Importing Libraries:

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib as mpl
import matplotlib.pyplot as plt
import matplotlib.dates as md
%matplotlib inline
import seaborn as sns
import statsmodels.api as sm
```

Setting the Dataset Path:

In [2]:

```
%cd C:\Musfique\Springboard Data Analytics CT\Capstone 2\Telco Customer Churn
```

```
C:\Musfique\Springboard Data Analytics CT\Capstone 2\Telco Customer Churn
```

Reading the Dataset in the Notebook:

In [3]:

```
telco_df = pd.read_csv('WA_Fn-UseC_-Telco-Customer-Churn.csv')
telco_df.head()
```

Out[3]:

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

5 rows × 21 columns

Exploring & Cleaning the Dataset:

In [4]:

```
telco_df.dtypes
```

Out[4]:

```
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
```

- **The 'TotalCharges' column is supposed to be numeric.**

Converting 'TotalCharges' to a Numeric Data Type:

In [5]:

```
telco_df.TotalCharges = pd.to_numeric(telco_df.TotalCharges, errors='coerce')
telco_df['TotalCharges'].dtypes
```

Out[5]:

```
dtype('float64')
```

Checking Missing Values in the Dataset:

In [6]:

```
telco_df.isnull().sum()
```

Out[6]:

```
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
```

Removing Rows having Missing Values from the Dataset:

In [7]:

```
telco_df.dropna(inplace=True)
telco_df.isnull().sum()
```

Out[7]:

```
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
```

Removing 'customerID' from the Dataset

In [8]:

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

Out[8]:

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

Converting All Strings to Lowercase:

In [9]:

```
for item in df_cleaned.columns:
    try:
        df_cleaned[item] = df_cleaned[item].str.lower()
    except:
        print(item, "couldn't convert")
```

```
df_cleaned.head(20)
```

```
SeniorCitizen couldn't convert
tenure couldn't convert
MonthlyCharges couldn't convert
TotalCharges couldn't convert
```

Out[9]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBa
0	female	0	yes	no	1	no	no phone service	dsl	no	
1	male	0	no	no	34	yes	no	dsl	yes	
2	male	0	no	no	2	yes	no	dsl	yes	
3	male	0	no	no	45	no	no phone service	dsl	yes	
4	female	0	no	no	2	yes	no	fiber optic	no	
5	female	0	no	no	8	yes	yes	fiber optic	no	
6	male	0	no	yes	22	yes	yes	fiber optic	no	
7	female	0	no	no	10	no	no phone service	dsl	yes	
8	female	0	yes	no	28	yes	yes	fiber optic	no	
9	male	0	no	yes	62	yes	no	dsl	yes	
10	male	0	yes	yes	13	yes	no	dsl	yes	
11	male	0	no	no	16	yes	no	no	no internet service	no int se
12	male	0	yes	no	58	yes	yes	fiber optic	no	
13	male	0	no	no	49	yes	yes	fiber optic	no	
14	male	0	no	no	25	yes	no	fiber optic	yes	
15	female	0	yes	yes	69	yes	yes	fiber optic	yes	
16	female	0	no	no	52	yes	no	no	no internet service	no int se
17	male	0	no	yes	71	yes	yes	fiber optic	yes	
18	female	0	yes	yes	10	yes	no	dsl	no	
19	female	0	no	no	21	yes	no	fiber optic	no	

Converting All 'yes/no' Variables to '1/0':

In [10]:

```
columns_to_convert = ['Partner', 'Dependents', 'PhoneService', 'PaperlessBilling', 'Churn
']
for item in columns_to_convert:
    df_cleaned[item].replace(to_replace='yes', value=1, inplace=True)
    df_cleaned[item].replace(to_replace='no',  value=0, inplace=True)
df_cleaned.head()
```

Out[10]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBac
0	female	0	1	0	1	0	no phone service	dsl	no	
1	male	0	0	0	34	1	no	dsl	yes	
2	male	0	0	0	2	1	no	dsl	yes	
3	male	0	0	0	45	0	no phone service	dsl	yes	
4	female	0	0	0	2	1	no	fiber optic	no	

Exploratory Data Analysis (EDA)

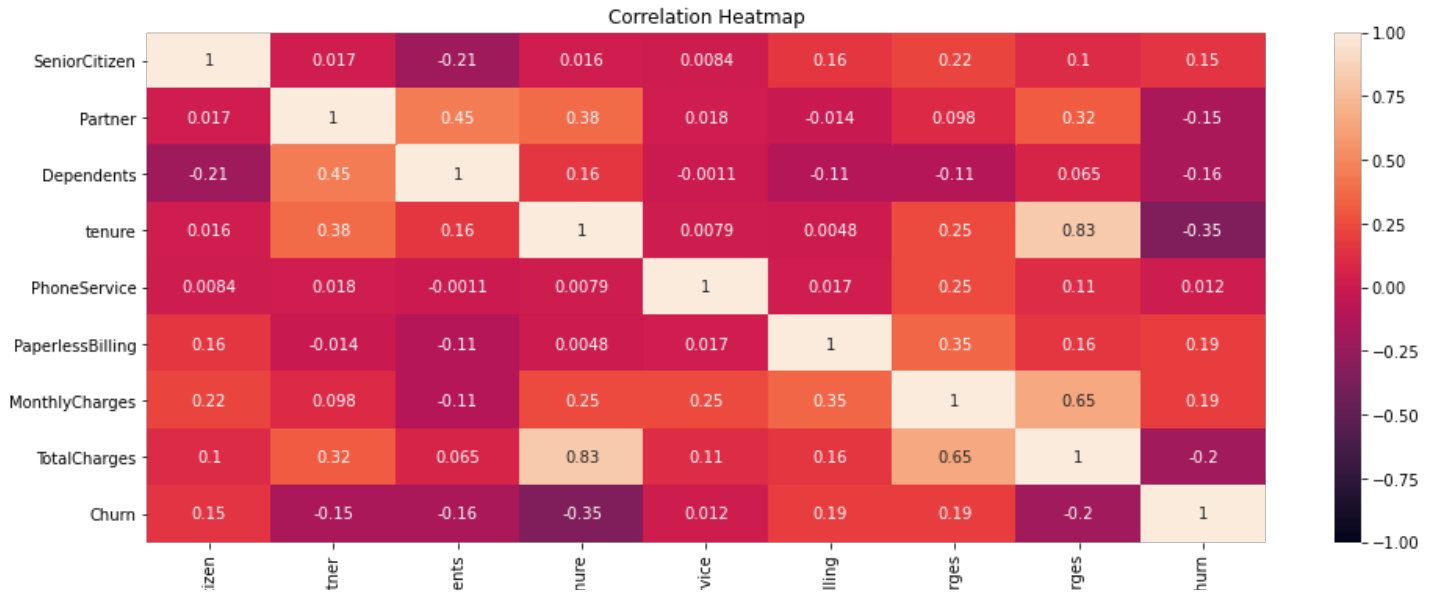
Correlation Heatmap:

In [11]:

```
corr_mat = df_cleaned.corr()
plt.figure(figsize=(16, 6))
heat_map = sns.heatmap(corr_mat, vmin=-1, vmax=1, annot=True)
heat_map.set_title('Correlation Heatmap')
```

Out[11]:

```
Text(0.5, 1.0, 'Correlation Heatmap')
```

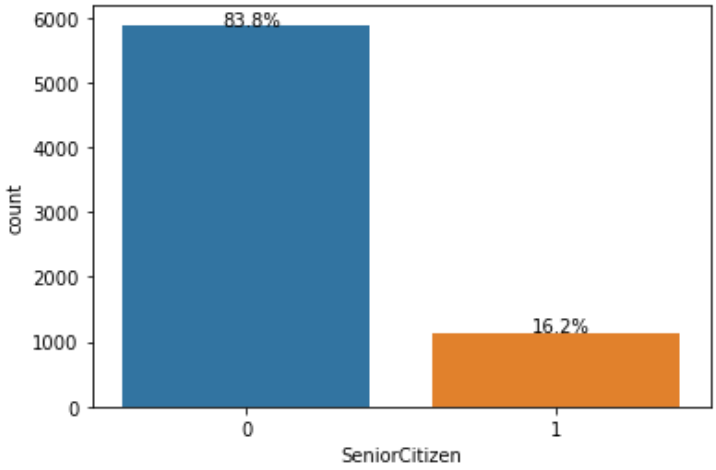


Insights: Churn clearly shows some correlation with all variables shown on the heatmap except phone service.

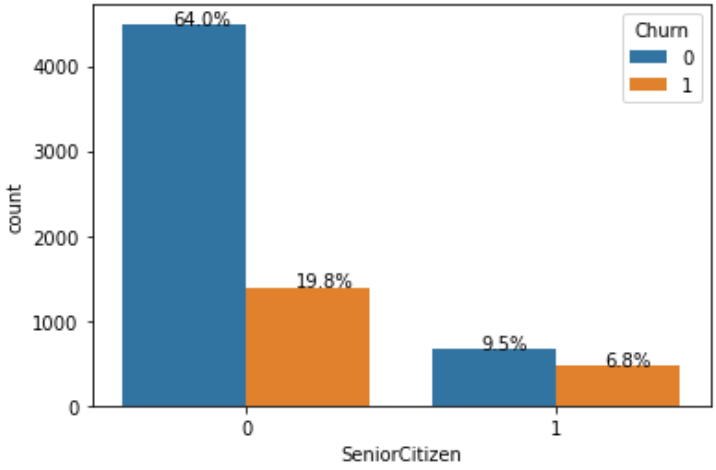
Analyzing Binary Categorical Variables:

In [12]:

