A

1

How can the organization best allocate resources to direct sales, improve service provision, and or client facing services in order to maximize monthly revenue or 'MonthlyCharge' ?

2

The goals of this data analysis are to indentify correlations and relationships in the data set that are actionable and have a positive correlation with 'MonthlyCharge'.

B.

1.

Linear Relationship: The core premise of multiple linear regression is the existence of a linear relationship between the dependent (outcome) variable and the independent variables. This linearity can be visually inspected using scatterplots, which should reveal a straight-line relationship rather than a curvilinear one.

Multivariate Normality: The analysis assumes that the residuals (the differences between observed and predicted values) are normally distributed. This assumption can be assessed by examining histograms or Q-Q plots of the residuals, or through statistical tests such as the Kolmogorov-Smirnov test.

No Multicollinearity: It is essential that the independent variables are not too highly correlated with each other, a condition known as multicollinearity. This can be checked using: Correlation matrices, where correlation coefficients should ideally be below 0.80.

Variance Inflation Factor (VIF), with VIF values above 10 indicating problematic multicollinearity. Solutions may include centering the data (subtracting the mean score from each observation) or removing the variables causing multicollinearity.

Homoscedasticity: The variance of error terms (residuals) should be consistent across all levels of the independent variables. A scatterplot of residuals versus predicted values should not display any discernible pattern, such as a cone-shaped distribution, which would indicate heteroscedasticity. Addressing heteroscedasticity might involve data transformation or adding a quadratic term to the model.

(Assumptions of multiple linear regression 2024)

2.

One benefit of python is that it is an interpreted language. There is no compile time, so it is much quicker for iterative processes such as the backward elimination process when we are reducing the regression model and removing independent variables.

Another benefit of python language is that it has many libraries and packages that can automate the regression model creation process and simplify it to just a few lines of code. When it is time to compare the reduced model, the python packages can help us quickly compare the models by showing us important regression model metrics such as adjusted R squared, and the p values of coefficients.

3

Multiple linear regression is an appropriate technique to use for analyzing the research question in part 1 because the question we are answering involves predicting a continuous variable 'MonthlyCharge'. Another reason multiple linear regression is an appropriate technique is because part of the question involves identifying correlations between multiple predictor variables and one continuous dependent variable.

C.

1.

My data cleaning goals are as follows:

Identify any duplicate rows and remove them. I will do this by comparing rows by 'CaseOrder'. If there are any duplicates I will drop one of the duplicate rows.

Identify any missing values. I will use the df.isna() function to list columns with missing values. I will impute the values with different techniques depending on the data type and context of each column.

Identify any outliers. I will use z-scores, IQR tests and the describe() method to identify outliers. I will first use the describe() function to get an overview, and if further analysis is needed I can use z-scores and IQR tests to further identify outliers. If a value is clearly an outlier, it can be imputed from other values or the row dropped.

See cells below for further explanation of each step and annotated code.

In [1]:

```
#import libraries and read in the data from file.
import pandas as pd
from scipy.stats import zscore
import matplotlib.pyplot as plt
import seaborn as sns
```

```
import numpy as np
# Assuming your CSV file is named 'data.csv', adjust the file path as needed
file_path = '/home/dj/skewl/d208/churn_clean.csv'
pd.set_option('display.max_columns', None)
# Read the data from the CSV file into a DataFrame
df = pd.read_csv(file_path)
#drop index column
df = df.loc[:, ~df.columns.str.contains('Unnamed')]
```

In [2]:
```
# helper functions

#function to plot histogram univariate
def plot_hist(col_name, num_bins, do_rotate=False):
    plt.hist(df[col_name], bins=num_bins)
    plt.xlabel(col_name)
    plt.ylabel('Frequency')
    plt.title(f'Histogram of {col_name}')
    if do_rotate:
        plt.xticks(rotation=90)
    plt.show()

def line_plot(indep):
    # hexbin plot for continuous variables
    plt.hexbin(df[indep], df['MonthlyCharge'], gridsize=10)
    plt.colorbar()
    plt.title('Hexbin Plot')
    plt.xlabel(indep)
    plt.ylabel('MonthlyCharge')
    plt.show()

def box_plot(indep):
    # Box plot for categorical predictor and continuous outcome variable
    df.boxplot(column='MonthlyCharge', by=indep)
    plt.title('Box Plot',y=.5)
    plt.xlabel(indep)
    plt.ylabel('MonthlyCharge')
    plt.show()
```

identify duplicate rows by 'CaseOrder' {-}

In [3]:
```
# Find duplicate rows
duplicate_rows = df.duplicated(["CaseOrder"]).sum()

# Print duplicate rows   # found NO duplicate rows here!
print(duplicate_rows)
```

0

identify missing values

In [4]:

```
# Identify missing values using isna() method
missing_values = df.isna().sum()
# Print DataFrame with True for missing values and False for non-missing values
print(missing_values)

# no missing values here!
```

```
CaseOrder              0
Customer_id            0
Interaction            0
UID                    0
City                   0
State                  0
County                 0
Zip                    0
Lat                    0
Lng                    0
Population             0
Area                   0
TimeZone               0
Job                    0
Children               0
Age                    0
Income                 0
Marital                0
Gender                 0
Churn                  0
Outage_sec_perweek     0
Email                  0
Contacts               0
Yearly_equip_failure   0
Techie                 0
Contract               0
Port_modem             0
Tablet                 0
InternetService        0
Phone                  0
Multiple               0
OnlineSecurity         0
OnlineBackup           0
DeviceProtection       0
TechSupport            0
StreamingTV            0
StreamingMovies        0
PaperlessBilling       0
PaymentMethod          0
Tenure                 0
MonthlyCharge          0
Bandwidth_GB_Year      0
Item1                  0
Item2                  0
Item3                  0
Item4                  0
Item5                  0
Item6                  0
```

```
Item7                 0
Item8                 0
dtype: int64
```

Check for outliers

In [5]:
```
# check for outliers. Doesn't seem to be any outliers.
df.describe()
```

Out[5]:

	CaseOrder	Zip	Lat	Lng	Population	Children	Age	Income	Outage_sec_pe
count	10000.00000	10000.000000	10000.000000	10000.000000	10000.000000	10000.0000	10000.000000	10000.000000	10000.0
mean	5000.50000	49153.319600	38.757567	-90.782536	9756.562400	2.0877	53.078400	39806.926771	10.0
std	2886.89568	27532.196108	5.437389	15.156142	14432.698671	2.1472	20.698882	28199.916702	2.9
min	1.00000	601.000000	17.966120	-171.688150	0.000000	0.0000	18.000000	348.670000	0.0
25%	2500.75000	26292.500000	35.341828	-97.082812	738.000000	0.0000	35.000000	19224.717500	8.0
50%	5000.50000	48869.500000	39.395800	-87.918800	2910.500000	1.0000	53.000000	33170.605000	10.0
75%	7500.25000	71866.500000	42.106908	-80.088745	13168.000000	3.0000	71.000000	53246.170000	11.9
max	10000.00000	99929.000000	70.640660	-65.667850	111850.000000	10.0000	89.000000	258900.700000	21.2

2. Describe dependent and independent variables {-}

In [6]:
```
## dependent variable

df['MonthlyCharge'].describe()
```

Out[6]:
```
count    10000.000000
mean       172.624816
std         42.943094
min         79.978860
25%        139.979239
50%        167.484700
75%        200.734725
max        290.160419
Name: MonthlyCharge, dtype: float64
```

