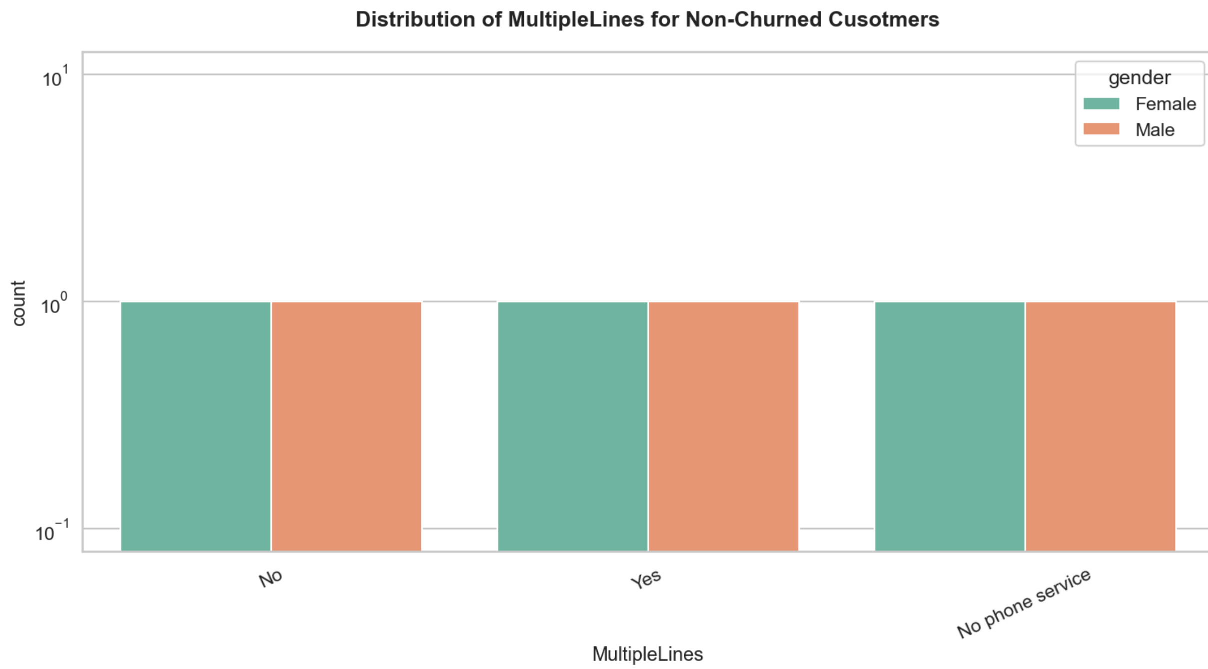

Distribution of SeniorCitizen for Churned Customers
gender
Male
Female
count
10^1
10^0
10^{-1}
No
Yes
SeniorCitizen


Distribution of SeniorCitizen for Non-Churned Cusotmers
gender
Female
Male
count
10^1
10^0
10^{-1}
No
Yes
SeniorCitizen


Distribution of StreamingTV for Churned Customers
count
10^1
10^0
10^{-1}
gender
Male
Female
No
Yes
No internet service
StreamingTV


Distribution of StreamingTV for Non-Churned Cusotmers
count
10^1
10^0
10^{-1}
gender
Female
Male
Yes
No
No internet service
StreamingTV





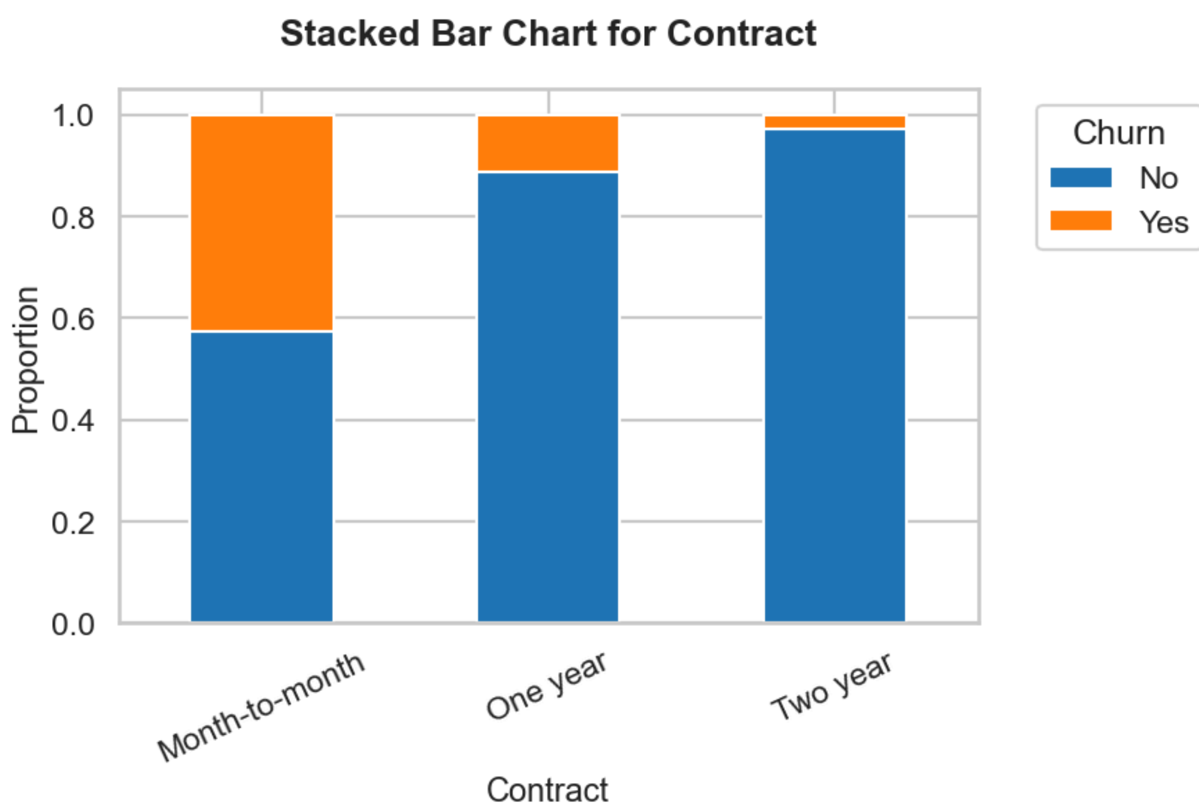
Bivariate Analysis:

- Both males and females have similar churn patterns.
- Churned customers are almost equally split between having Streaming TV and not having it.
- Gender doesn’t make much difference in churn behavior for Streaming TV users.
- Fiber optics Internet Service users are more churners.
- DSL InternetService users are less churners.
- Non-churned customers are slightly more likely to have Streaming TV.

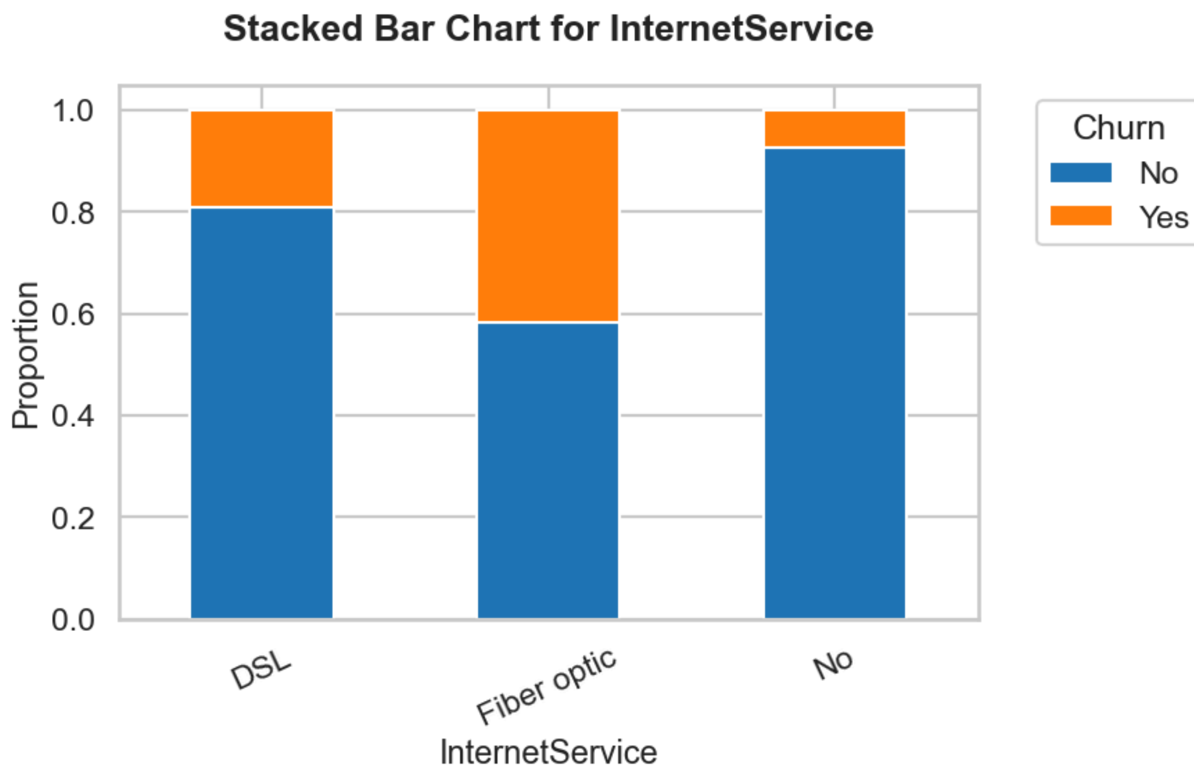
- Churned customers are also almost equally split between having multiple lines and not.
- A few churned customers don't even have phone service.
- Non-churned customers slightly lean towards not having multiple lines.
- Gender impact is minimal across all categories.