```
ax = sns.countplot(x='SeniorCitizen', data=df_cleaned)
plt.figure()
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['SeniorCitizen'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

ax = sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')
plt.figure()
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['SeniorCitizen'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```



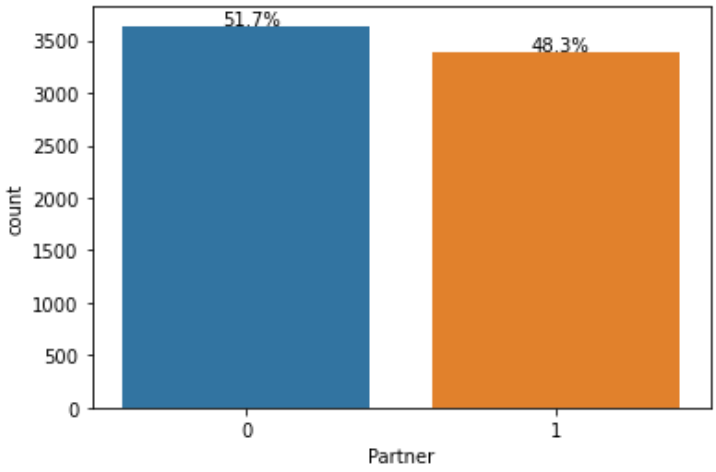

```
<Figure size 432x288 with 0 Axes>
```



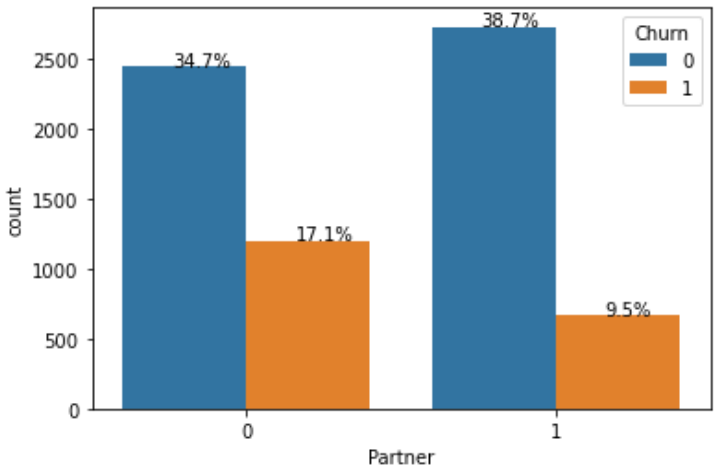

```
<Figure size 432x288 with 0 Axes>
```

In [13]:

```
ax = sns.countplot(x='Partner', data=df_cleaned)
plt.figure()
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['Partner'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

ax = sns.countplot(x='Partner', data=df_cleaned, hue='Churn')
plt.figure()
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['Partner'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```



<Figure size 432x288 with 0 Axes>

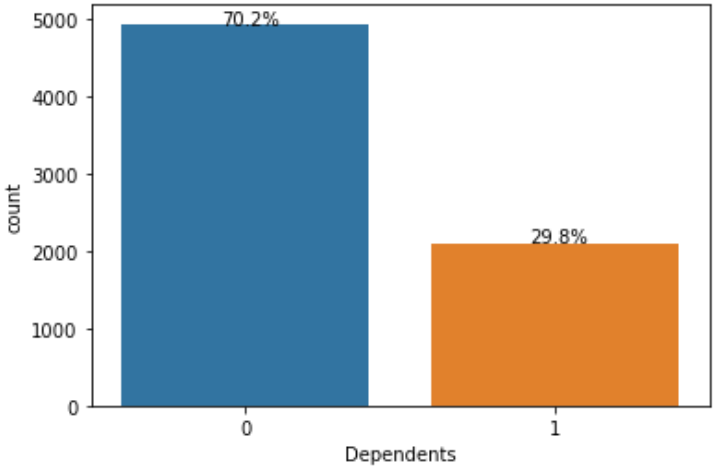


<Figure size 432x288 with 0 Axes>

In [14]:

```
ax = sns.countplot(x='Dependents', data=df_cleaned)
plt.figure()
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['Dependents'])
for p in ax.patches:
```

```
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

ax = sns.countplot(x='Dependents', data=df_cleaned, hue='Churn')
plt.figure()
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['Dependents'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```




```
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```
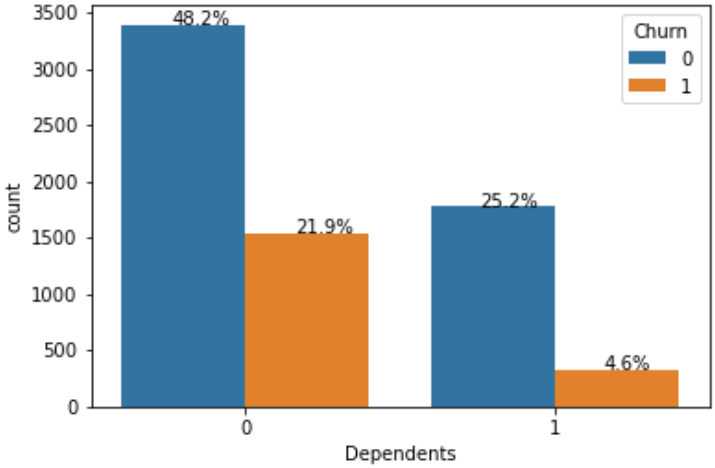
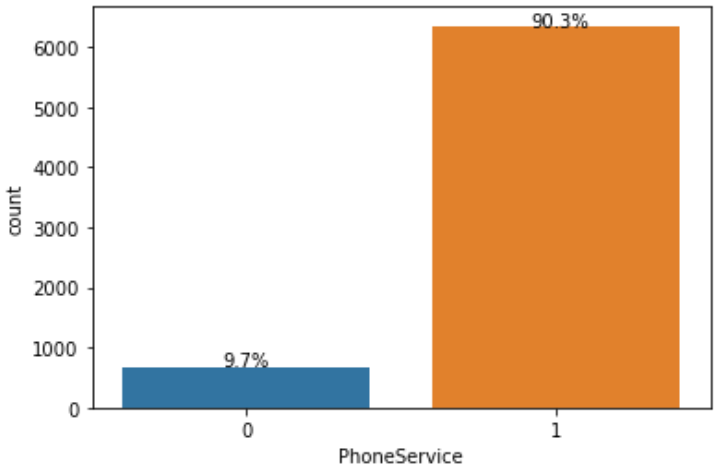




```
<Figure size 432x288 with 0 Axes>
```

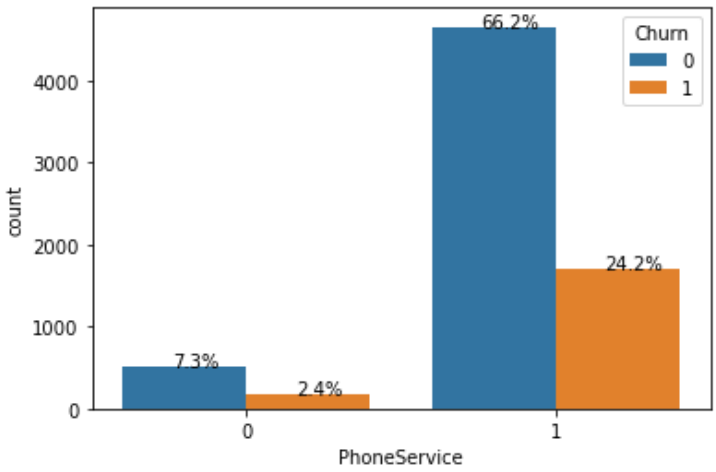
In [15]:

```
ax = sns.countplot(x='PhoneService', data=df_cleaned)
plt.figure()
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['PhoneService'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

ax = sns.countplot(x='PhoneService', data=df_cleaned, hue='Churn')
plt.figure()
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')
```

```
total = len(df_cleaned['PhoneService'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```



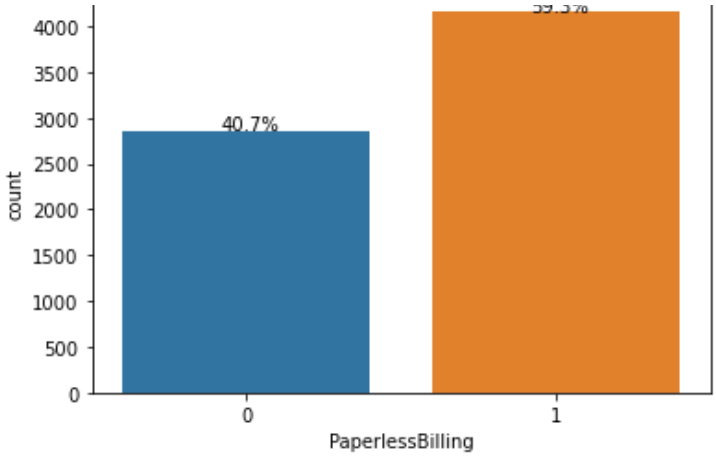

```
<Figure size 432x288 with 0 Axes>
```



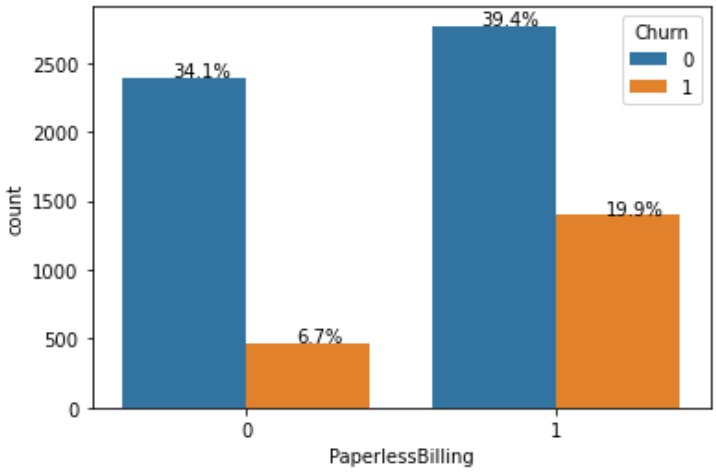

```
<Figure size 432x288 with 0 Axes>
```

In [16]:

```
ax = sns.countplot(x='PaperlessBilling', data=df_cleaned)
plt.figure()
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['PaperlessBilling'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

ax = sns.countplot(x='PaperlessBilling', data=df_cleaned, hue='Churn')
plt.figure()
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['PaperlessBilling'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```



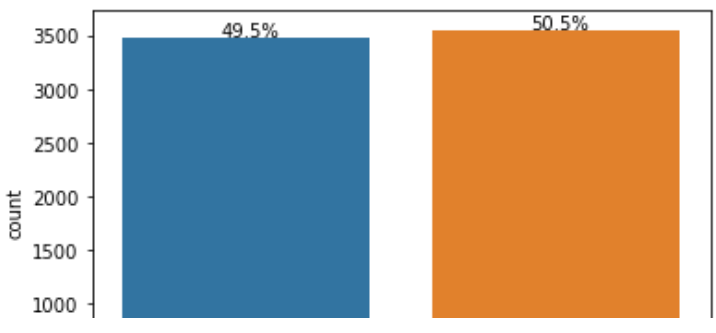
<Figure size 432x288 with 0 Axes>

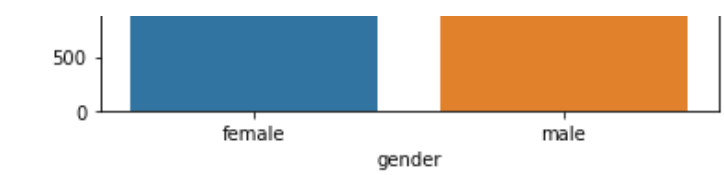


<Figure size 432x288 with 0 Axes>

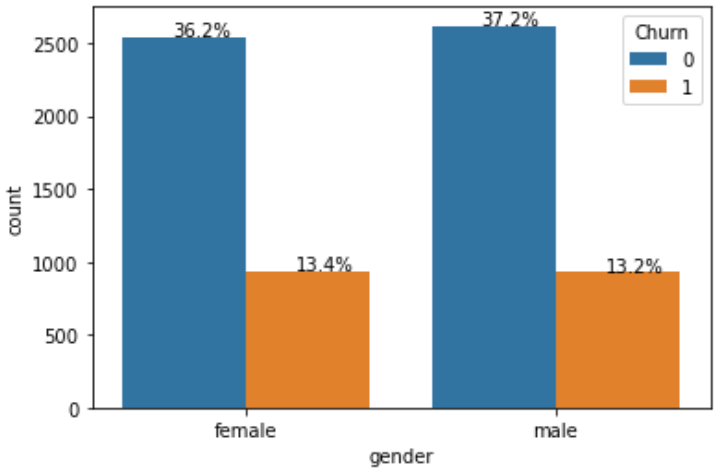
In [17]:

```
ax = sns.countplot(x='gender', data=df_cleaned)
plt.figure()
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['gender'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

ax = sns.countplot(x='gender', data=df_cleaned, hue='Churn')
plt.figure()
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['gender'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```






```
<Figure size 432x288 with 0 Axes>
```




```
<Figure size 432x288 with 0 Axes>
```

Insights:

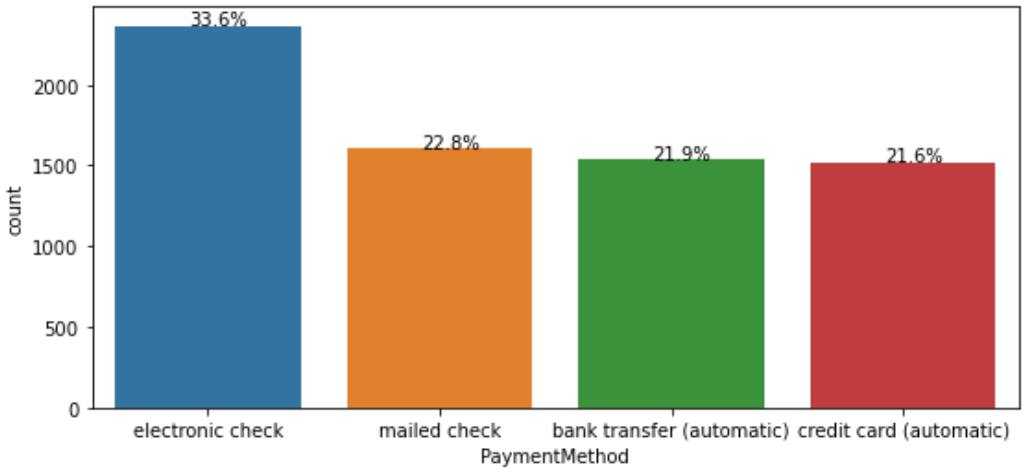
1. **16.2% of the customers are seen to have churned. Churn is significantly higher in Senior Citizens (42%) compared to customers who aren't Senior Citizens (23.6%).**
2. **48.3% of the customers have Partners. Churn is significantly higher in customers that don't have partners (33.1%) compared to those having Partners (19.7%).**
3. **29.8% of customers have Dependents. Churn is significantly lower in customers having Dependents (15.4%) compared to those not having Dependents (31.2%).**
4. **59.3% of the customers have Paperless Billing. Churn is significantly higher in customers having paperless billing (33.6%) compared to those not having Paperless Billing (16.5%).**
5. **90.3% of the customers have Phone Service. Churn is not much different irrespective of customers enjoying a Phone Service (26.8%) or not (24.7%).**
6. **Male - Female ratio is 50.5% vs 49.5%. Churn is almost unbiased in terms of gender.**