In [7]:
```
# independent variable
```

```
df['Gender'].describe()
```

Out[7]:
```
count      10000
unique         3
top       Female
freq        5025
Name: Gender, dtype: object
```

In [8]:
```
df['Area'].describe()
```

Out[8]:
```
count        10000
unique           3
top       Suburban
freq          3346
Name: Area, dtype: object
```

In [9]:
```
df['Age'].describe()
```

Out[9]:
```
count    10000.000000
mean        53.078400
std         20.698882
min         18.000000
25%         35.000000
50%         53.000000
75%         71.000000
max         89.000000
Name: Age, dtype: float64
```

In [10]:
```
df['Income'].describe()
```

Out[10]:
```
count     10000.000000
mean      39806.926771
std       28199.916702
min         348.670000
25%       19224.717500
50%       33170.605000
75%       53246.170000
max      258900.700000
Name: Income, dtype: float64
```

In [11]:
```
df['Outage_sec_perweek'].describe()
```

```
Out[11]: count    10000.000000
         mean        10.001848
         std          2.976019
         min          0.099747
         25%          8.018214
         50%         10.018560
         75%         11.969485
         max         21.207230
         Name: Outage_sec_perweek, dtype: float64
```

```
In [12]: df['InternetService'].describe()
```

```
Out[12]: count            10000
         unique               3
         top        Fiber Optic
         freq              4408
         Name: InternetService, dtype: object
```

```
In [13]: df['Phone'].describe()
```

```
Out[13]: count     10000
         unique        2
         top         Yes
         freq       9067
         Name: Phone, dtype: object
```

```
In [14]: df['OnlineSecurity'].describe()
```

```
Out[14]: count     10000
         unique        2
         top          No
         freq       6424
         Name: OnlineSecurity, dtype: object
```

```
In [15]: df['DeviceProtection'].describe()
```

```
Out[15]: count     10000
         unique        2
         top          No
         freq       5614
         Name: DeviceProtection, dtype: object
```

```
In [16]: df['StreamingMovies'].describe()
```

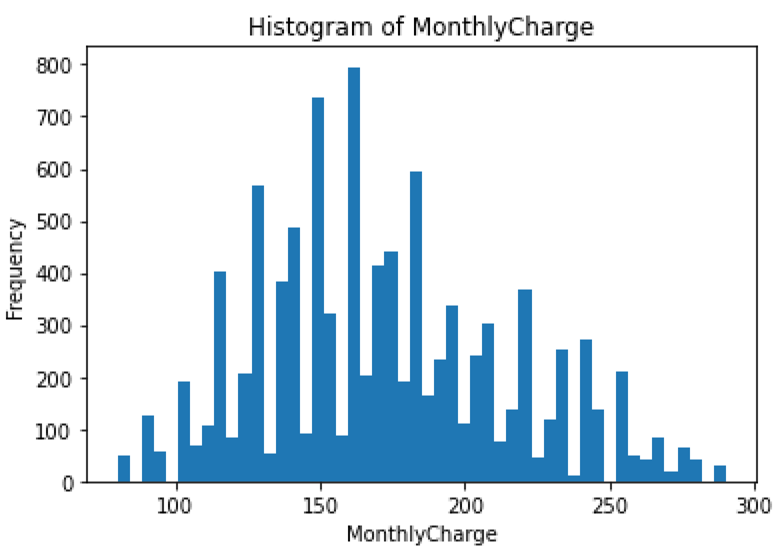
Out[16]:
```
count     10000
unique        2
top          No
freq       5110
Name: StreamingMovies, dtype: object
```

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

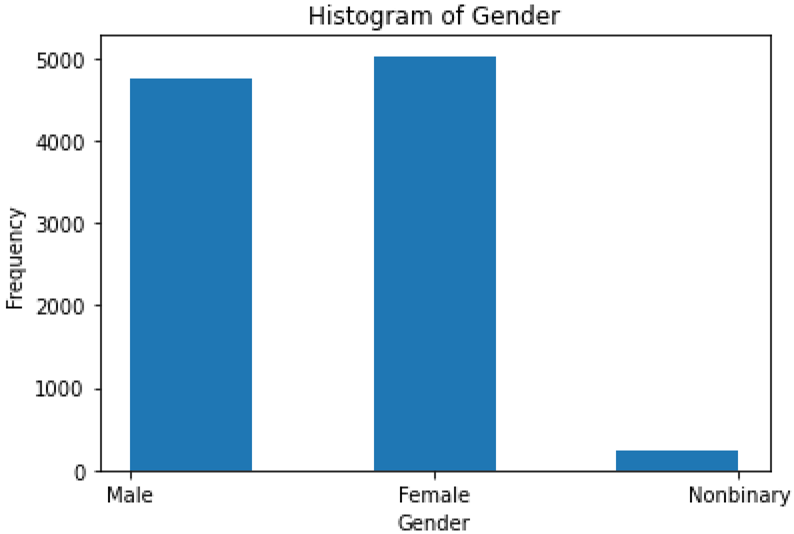
Out[17]:
```
count     10000
unique        2
top          No
freq       5494
Name: OnlineBackup, dtype: object
```

3. Generate univariate and bivariate visualizations of the distributions of the dependent and independent variables, including the dependent variable in your bivariate visualizations.

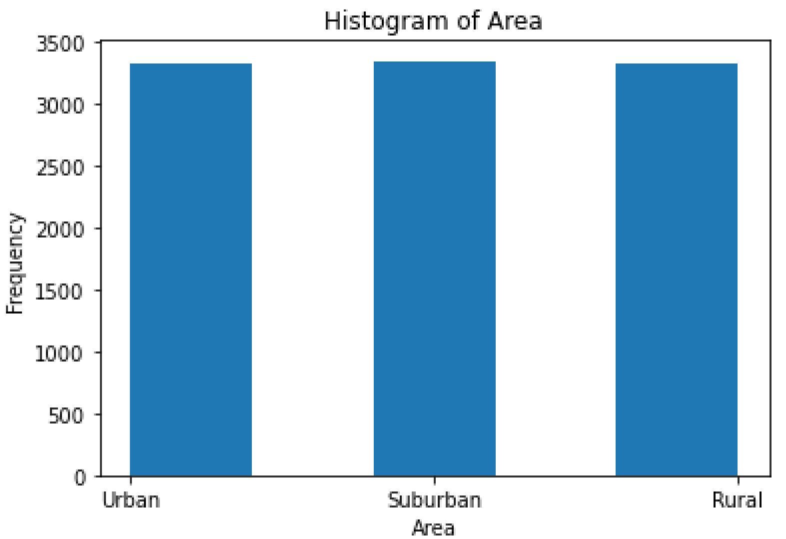
In [18]:
```
plot_hist('MonthlyCharge',50)
```