In [55]:
```
def plot_stacked_bar(feature):
    crosstab = pd.crosstab(df[feature], df['Churn'])
    crosstab_norm = crosstab.div(crosstab.sum(axis=1), axis=0)
    crosstab_norm.plot(kind='bar', stacked=True, figsize=(8,5))
    plt.title(f"Stacked Bar Chart for {feature}", fontweight='bold')
    plt.ylabel('Proportion')
    plt.legend(title='Churn', bbox_to_anchor=(1.05, 1))
    plt.xticks(rotation=25)
    plt.show()
```

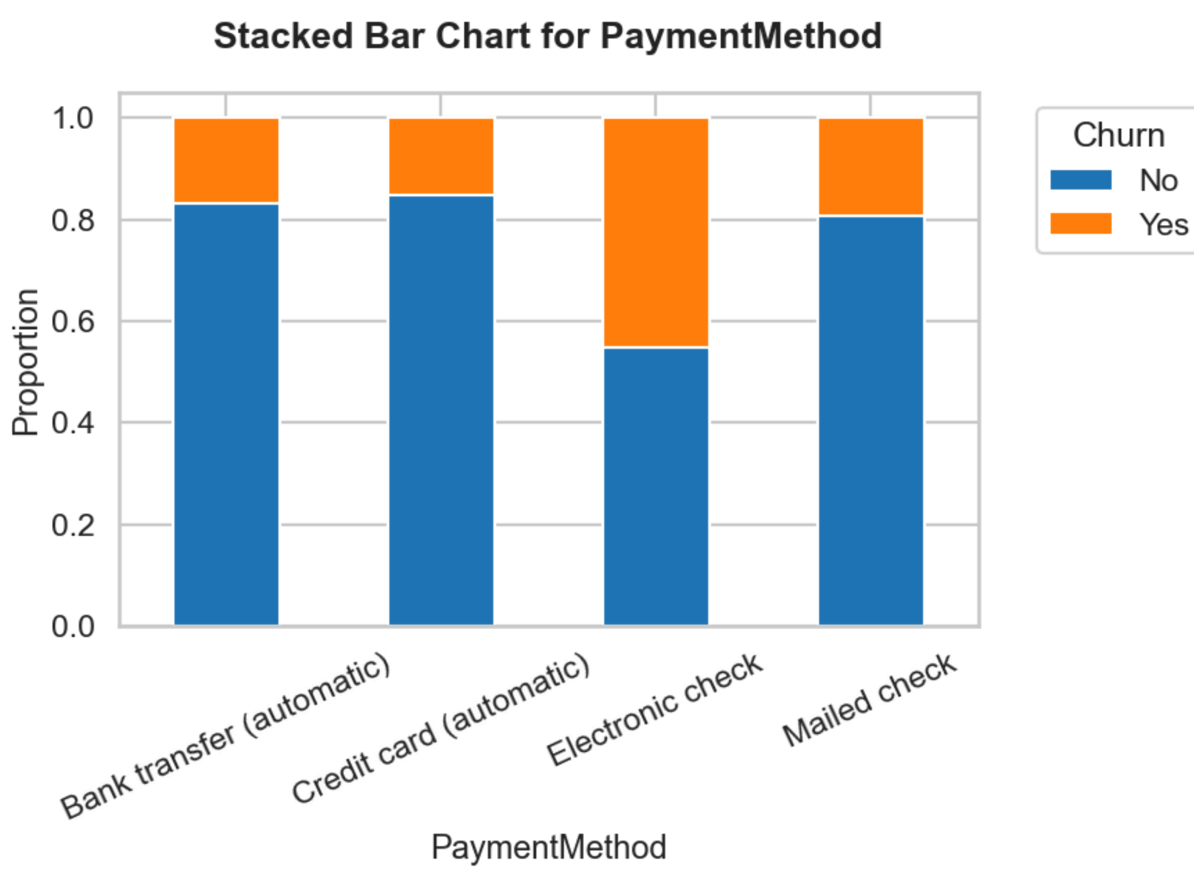
In [56]:
```
plot_stacked_bar('Contract')
```