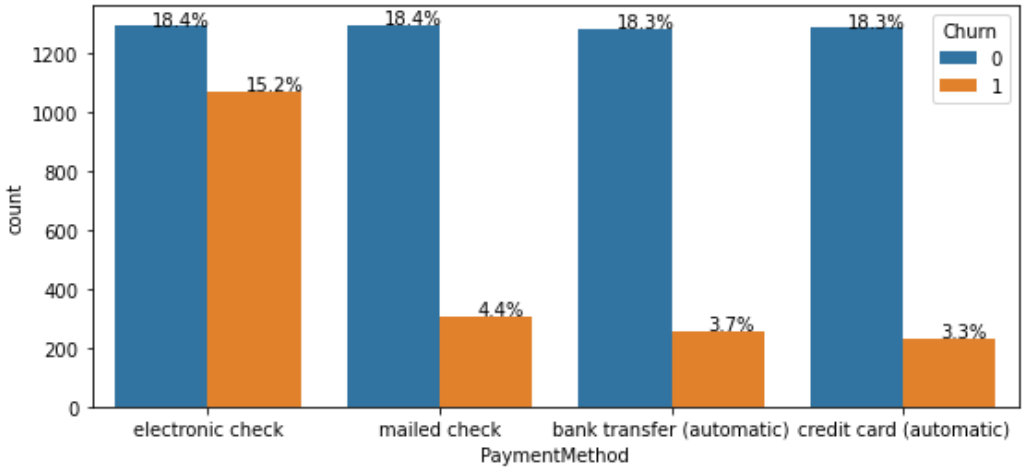
Analyzing Other Categorical Variables:

In [18]:

```
plt.figure(figsize=(9, 4))
ax = sns.countplot(x='PaymentMethod', data=df_cleaned)
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['PaymentMethod'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

plt.figure(figsize=(9, 4))
ax = sns.countplot(x='PaymentMethod', data=df_cleaned, hue='Churn')
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['PaymentMethod'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
```

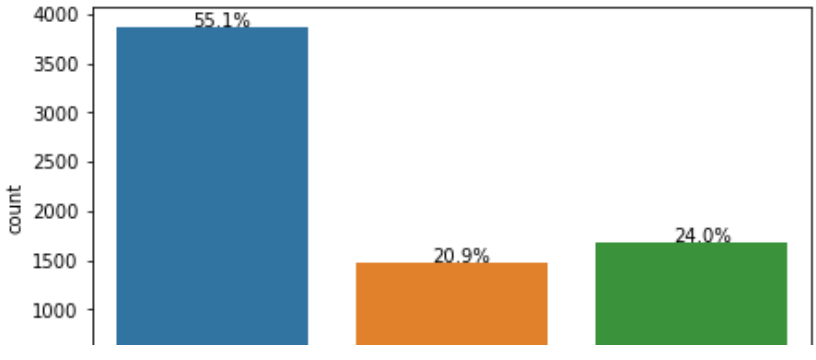
```
plt.show()
```

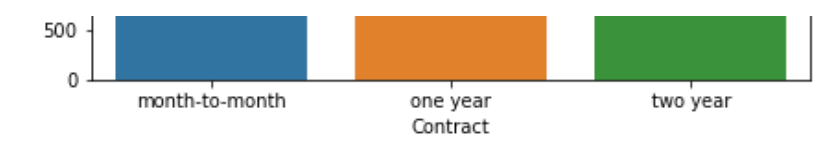


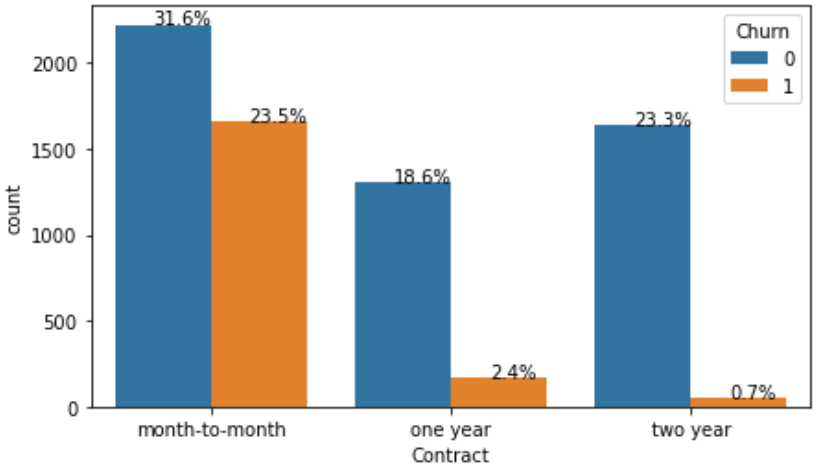


In [19]:

```
plt.figure(figsize=(7, 4))
ax = sns.countplot(x='Contract', data=df_cleaned)
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['Contract'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

plt.figure(figsize=(7, 4))
ax = sns.countplot(x='Contract', data=df_cleaned, hue='Churn')
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['Contract'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```

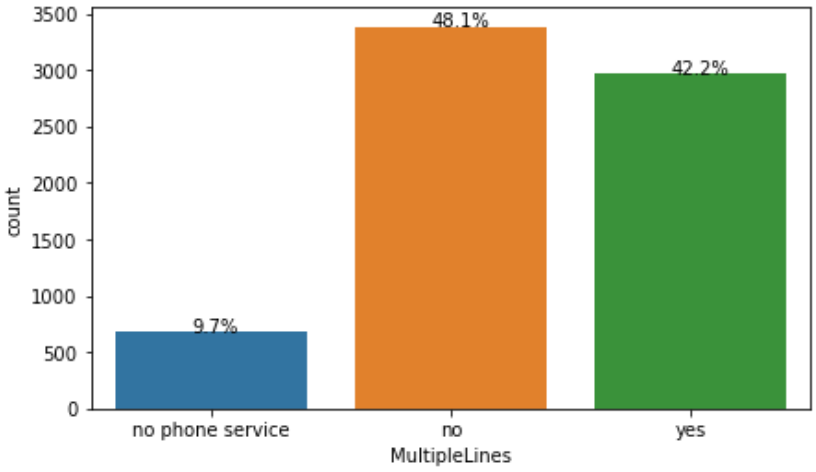


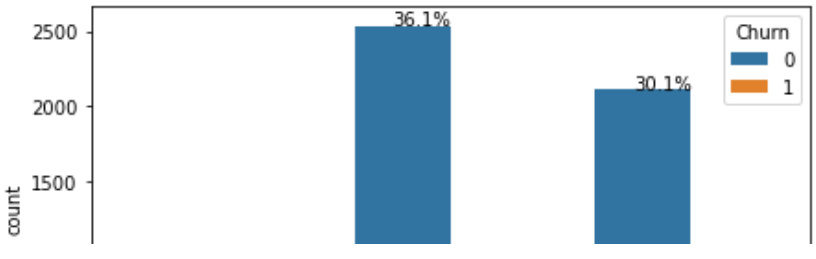


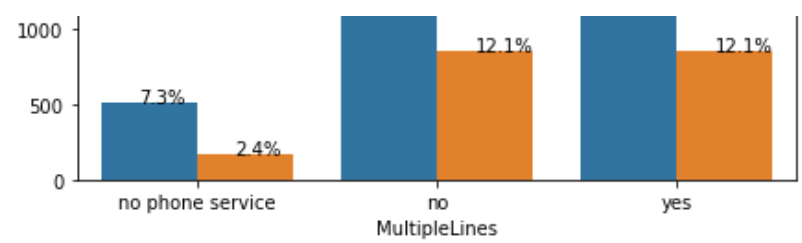


In [20]:

```
plt.figure(figsize=(7, 4))
ax = sns.countplot(x='MultipleLines', data=df_cleaned)
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['MultipleLines'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

plt.figure(figsize=(7, 4))
ax = sns.countplot(x='MultipleLines', data=df_cleaned, hue='Churn')
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['MultipleLines'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```