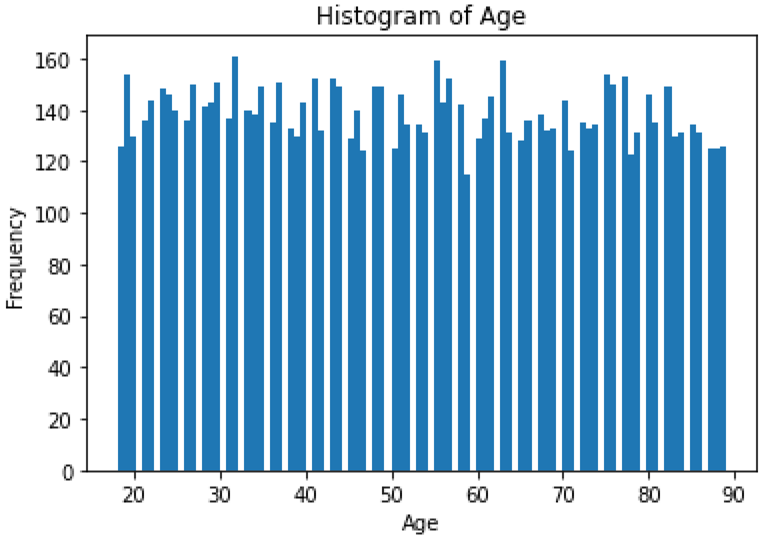
In [19]:
```
plot_hist('Gender',5)
```



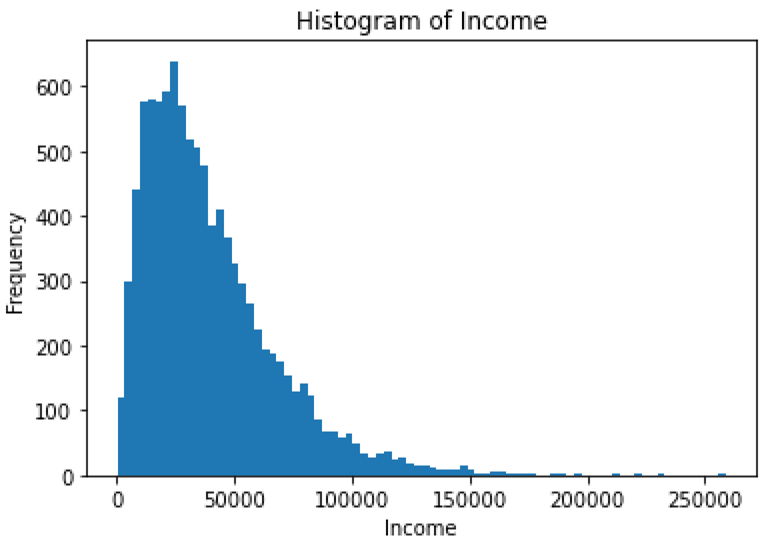
In [20]:
```
plot_hist('Area',5)
```



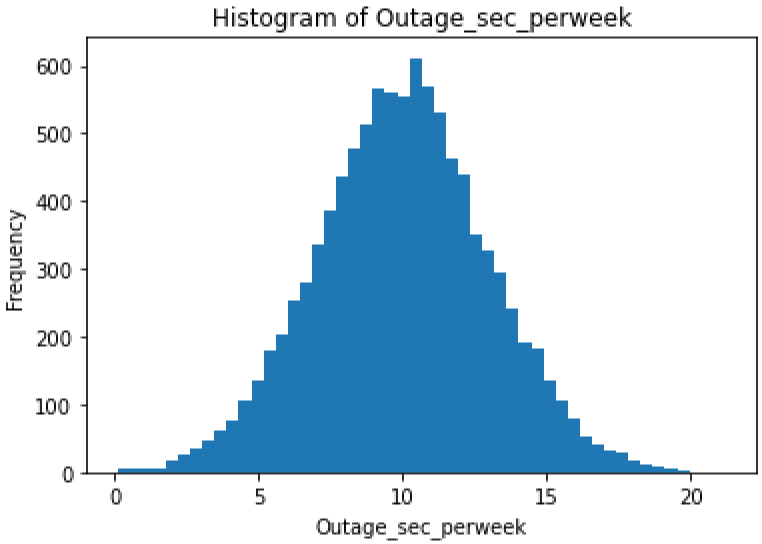
In [21]:
```
plot_hist('Age',100)
```



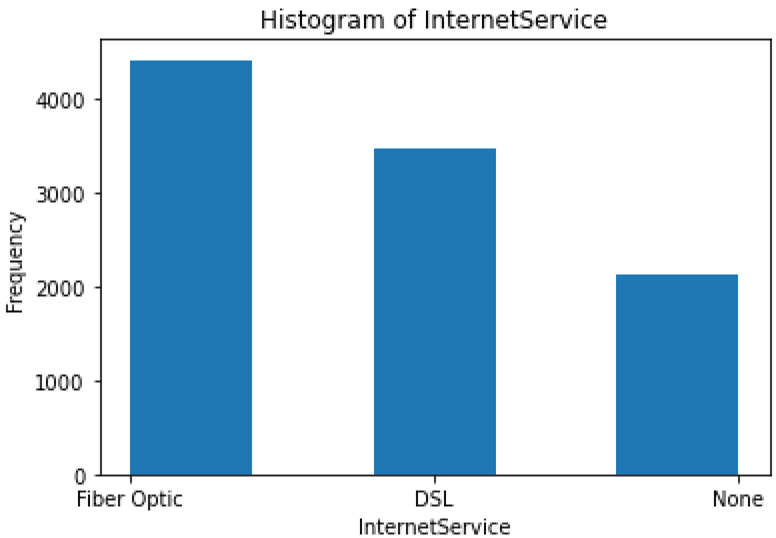
In [22]:
```
plot_hist('Income',80)
```



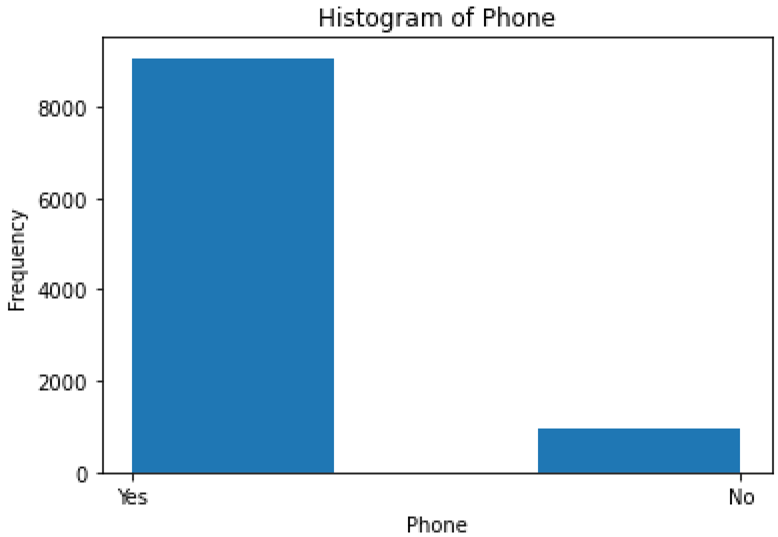
In [23]:
```
plot_hist('Outage_sec_perweek',50)
```