In [57]:
```
plot_stacked_bar('InternetService')
```

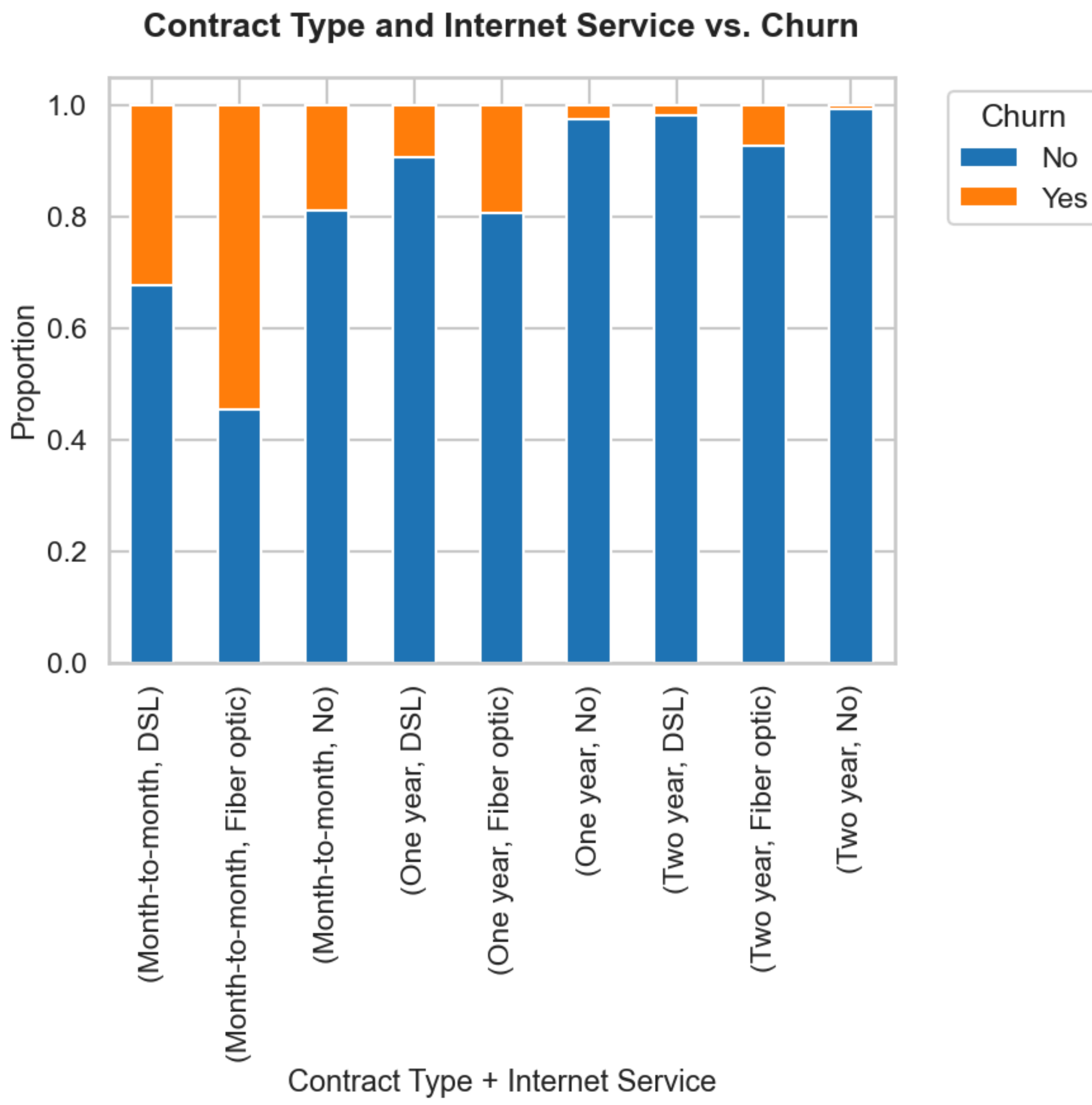


In [58]:
```
plot_stacked_bar('PaymentMethod')
```



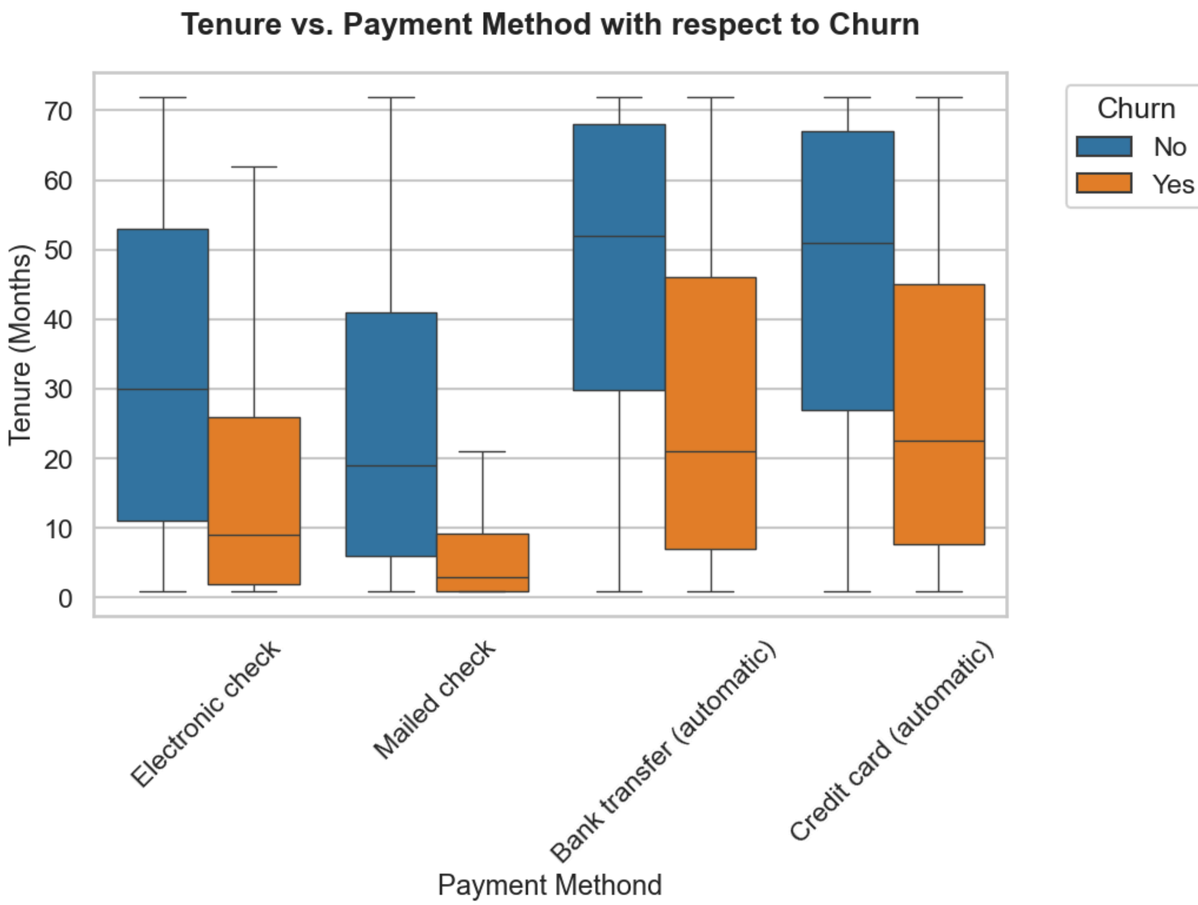
6️⃣ Multivariate Analysis

In [60]:
```
# contract + internet service vs churn
ci = pd.crosstab(index=[df['Contract'], df['InternetService']], columns=df['
ci.plot(kind='bar', stacked=True, figsize=(8,6))
plt.title("Contract Type and Internet Service vs. Churn", fontweight='bold')
plt.xlabel("Contract Type + Internet Service")
plt.ylabel("Proportion")
plt.legend(title='Churn', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



- Customers with **month-to-month contracts and fiber optic internet** have the highest churn rate.