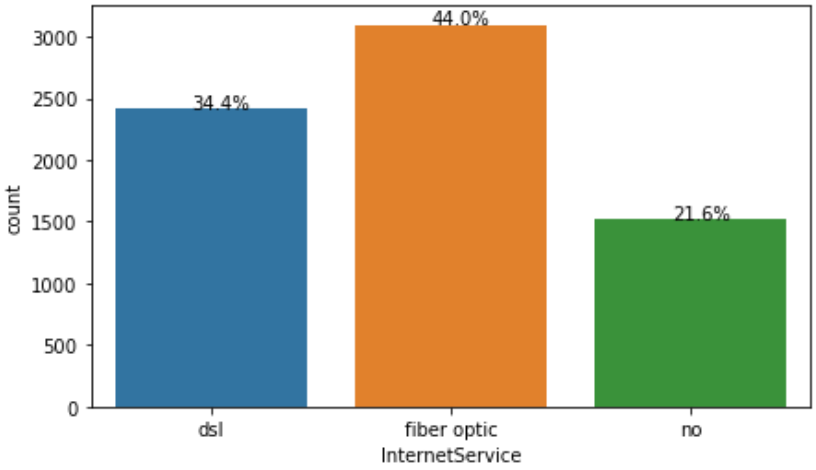


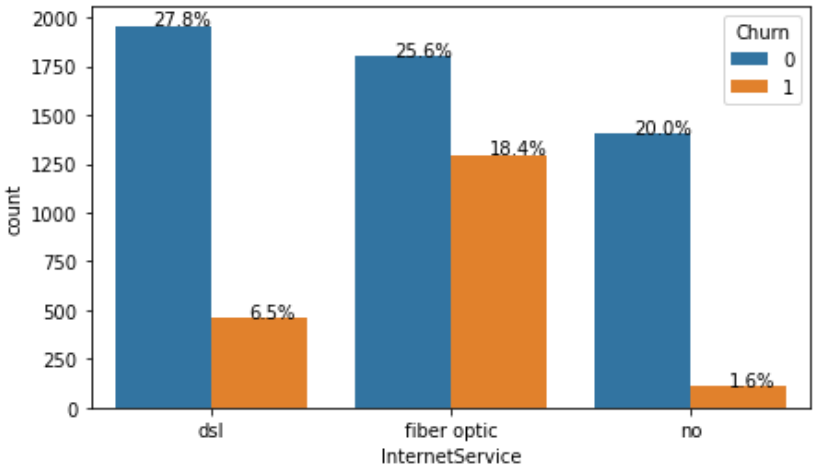




In [21]:

```
plt.figure(figsize=(7, 4))
ax = sns.countplot(x='InternetService', data=df_cleaned)
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['InternetService'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

plt.figure(figsize=(7, 4))
ax = sns.countplot(x='InternetService', data=df_cleaned, hue='Churn')
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['InternetService'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```

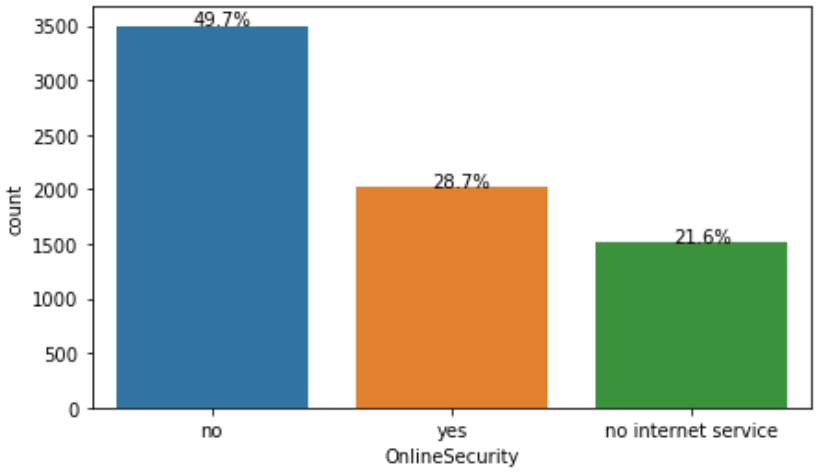




In [22]:

```
plt.figure(figsize=(7, 4))
ax = sns.countplot(x='OnlineSecurity', data=df_cleaned)
```

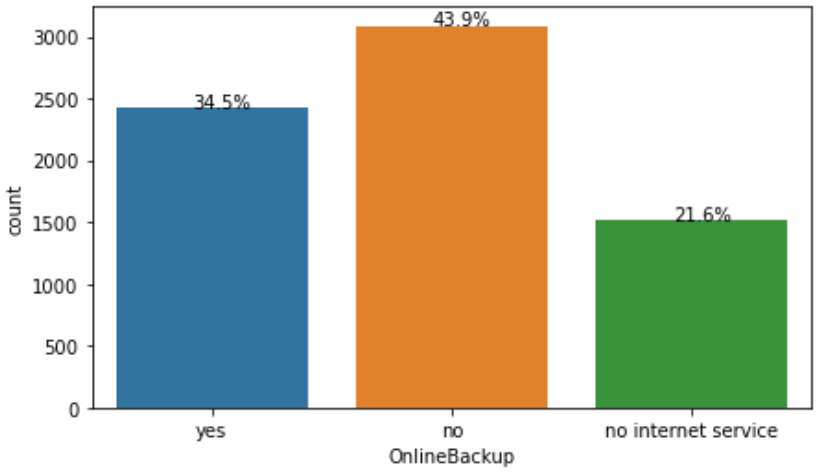
```
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['OnlineSecurity'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

plt.figure(figsize=(7, 4))
ax = sns.countplot(x='OnlineSecurity', data=df_cleaned, hue='Churn')
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['OnlineSecurity'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```

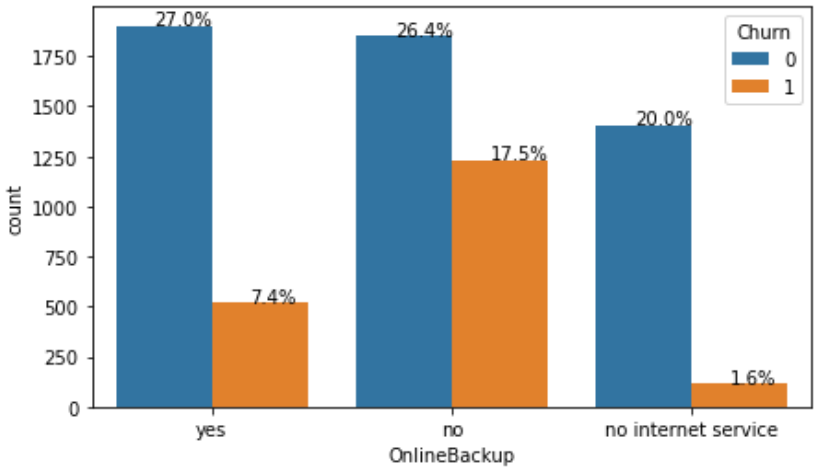


In [23]:

```
plt.figure(figsize=(7, 4))
ax = sns.countplot(x='OnlineBackup', data=df_cleaned)
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['OnlineBackup'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

plt.figure(figsize=(7, 4))
ax = sns.countplot(x='OnlineBackup', data=df_cleaned, hue='Churn')
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')
```

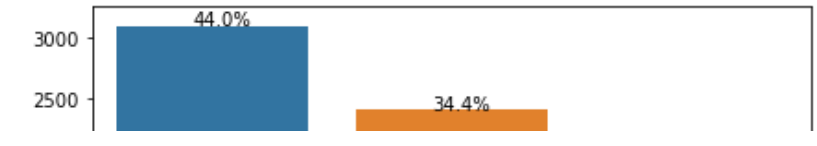
```
total = len(df_cleaned['OnlineBackup'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```

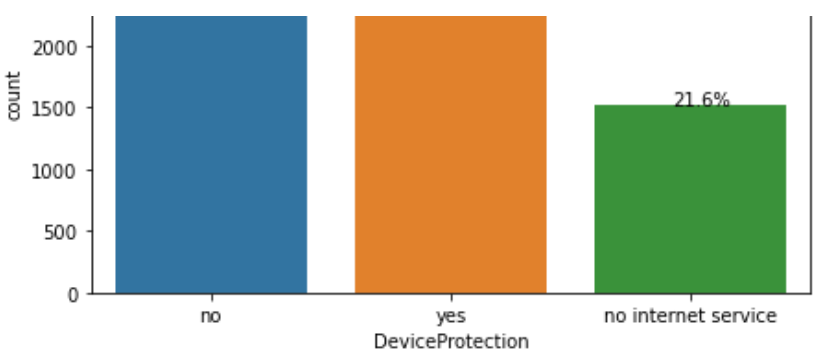


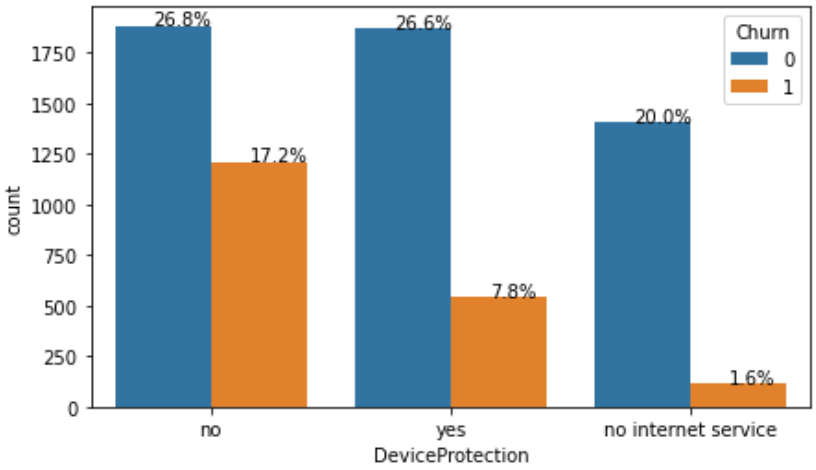


In [24]:

```
plt.figure(figsize=(7, 4))
ax = sns.countplot(x='DeviceProtection', data=df_cleaned)
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['DeviceProtection'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

plt.figure(figsize=(7, 4))
ax = sns.countplot(x='DeviceProtection', data=df_cleaned, hue='Churn')
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['DeviceProtection'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```

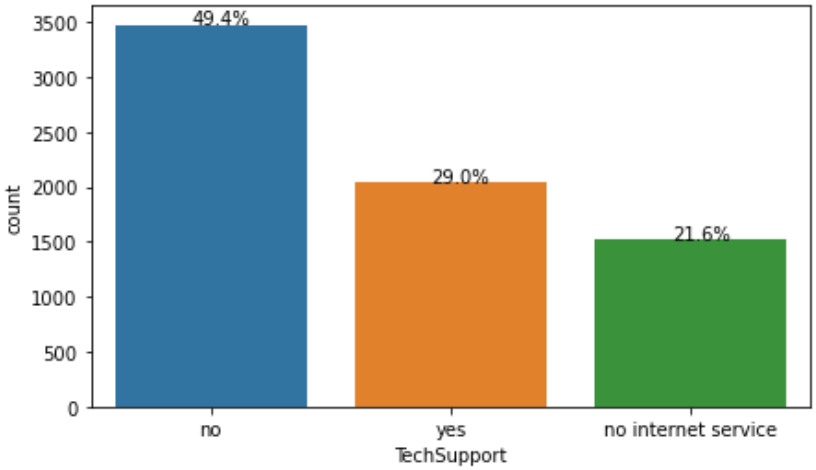


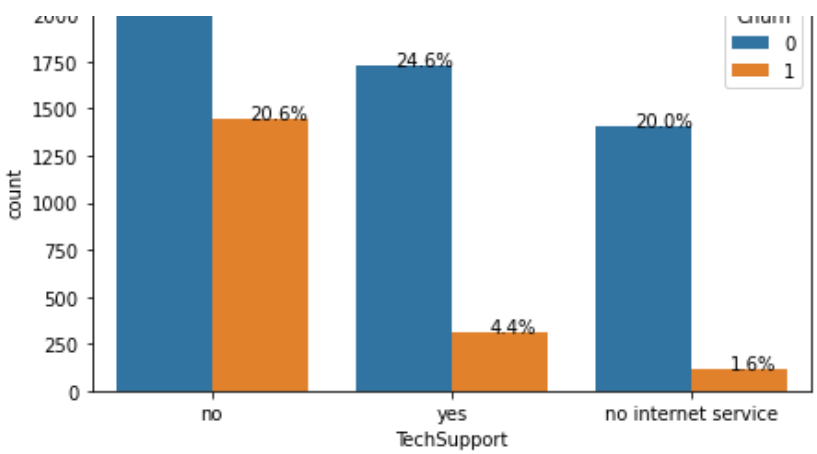




In [25]:

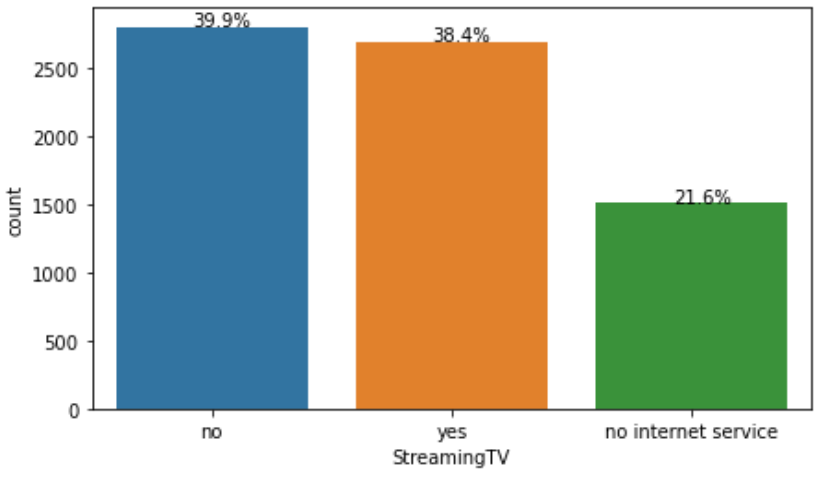
```
plt.figure(figsize=(7, 4))
ax = sns.countplot(x='TechSupport', data=df_cleaned)
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['TechSupport'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

plt.figure(figsize=(7, 4))
ax = sns.countplot(x='TechSupport', data=df_cleaned, hue='Churn')
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['TechSupport'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```

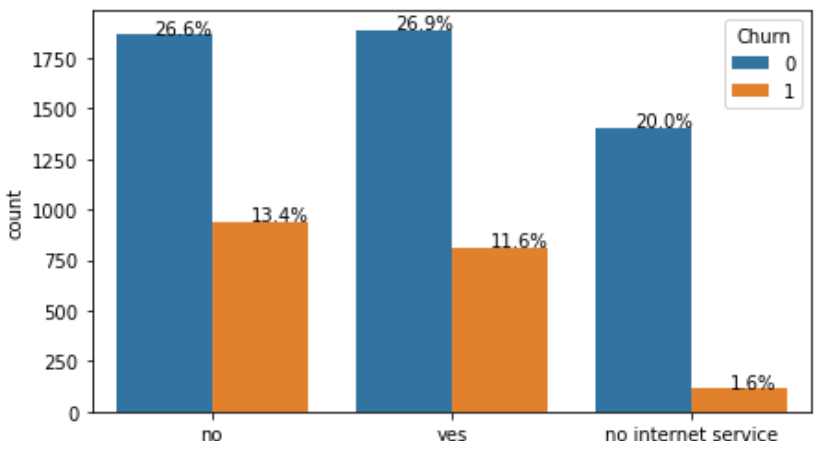




In [26]:

```
plt.figure(figsize=(7, 4))
ax = sns.countplot(x='StreamingTV', data=df_cleaned)
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['StreamingTV'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

plt.figure(figsize=(7, 4))
ax = sns.countplot(x='StreamingTV', data=df_cleaned, hue='Churn')
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['StreamingTV'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```

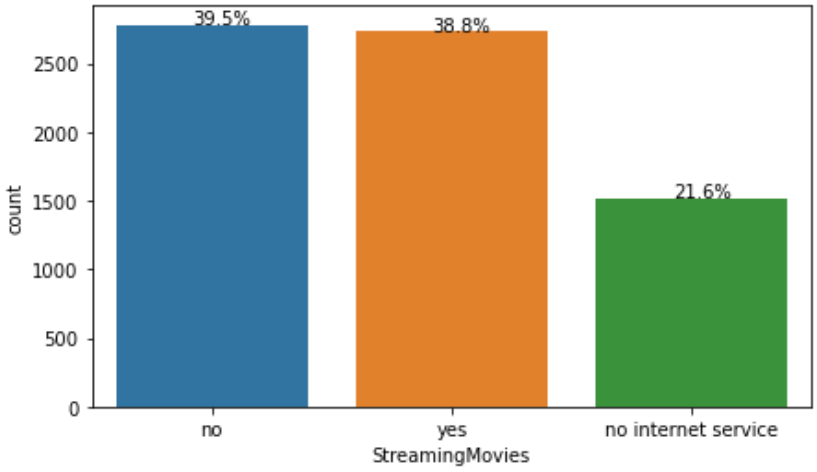


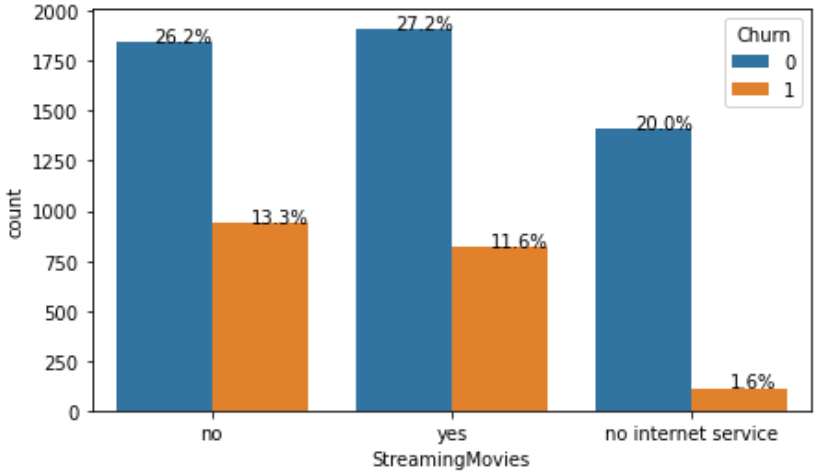


StreamingTV

In [27]:

```
plt.figure(figsize=(7, 4))
ax = sns.countplot(x='StreamingMovies', data=df_cleaned)
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['StreamingMovies'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()

plt.figure(figsize=(7, 4))
ax = sns.countplot(x='StreamingMovies', data=df_cleaned, hue='Churn')
#ax=sns.countplot(x='SeniorCitizen', data=df_cleaned, hue='Churn')

total = len(df_cleaned['StreamingMovies'])
for p in ax.patches:
        percentage = '{:.1f}%'.format(100 * p.get_height()/total)
        x = p.get_x() + p.get_width() /2.5
        y = p.get_y() + p.get_height()+1
        ax.annotate(percentage, (x, y))
plt.show()
```