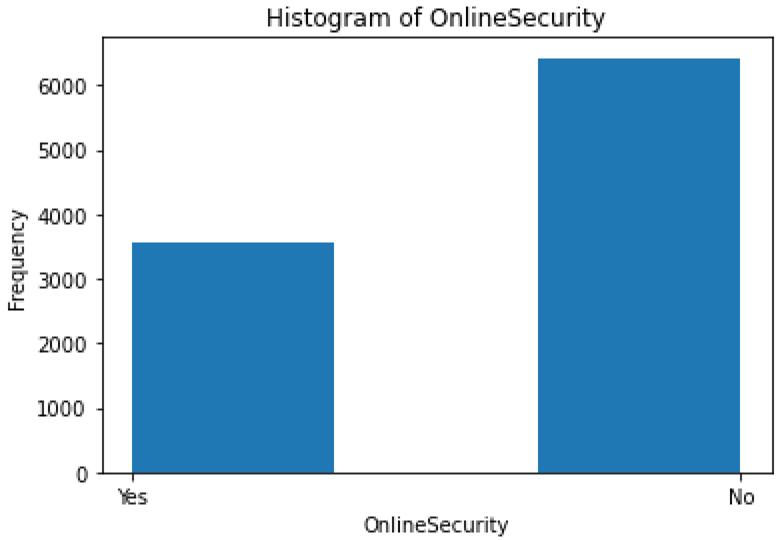
In [24]:
```
plot_hist('InternetService',5)
```



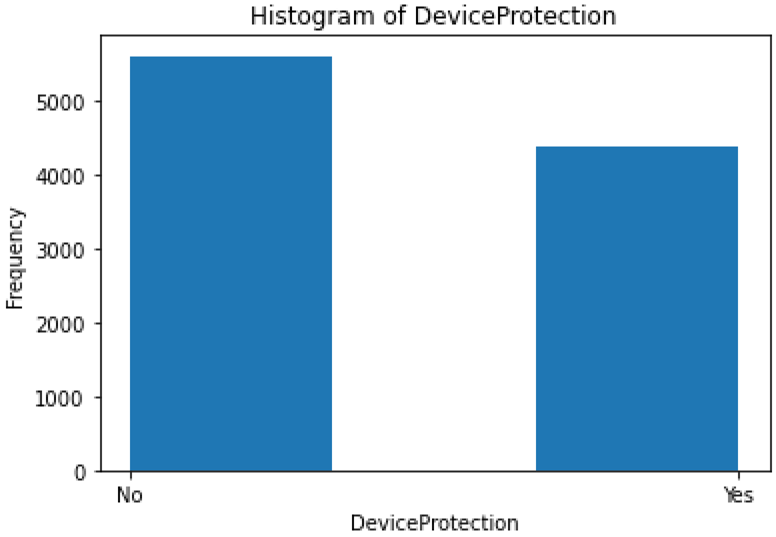
In [25]:
```
plot_hist('Phone',3)
```



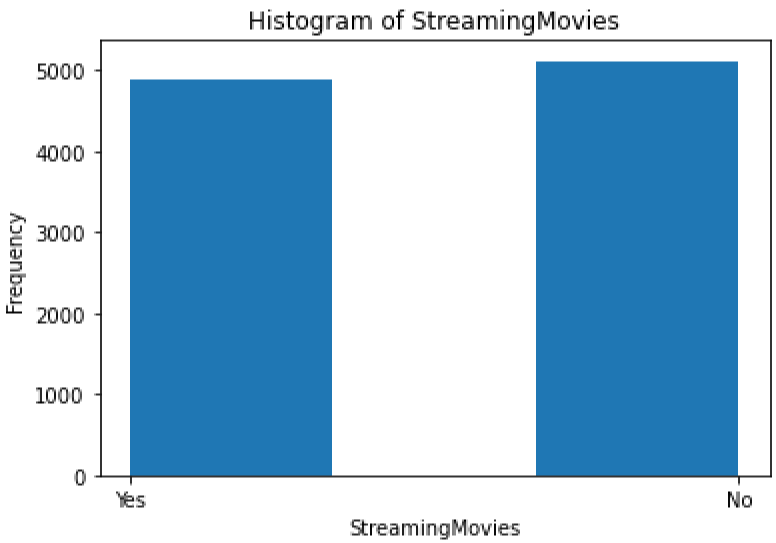
In [26]:
```
plot_hist('OnlineSecurity',3)
```



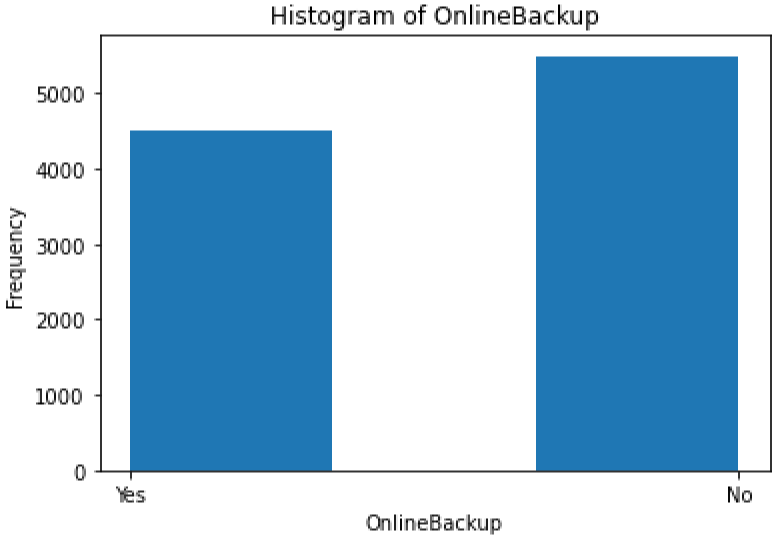
In [27]:
```
plot_hist('DeviceProtection',3)
```