- On the other hand, customers with **two-year contracts** and either **DSL** or **no internet service** churn the least.
- This makes sense, as longer contracts and simpler services lead to customer loyalty, while high-cost, short-term plans result in more churn.

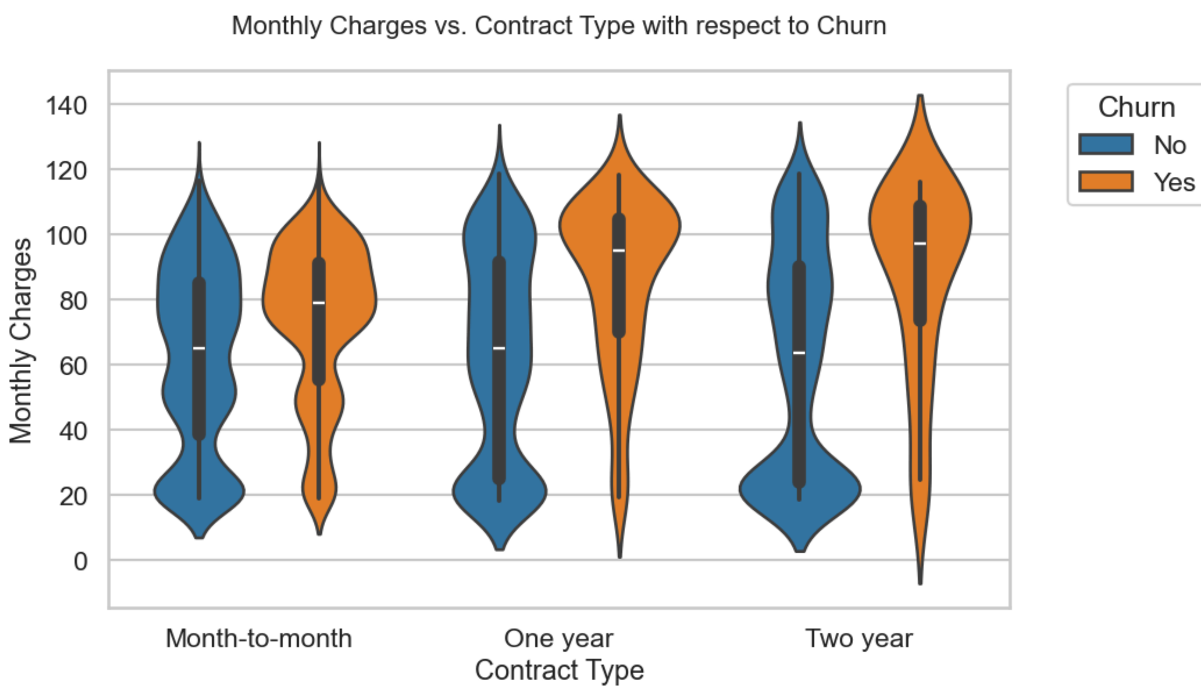
In [62]:
```
# tenure + payment method vs churn
plt.figure(figsize=(10,6))
sns.boxplot(df, x='PaymentMethod', y='tenure', hue='Churn', showfliers=False
plt.title('Tenure vs. Payment Method with respect to Churn', fontweight='bol
plt.xlabel('Payment Methond')
plt.ylabel('Tenure (Months)')
plt.xticks(rotation=45)
plt.legend(title='Churn', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