Insights:

1. **33.6% customers paying through Electronic Checks. Churn is significantly higher in customers paying through electronic checks (45.2%) compared to those having other Payments Methods (15-19%).**
2. **55.1% of the customers have Month-to-Month Contract. Churn is significantly higher in customers having a month-to-month contract (42.6%) compared to those having other Contracts (3-11%).**
3. **9.7% of the customers don't have Phone Service. Of the 90.3% having Phone Service, 46.7% have Multiple Lines. Churn is observed to be bit lower in customers not having Multiple Lines (25.1%) compared to those having Multiple Lines (28.7%).**

4. **78.4% customers have Internet Service. Higher proportion of the customers subscribed Internet Service through Fiber Optic (41.8%) have churned compared to those subscribed the service through DSL (18.9%).**
5. **Churn is significantly higher in customers who haven't subscribed to these serives - Online Security, Online Backup, Device Protection and Tech Support (41.9%, 39.9%, 39.1% and 41.7% respectively) compared to those who subcribed these services (14.6%, 21.4%, 22.7% and 15.2% respectively)**
6. **Churn is slightly higher (less than 3%) in customers who haven't subscribed streaming TV or movies too.**

Analyzing Continuous Variables:

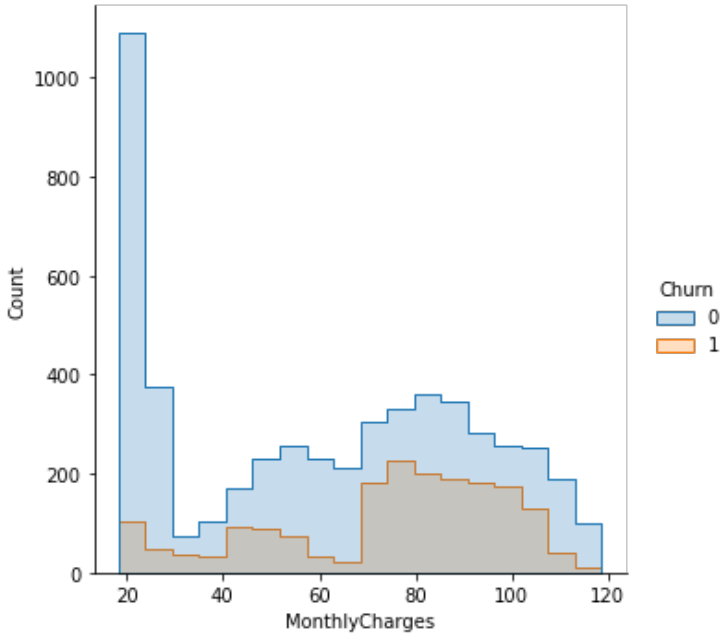
Plotting Distributions:

In [28]:

```
sns.displot(df_cleaned, x='MonthlyCharges', hue='Churn', element='step')
```

Out[28]:

```
<seaborn.axisgrid.FacetGrid at 0x2a2cbc6aac0>
```

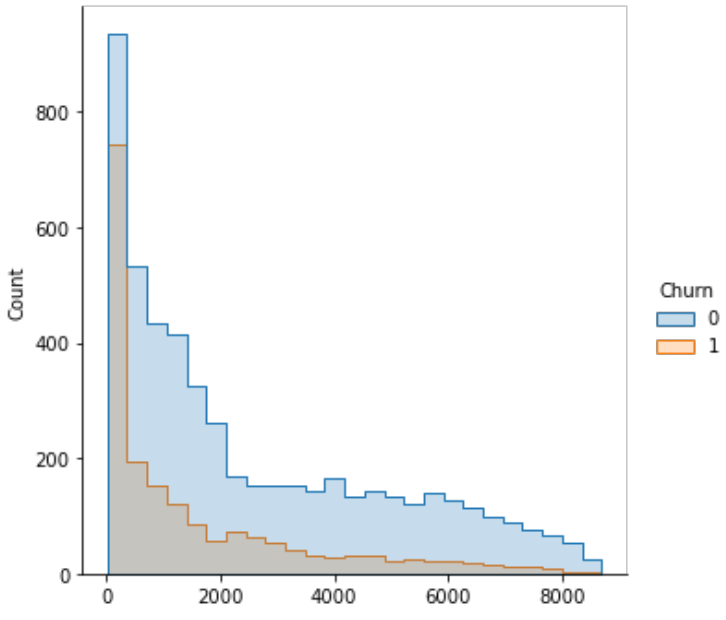


In [29]:

```
sns.displot(df_cleaned, x='TotalCharges', hue='Churn', element='step')
```

Out[29]:

```
<seaborn.axisgrid.FacetGrid at 0x2a2cbbd4a90>
```



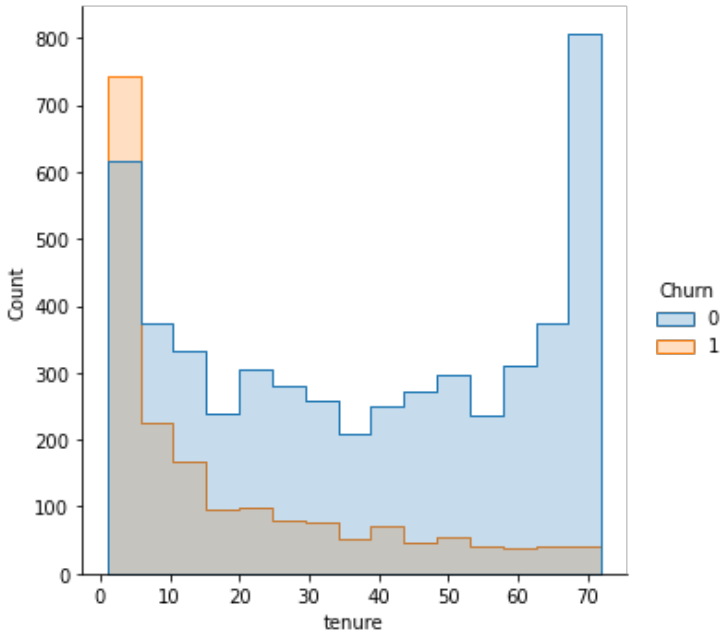
TotalCharges

In [30]:

```
sns.displot(df_cleaned, x='tenure', hue='Churn', element='step')
```

Out[30]:

<seaborn.axisgrid.FacetGrid at 0x2a2cc046ee0>



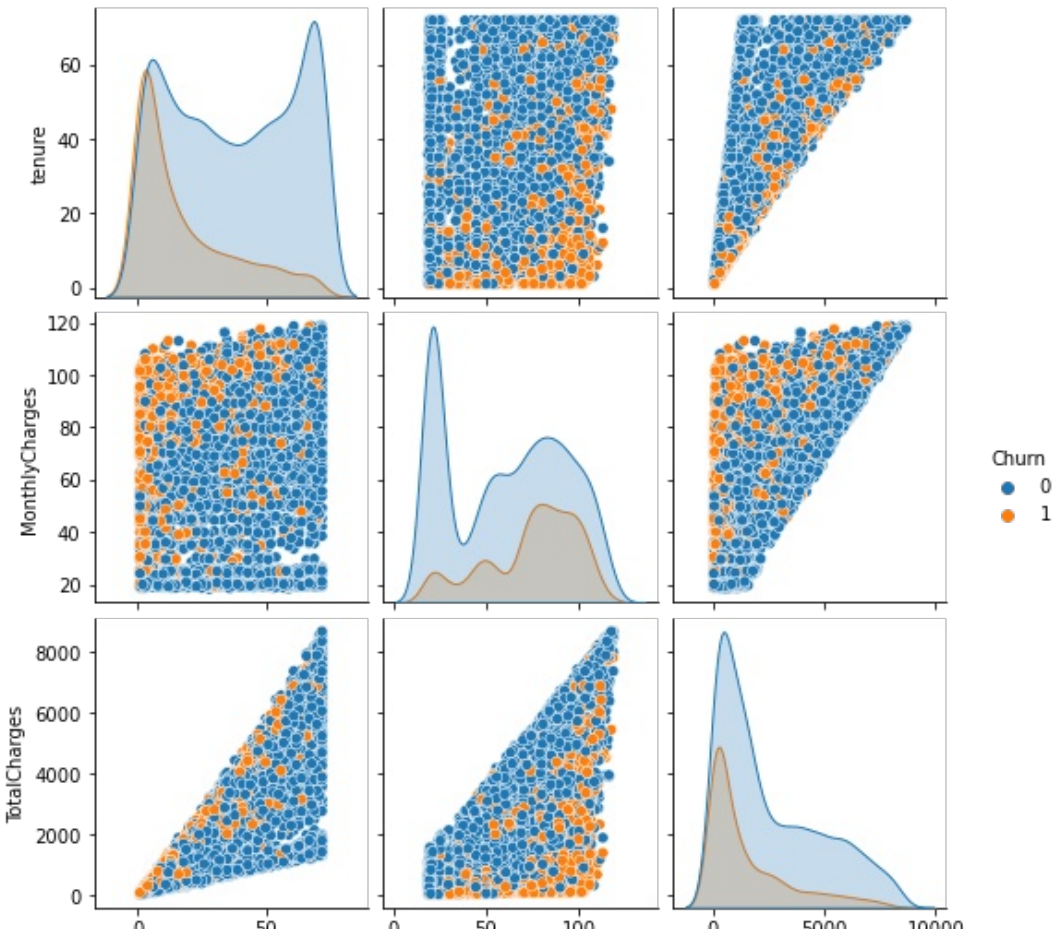
Pair Plots:

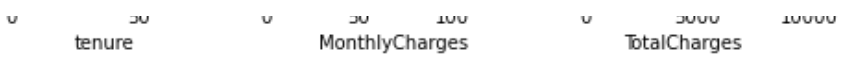
In [31]:

```
sns.pairplot(df_cleaned,vars = ['tenure','MonthlyCharges','TotalCharges'], hue="Churn")
```

Out[31]:

<seaborn.axisgrid.PairGrid at 0x2a2cbbc3070>





Insights:

Both distributions and pair plot confirms the following:

1. **The lower the total charges and tenure, the higher the churn.**
2. **Churn, conversely, is higher for highers bands of monthly charges.**

Testing Logistic Regression as a Predictive Model:

Step 1: Get data

In [32]:

```
df_lr = df_cleaned.drop('gender', 1)
df_lr.head()
```

Out[32]:

	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	De
0	0	1	0	1	0	no phone service	dsl	no	yes	
1	0	0	0	34	1	no	dsl	yes	no	
2	0	0	0	2	1	no	dsl	yes	yes	
3	0	0	0	45	0	no phone service	dsl	yes	no	
4	0	0	0	2	1	no	fiber optic	no	no	

- **Since the gender is seen to remain unbiased towards churn, gender has been dropped.**

Let's convert all the categorical variables into dummy variables

In [33]:

```
df_dummies = pd.get_dummies(df_lr)
df_dummies.head()
```

Out[33]:

	SeniorCitizen	Partner	Dependents	tenure	PhoneService	PaperlessBilling	MonthlyCharges	TotalCharges	Churn	Multiple
0	0	1	0	1	0	1	29.85	29.85	0	
1	0	0	0	34	1	0	56.95	1889.50	0	
2	0	0	0	2	1	1	53.85	108.15	1	
3	0	0	0	45	0	0	42.30	1840.75	0	
4	0	0	0	2	1	1	70.70	151.65	1	

5 rows × 40 columns

In [34]:

```
X = df_dummies.drop('Churn', 1)
y = df_dummies['Churn']
```

In [35]:

```
# split X and y into training and testing sets

from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.25,random_state=0)
```

In [36]:

```
# import the class
from sklearn.linear_model import LogisticRegression
```

In [37]:

```
# instantiate the model (using the default parameters)
logreg = LogisticRegression()
```

In [38]:

```
# fit the model with data
logreg.fit(X_train,y_train)
```

```
C:\Users\mmrez\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:762: Converg
enceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[38]:

```
LogisticRegression()
```

In [39]:

```
#
y_pred=logreg.predict(X_test)
```

In [40]:

```
# import the metrics class
from sklearn import metrics
cnf_matrix = metrics.confusion_matrix(y_test, y_pred)
cnf_matrix
```

Out[40]:

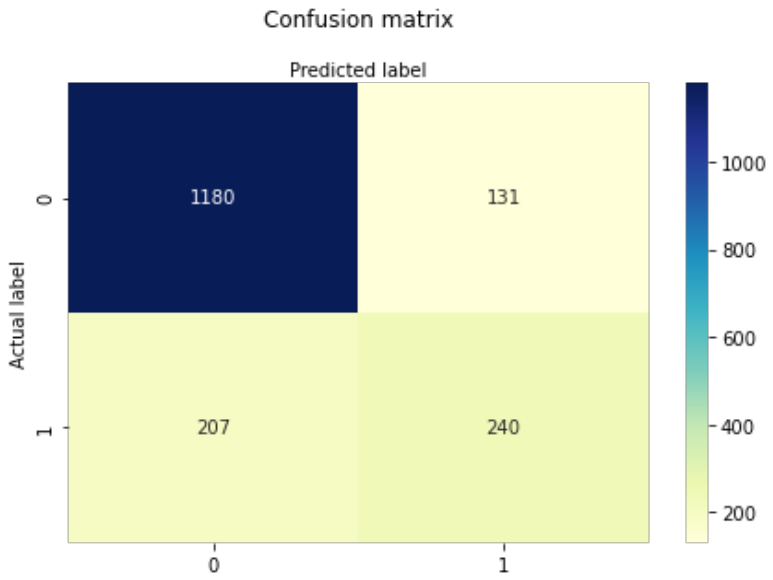
```
array([[1180,  131],
       [ 207,  240]], dtype=int64)
```

In [41]:

```
class_names=[0,1] # name  of classes
fig, ax = plt.subplots()
tick_marks = np.arange(len(class_names))
plt.xticks(tick_marks, class_names)
plt.yticks(tick_marks, class_names)
# create heatmap
sns.heatmap(pd.DataFrame(cnf_matrix), annot=True, cmap="YlGnBu" ,fmt='g')
ax.xaxis.set_label_position("top")
plt.tight_layout()
plt.title('Confusion matrix', y=1.1)
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

Out[41]:

```
Text(0.5, 257.44, 'Predicted label')
```



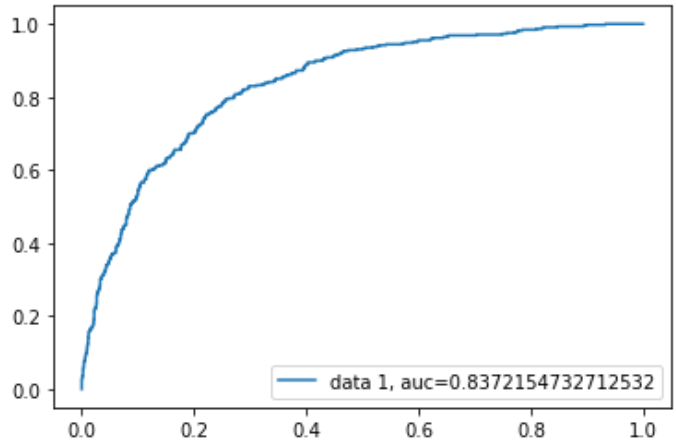
In [42]:

```
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("Precision:",metrics.precision_score(y_test, y_pred))
print("Recall:",metrics.recall_score(y_test, y_pred))
```

```
Accuracy: 0.8077360637087599
Precision: 0.6469002695417789
Recall: 0.5369127516778524
```

In [43]:

```
y_pred_proba = logreg.predict_proba(X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(y_test,  y_pred_proba)
auc = metrics.roc_auc_score(y_test, y_pred_proba)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



Insights:

The accuracy of predicting churn using logistic regression looks quite high (80.77%).