In [28]:
```
plot_hist('StreamingMovies',3)
```

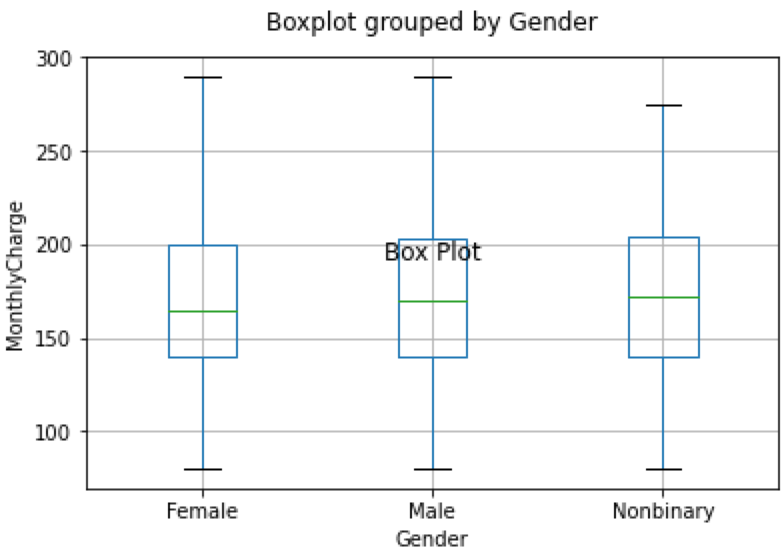


In [29]:
```
plot_hist('OnlineBackup',3)
```

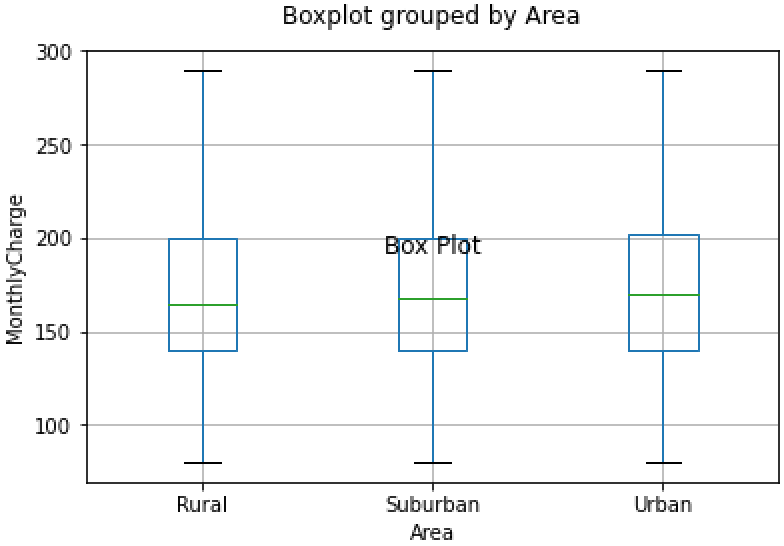


bivariate - graphing against the dependent variable {-}

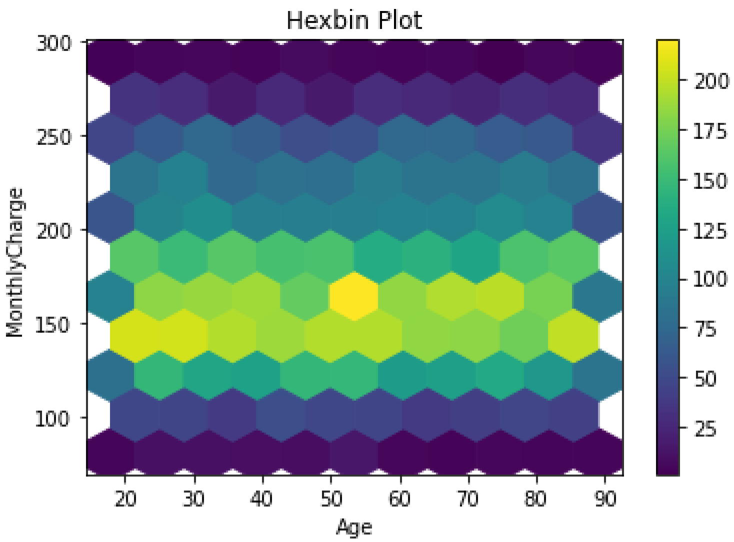
In [30]:
```
box_plot('Gender')
```



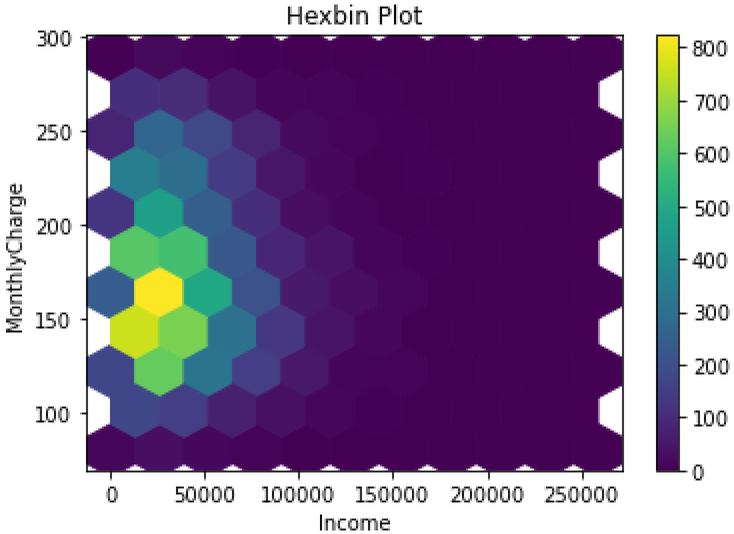
In [31]:
```
box_plot('Area')
```



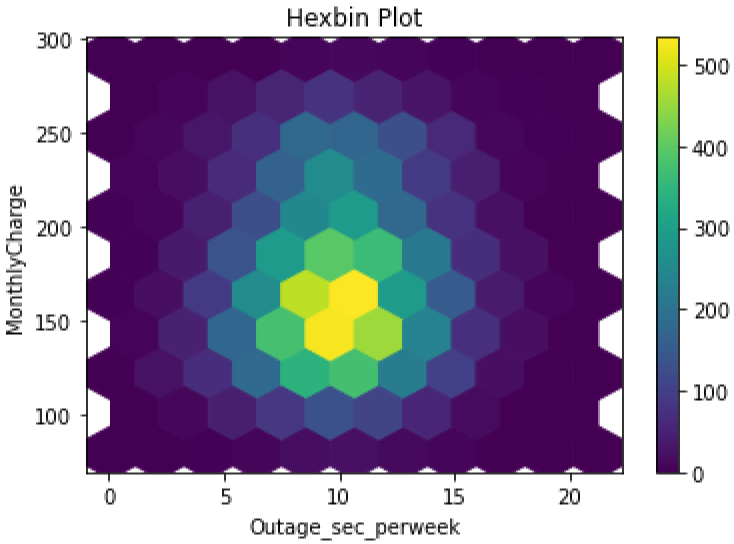

```
In [32]: line_plot('Age')
```



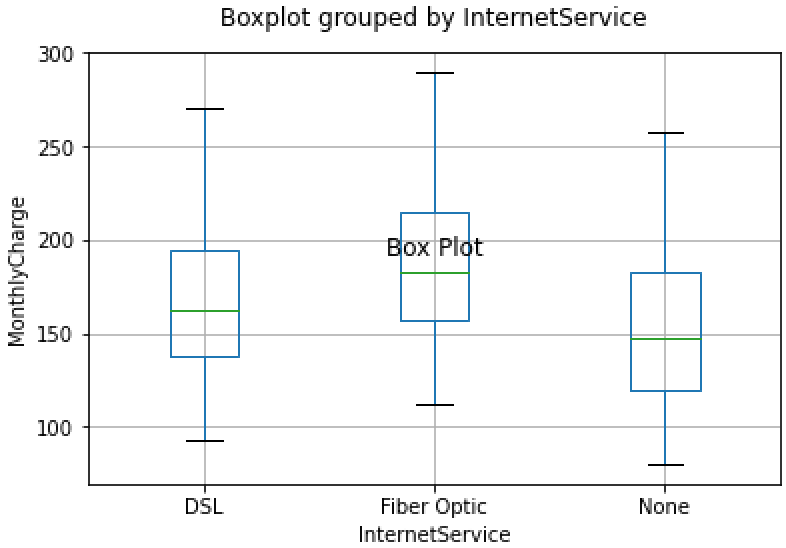

```
In [33]: line_plot('Income')
```



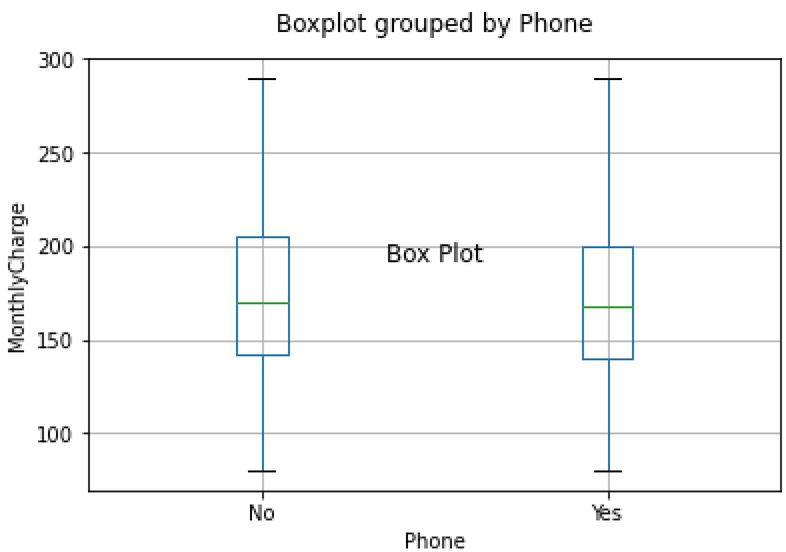
In [34]:
```
line_plot('Outage_sec_perweek')
```