- Customers using **electronic checks** have higher churn rates and generally lower tenure.
- People paying with **mailed checks** also leave earlier, but it's not as extreme.
- **Automatic payments** (bank transfer or credit card) are clearly associated with longer customer retention.
- Longer tenure usually means more loyalty, and automatic payment methods seem to encourage that.

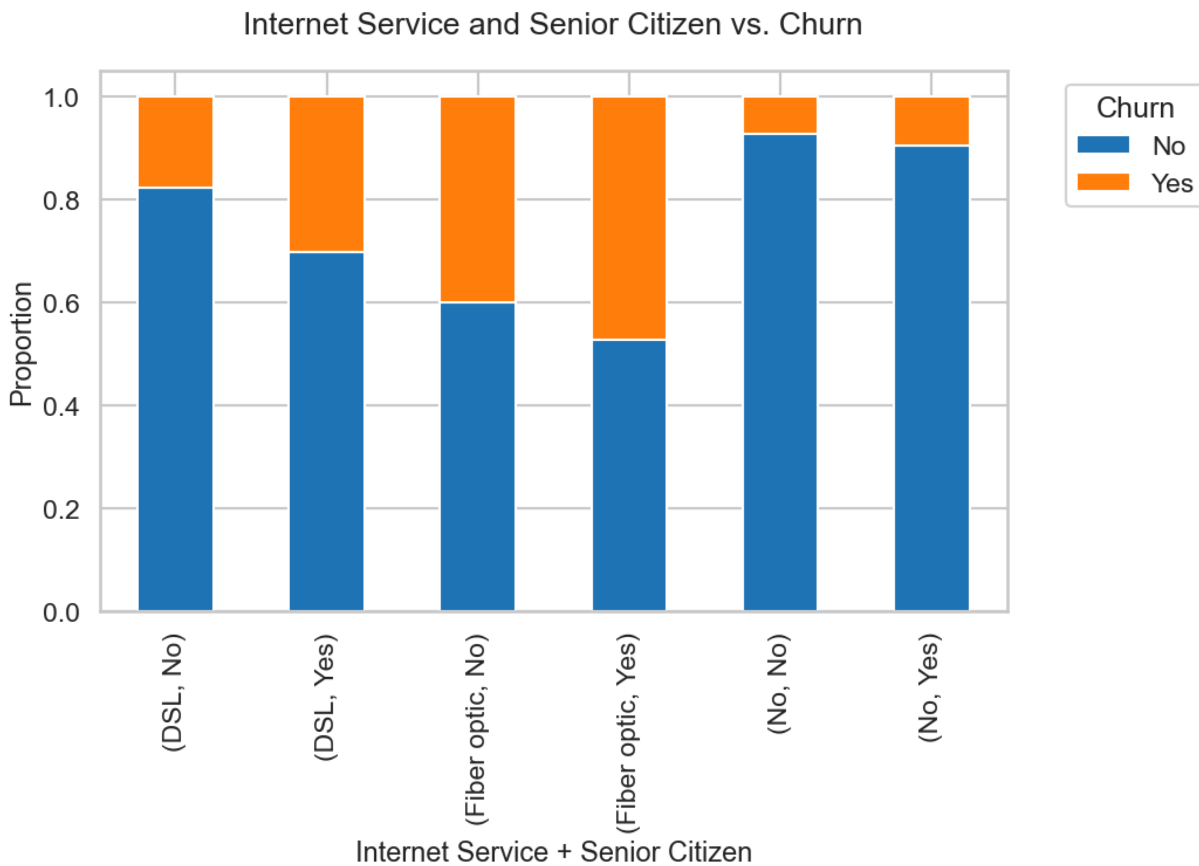
In [64]:
```
# monthly charges + contract vs. churn
plt.figure(figsize=(10,6))
sns.violinplot(df, x='Contract', y='MonthlyCharges', hue="Churn")
plt.title('Monthly Charges vs. Contract Type with respect to Churn', fontsiz
plt.xlabel("Contract Type")
```

```
plt.ylabel("Monthly Charges")
plt.legend(title= "Churn", bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



- Churn is highest among **month-to-month** contract holders, especially those with higher monthly charges.
- **One-year** and **two-year** contract customers have much lower churn, and their charges seem more balanced.
- Customers locked into long-term contracts are clearly more stable and less likely to leave.
- Overall, flexibility in contracts seems to lead to higher churn.

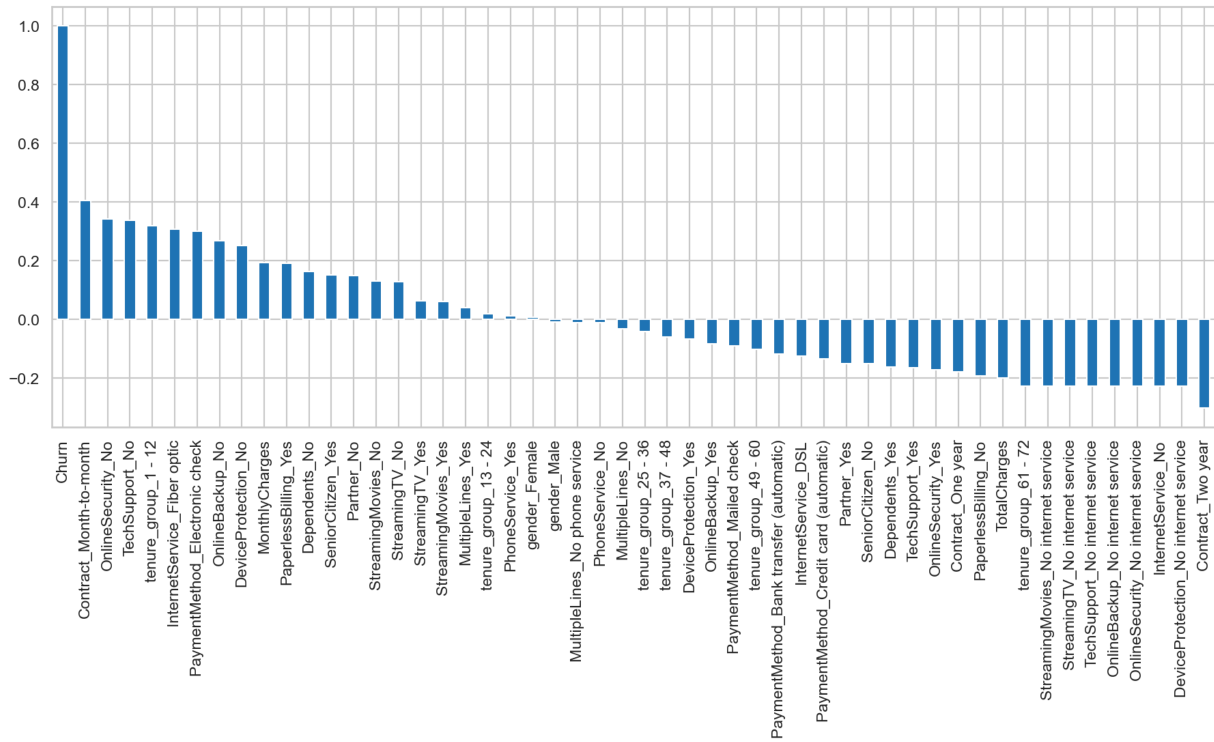
In [66]:
```
# Internet Service + Senior Citizen vs Churn
its = pd.crosstab(index=[df['InternetService'], df["SeniorCitizen"]], columr
its.plot(kind='bar', stacked=True, figsize=(10,6))