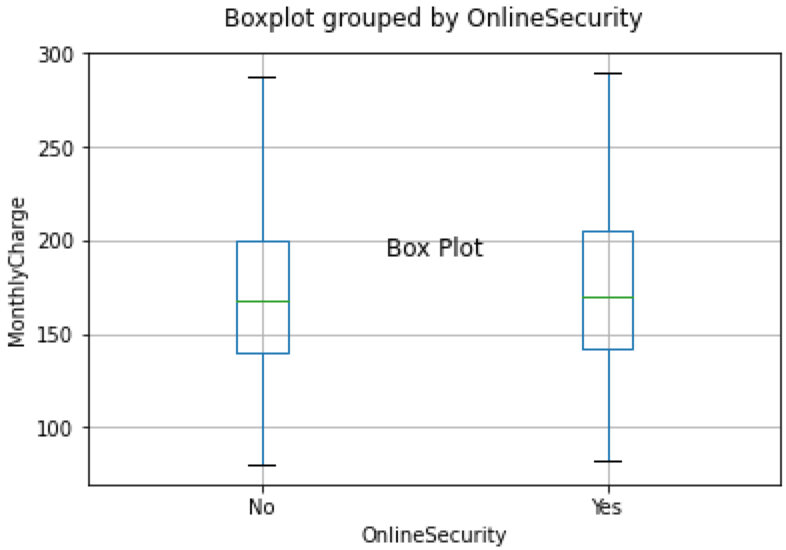
In [35]:
```
box_plot('InternetService')
```



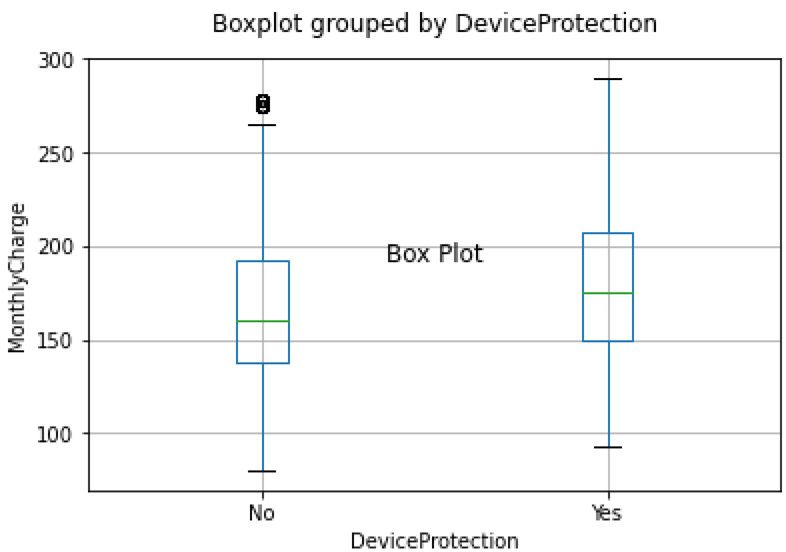
In [36]:
```
box_plot('Phone')
```



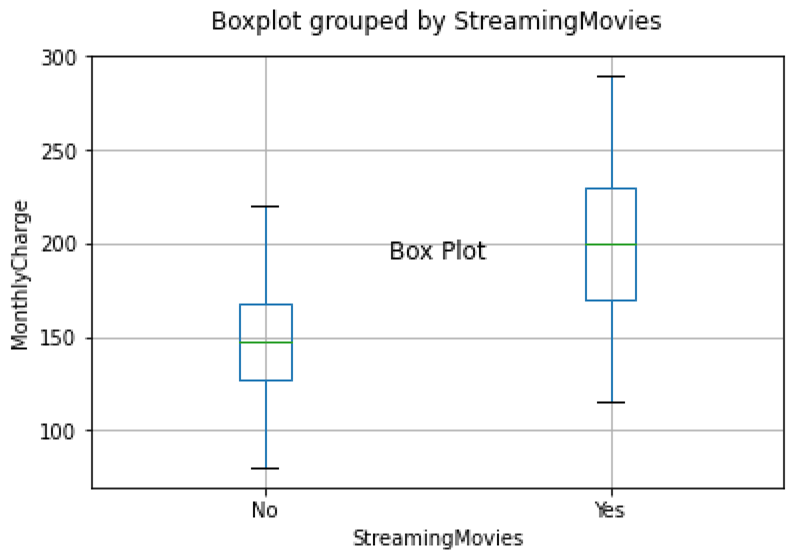
In [37]:
```
box_plot('OnlineSecurity')
```



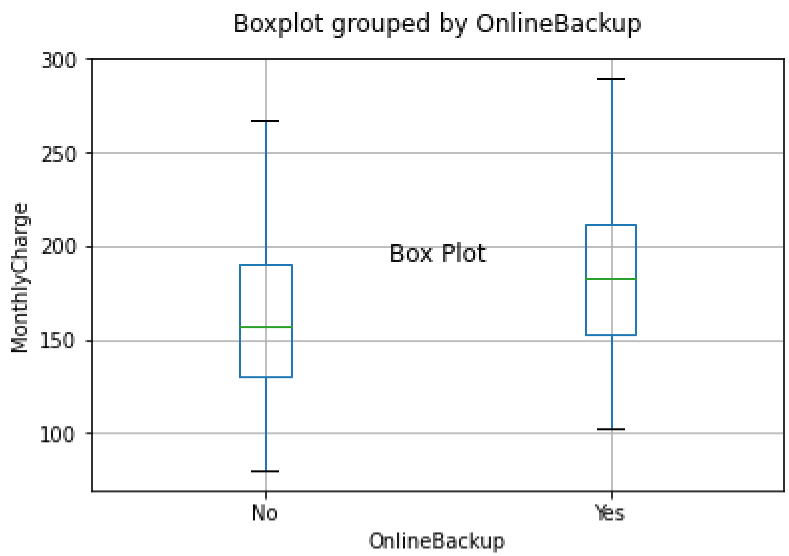
In [38]:
```
box_plot('DeviceProtection')
```



In [39]:
```
box_plot('StreamingMovies')
```



In [40]:
```
box_plot('OnlineBackup')
```



4)

My goals for data transformation are to one-hot encode the categorical variables. I will use the getDummies() function to one-hot encode the categorical variables. I will need to encode the categorical variables to create a regression model to analyze so I can answer my research question.