plt.title("Internet Service and Senior Citizen vs. Churn")
plt.xlabel('Internet Service + Senior Citizen')
plt.ylabel("Proportion")
plt.legend(title="Churn", bbox_to_anchor=(1.05,1), loc='upper left')
plt.show()
```



- Senior citizens with **fiber optic internet** show the highest churn rate.
- Even non-senior fiber optic users have a higher churn rate compared to those using DSL.
- **DSL users** appear to be more loyal and stable.
- Customers without internet service almost never churn, probably because they use fewer services and have fewer frustrations.
- Fiber optic + older customers = biggest churn risk zone.

In [68]:
```
temp = df.copy()
temp['Churn'] = np.where(temp.Churn == 'Yes', 1, 0)
temp = temp.drop('tenure', axis=1)
```

In [69]:
```
plt.figure(figsize=(22, 8))
temp1 = pd.get_dummies(temp, dtype=np.int32)
temp1.corr()['Churn'].sort_values(ascending=False).plot(kind='bar')
plt.show()
```



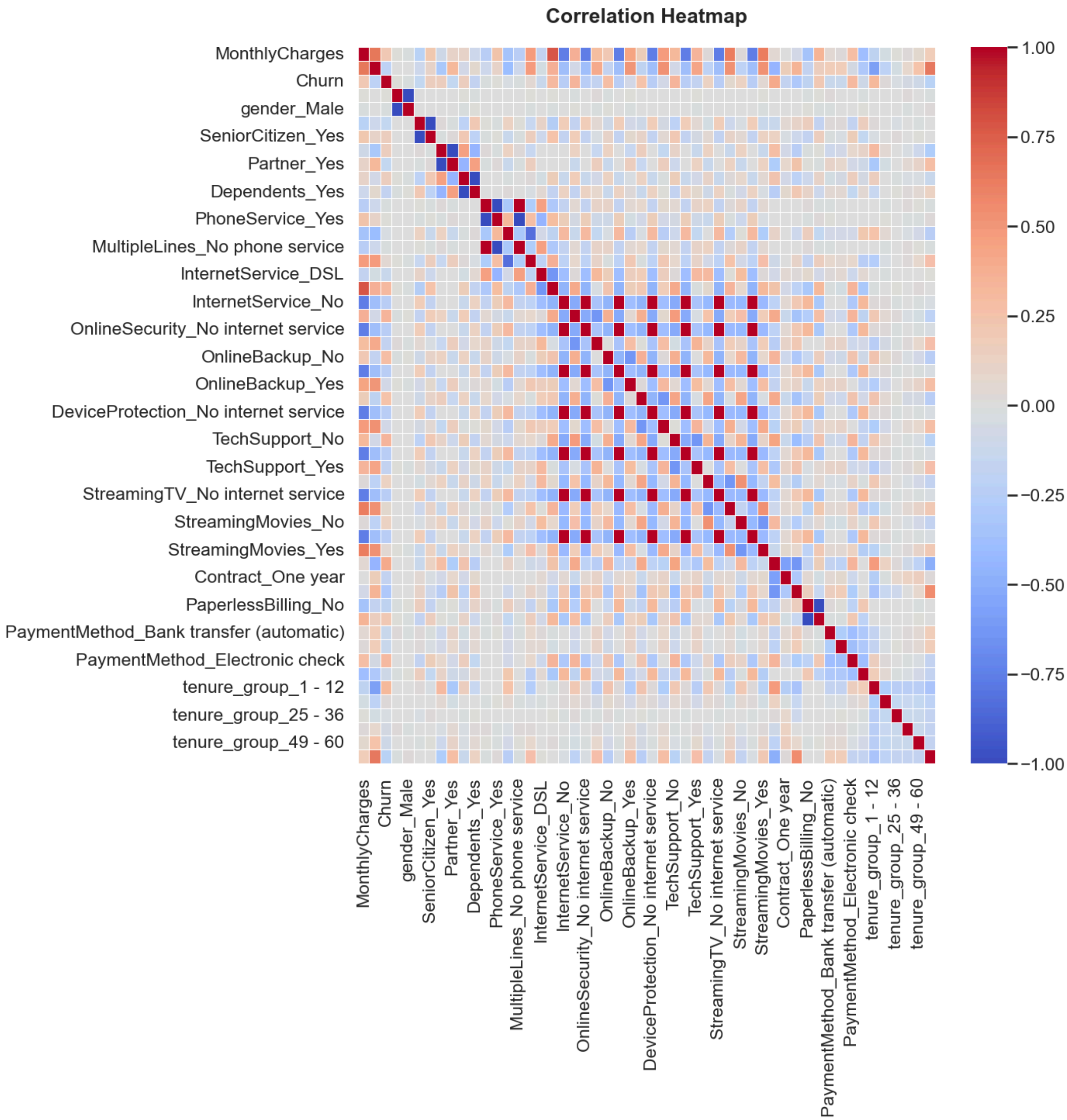
Key Observations:

- **More churn** seen in:
  - **Fiber optic users**
  - **Electronic check payments**
  - **High monthly charges** and **paperless billing**
- **Less churn** seen in:
  - **Long-term customers (5+ years)**
  - **Two-year contracts**
  - Customers with **tech support, security, and backup services**
  - **Auto credit card payments**
- **No real impact** from:
  - **Gender**, **phone service**, and **multiple lines**

In short:

People with high bills and fiber internet leave more. Long contracts, loyalty, and extra services help keep customers.

In [71]:
```
plt.figure(figsize=(12,12))
sns.heatmap(temp1.corr(), cmap='coolwarm', linewidths=0.5)
plt.title("Correlation Heatmap", fontweight='bold')
plt.show()
```



🎯 What I Found from the Telco Churn Data

After going through the Telco churn data, here's what I noticed:

1. **Churn Rate:**
   - About **26.5%** customers have left — that's pretty high and something to worry about.
2. **Who's Leaving More:**
   - **Senior citizens** are more likely to churn.
   - **Gender** doesn't seem to matter much.
3. **Tenure Insight:**

- People with **less than a year** with the company leave the most.
- Long-time customers usually stay loyal.

4. **Contract Type:**

   - **Month-to-month** plans have the highest churn.
   - **One or two-year contracts** are much more stable.

5. **Internet Service:**

   - **Fiber optic** customers leave more compared to DSL or no-internet users. Probably due to cost or service issues.

6. **Charges Factor:**

   - Customers paying **higher monthly charges** churn more.
   - But those with **high total charges** (been around longer) usually stay.

7. **Payments:**

   - **Electronic checks** are linked to more churn.
   - Auto-pay methods seem to help keep customers.

8. **Add-ons:**

   - People without **security, backup, or tech support** are leaving more.
   - Adding these services might help reduce churn.