In [41]:
```
#split continuous and categorical variables into separate dataframes
dfcon = df[['Age','Income','Outage_sec_perweek']]
```

```
dfcat = df[['Gender','Area','InternetService','Phone','OnlineSecurity','DeviceProtection','StreamingMovies','OnlineBack
#one-hot encode categorical data and drop first level of each
dfcat_encoded = pd.get_dummies(dfcat,drop_first=True)
#concatenate the columns
data = pd.concat([dfcon, dfcat_encoded], axis=1)
data['MonthlyCharge']=df['MonthlyCharge']
#write the prepared data to .csv file
data.to_csv('prepared-data.csv', index=False)
del data['MonthlyCharge']
```

D. Compare an initial and a reduced linear regression model

1. Construct an initial multiple linear regression model from all independent variables that were identified in part C2. {-}

In [42]:

```
#Initial Model

import statsmodels.api as sm
independent_vars = sm.add_constant(data)
model = sm.OLS(df['MonthlyCharge'], independent_vars).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.554
Model:                            OLS   Adj. R-squared:                  0.554
Method:                 Least Squares   F-statistic:                     887.1
Date:                Sun, 14 Apr 2024   Prob (F-statistic):               0.00
Time:                        14:11:47   Log-Likelihood:                -47747.
No. Observations:               10000   AIC:                         9.552e+04
Df Residuals:                    9985   BIC:                         9.563e+04
Df Model:                          14
Covariance Type:            nonrobust
===============================================================================================
                                  coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------------
const                         125.1255      1.781     70.269      0.000     121.635     128.616
Age                             0.0050      0.014      0.362      0.717      -0.022       0.032
Income                       2.762e-06   1.02e-05      0.271      0.786   -1.72e-05    2.27e-05
Outage_sec_perweek              0.0904      0.096      0.937      0.349      -0.099       0.279
Gender_Male                     0.2567      0.581      0.442      0.659      -0.883       1.396
Gender_Nonbinary                0.8091      1.932      0.419      0.675      -2.978       4.596
Area_Suburban                  -0.0939      0.703     -0.134      0.894      -1.471       1.283
Area_Urban                     -0.0938      0.704     -0.133      0.894      -1.473       1.286
InternetService_Fiber Optic    19.1922      0.652     29.449      0.000      17.915      20.470
InternetService_None          -13.9434      0.790    -17.642      0.000     -15.493     -12.394
Phone_Yes                      -1.3398      0.987     -1.357      0.175      -3.275       0.595
OnlineSecurity_Yes              2.7922      0.599      4.661      0.000       1.618       3.966
DeviceProtection_Yes           12.6749      0.579     21.888      0.000      11.540      13.810
StreamingMovies_Yes            51.8440      0.574     90.284      0.000      50.718      52.970
OnlineBackup_Yes               22.0936      0.577     38.288      0.000      20.962      23.225
==============================================================================
Omnibus:                      901.877   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              280.582
Skew:                           0.059   Prob(JB):                     1.18e-61
Kurtosis:                       2.188   Cond. No.                     3.34e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.34e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

2. Justify a statistically based feature selection procedure or a model evaluation metric to reduce the initial model in a way that aligns with the research question.

I have chosen to use backward elimination of predictor variables as my feature selection procedure. This is so I can iteratively choose which predictor variables I want to keep based on p values. This is an effective way to reduce the model because I can observe how removing each variable changes the evaluation metric on each iteration.

I have chosen to use the adjusted r squared value as an evaluation metric. I have chose this one in particular because it will penalize for overfitting the model. It will accurately predict goodness of fit with models with large numbers of predictor variables such as this one. Since it takes into account overfitting, I am less likely to create a model that uses redundant data and inaccurately defines the correlations of each predictor variable leading to false information about correlations to 'MonthlyCharge'.

3. Provide a reduced linear regression model that follows the feature selection or model evaluation process in part D2, including a screenshot of the output for each model.

In [43]:
```
#original model
df_encoded = data.copy()
independent_vars = sm.add_constant(df_encoded)
model = sm.OLS(df['MonthlyCharge'], independent_vars).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.554
Model:                            OLS   Adj. R-squared:                  0.554
Method:                 Least Squares   F-statistic:                     887.1
Date:                Sun, 14 Apr 2024   Prob (F-statistic):               0.00
Time:                        14:11:47   Log-Likelihood:                -47747.
No. Observations:               10000   AIC:                         9.552e+04
Df Residuals:                    9985   BIC:                         9.563e+04
Df Model:                          14
Covariance Type:            nonrobust
=================================================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------------
const                        125.1255      1.781     70.269      0.000     121.635     128.616
Age                            0.0050      0.014      0.362      0.717      -0.022       0.032
Income                      2.762e-06   1.02e-05      0.271      0.786   -1.72e-05    2.27e-05
Outage_sec_perweek             0.0904      0.096      0.937      0.349      -0.099       0.279
Gender_Male                    0.2567      0.581      0.442      0.659      -0.883       1.396
Gender_Nonbinary               0.8091      1.932      0.419      0.675      -2.978       4.596
Area_Suburban                 -0.0939      0.703     -0.134      0.894      -1.471       1.283
Area_Urban                    -0.0938      0.704     -0.133      0.894      -1.473       1.286
InternetService_Fiber Optic   19.1922      0.652     29.449      0.000      17.915      20.470
InternetService_None         -13.9434      0.790    -17.642      0.000     -15.493     -12.394
Phone_Yes                     -1.3398      0.987     -1.357      0.175      -3.275       0.595
OnlineSecurity_Yes             2.7922      0.599      4.661      0.000       1.618       3.966
DeviceProtection_Yes          12.6749      0.579     21.888      0.000      11.540      13.810
StreamingMovies_Yes           51.8440      0.574     90.284      0.000      50.718      52.970
OnlineBackup_Yes              22.0936      0.577     38.288      0.000      20.962      23.225
==============================================================================
Omnibus:                      901.877   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              280.582
Skew:                           0.059   Prob(JB):                     1.18e-61
Kurtosis:                       2.188   Cond. No.                     3.34e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.34e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Reduced model

In [44]:

```
#Reduced model
df_encoded = data.copy()
del df_encoded['Area_Urban']
```

```
del df_encoded['Area_Suburban']
del df_encoded['Age']
del df_encoded['Outage_sec_perweek']
del df_encoded['Gender_Male']
del df_encoded['Gender_Nonbinary']
del df_encoded['Phone_Yes']
independent_vars = sm.add_constant(df_encoded)
model = sm.OLS(df['MonthlyCharge'], independent_vars).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.554
Model:                            OLS   Adj. R-squared:                  0.554
Method:                 Least Squares   F-statistic:                     1774.
Date:                Sun, 14 Apr 2024   Prob (F-statistic):               0.00
Time:                        14:11:47   Log-Likelihood:                -47749.
No. Observations:               10000   AIC:                         9.551e+04
Df Residuals:                    9992   BIC:                         9.557e+04
Df Model:                           7
Covariance Type:            nonrobust
===============================================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------------
const                        125.1365      0.809    154.599      0.000     123.550     126.723
Income                      2.581e-06   1.02e-05      0.254      0.800   -1.74e-05    2.25e-05
InternetService_Fiber Optic   19.1992      0.651     29.469      0.000      17.922      20.476
InternetService_None         -13.9427      0.790    -17.647      0.000     -15.491     -12.394
OnlineSecurity_Yes             2.7894      0.599      4.659      0.000       1.616       3.963
DeviceProtection_Yes          12.7137      0.578     21.984      0.000      11.580      13.847
StreamingMovies_Yes           51.8576      0.574     90.353      0.000      50.733      52.983
OnlineBackup_Yes              22.1012      0.577     38.333      0.000      20.971      23.231
==============================================================================
Omnibus:                      905.412   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              281.021
Skew:                           0.059   Prob(JB):                     9.49e-62
Kurtosis:                       2.187   Cond. No.                     1.79e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.79e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

E.

1.Explain your data analysis process by comparing the initial multiple linear regression model and reduced linear regression model

I used backwards elimination to reduce the model by P value. My model evaluation metric is R squared. Since I had predictor variables that had large coefficients, the R squared value was about the same in both models.This is because the predictor variables with the largest coefficients and smallest P values were not removed. I chose to leave the 'Income' variable in so I had one continuous variable in the model even though the P value was higher than .05. I simplified the model and was able to keep the same R squared value. The F statistic did improve as a result of reducing the independent variables.

Original F statistic = 887.1

Reduced model F statistic = 1774

Original R squared = .554

Reduced model R squared = .554

2. Provide the output and all calculations of the analysis you performed, including the following elements for your reduced linear regression model

In [45]:

```
# original model
df_encoded = data.copy()
independent_vars = sm.add_constant(df_encoded)
model = sm.OLS(df['MonthlyCharge'], independent_vars).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.554
Model:                            OLS   Adj. R-squared:                  0.554
Method:                 Least Squares   F-statistic:                     887.1
Date:                Sun, 14 Apr 2024   Prob (F-statistic):               0.00
Time:                        14:11:47   Log-Likelihood:                -47747.
No. Observations:               10000   AIC:                         9.552e+04
Df Residuals:                    9985   BIC:                         9.563e+04
Df Model:                          14
Covariance Type:            nonrobust
=================================================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------------
const                        125.1255      1.781     70.269      0.000     121.635     128.616
Age                            0.0050      0.014      0.362      0.717      -0.022       0.032
Income                      2.762e-06   1.02e-05      0.271      0.786   -1.72e-05    2.27e-05
Outage_sec_perweek             0.0904      0.096      0.937      0.349      -0.099       0.279
Gender_Male                    0.2567      0.581      0.442      0.659      -0.883       1.396
Gender_Nonbinary               0.8091      1.932      0.419      0.675      -2.978       4.596
Area_Suburban                 -0.0939      0.703     -0.134      0.894      -1.471       1.283
Area_Urban                    -0.0938      0.704     -0.133      0.894      -1.473       1.286
InternetService_Fiber Optic   19.1922      0.652     29.449      0.000      17.915      20.470
InternetService_None         -13.9434      0.790    -17.642      0.000     -15.493     -12.394
Phone_Yes                     -1.3398      0.987     -1.357      0.175      -3.275       0.595
OnlineSecurity_Yes             2.7922      0.599      4.661      0.000       1.618       3.966
DeviceProtection_Yes          12.6749      0.579     21.888      0.000      11.540      13.810
StreamingMovies_Yes           51.8440      0.574     90.284      0.000      50.718      52.970
OnlineBackup_Yes              22.0936      0.577     38.288      0.000      20.962      23.225
==============================================================================
Omnibus:                      901.877   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              280.582
Skew:                           0.059   Prob(JB):                     1.18e-61
Kurtosis:                       2.188   Cond. No.                     3.34e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.34e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Area_Urban P 0.894 > .05

In [46]:

```
#calculations to reduce original model
df_encoded = data.copy()
del df_encoded['Area_Urban']
```

```python
independent_vars = sm.add_constant(df_encoded)
model = sm.OLS(df['MonthlyCharge'], independent_vars).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.554
Model:                            OLS   Adj. R-squared:                  0.554
Method:                 Least Squares   F-statistic:                     955.4
Date:                Sun, 14 Apr 2024   Prob (F-statistic):               0.00
Time:                        14:11:47   Log-Likelihood:                -47747.
No. Observations:               10000   AIC:                         9.552e+04
Df Residuals:                    9986   BIC:                         9.562e+04
Df Model:                          13
Covariance Type:            nonrobust
=================================================================================================
                                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------------
const                         125.0790      1.746     71.633      0.000     121.656     128.502
Age                             0.0050      0.014      0.360      0.719      -0.022       0.032
Income                       2.759e-06   1.02e-05      0.271      0.786   -1.72e-05    2.27e-05
Outage_sec_perweek              0.0904      0.096      0.937      0.349      -0.099       0.279
Gender_Male                     0.2561      0.581      0.441      0.659      -0.883       1.395
Gender_Nonbinary                0.8100      1.932      0.419      0.675      -2.977       4.597
Area_Suburban                  -0.0471      0.608     -0.077      0.938      -1.239       1.145
InternetService_Fiber Optic    19.1925      0.652     29.451      0.000      17.915      20.470
InternetService_None          -13.9434      0.790    -17.643      0.000     -15.492     -12.394
Phone_Yes                      -1.3381      0.987     -1.356      0.175      -3.273       0.597
OnlineSecurity_Yes              2.7926      0.599      4.662      0.000       1.619       3.967
DeviceProtection_Yes           12.6741      0.579     21.889      0.000      11.539      13.809
StreamingMovies_Yes            51.8439      0.574     90.289      0.000      50.718      52.969
OnlineBackup_Yes               22.0926      0.577     38.291      0.000      20.962      23.224
==============================================================================
Omnibus:                      902.355   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              280.652
Skew:                           0.059   Prob(JB):                     1.14e-61
Kurtosis:                       2.188   Cond. No.                     3.32e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.32e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Area_Suburban   P   0.938 > .05

In [47]:

```
#calculations to reduce original model
df_encoded = data.copy()
del df_encoded['Area_Urban']
del df_encoded['Area_Suburban']
independent_vars = sm.add_constant(df_encoded)
model = sm.OLS(df['MonthlyCharge'], independent_vars).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.554
Model:                            OLS   Adj. R-squared:                  0.554
Method:                 Least Squares   F-statistic:                     1035.
Date:                Sun, 14 Apr 2024   Prob (F-statistic):               0.00
Time:                        14:11:47   Log-Likelihood:                -47747.
No. Observations:               10000   AIC:                         9.552e+04
Df Residuals:                    9987   BIC:                         9.561e+04
Df Model:                          12
Covariance Type:            nonrobust
=================================================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------------
const                        125.0639      1.735     72.079      0.000     121.663     128.465
Age                            0.0050      0.014      0.360      0.719      -0.022       0.032
Income                      2.757e-06   1.02e-05      0.271      0.787   -1.72e-05    2.27e-05
Outage_sec_perweek             0.0903      0.096      0.936      0.349      -0.099       0.279
Gender_Male                    0.2566      0.581      0.442      0.659      -0.882       1.396
Gender_Nonbinary               0.8094      1.932      0.419      0.675      -2.977       4.596
InternetService_Fiber Optic   19.1927      0.652     29.454      0.000      17.915      20.470
InternetService_None         -13.9432      0.790    -17.644      0.000     -15.492     -12.394
Phone_Yes                     -1.3384      0.987     -1.356      0.175      -3.273       0.596
OnlineSecurity_Yes             2.7920      0.599      4.662      0.000       1.618       3.966
DeviceProtection_Yes          12.6745      0.579     21.891      0.000      11.540      13.809
StreamingMovies_Yes           51.8436      0.574     90.294      0.000      50.718      52.969
OnlineBackup_Yes              22.0933      0.577     38.298      0.000      20.963      23.224
==============================================================================
Omnibus:                      902.469   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              280.666
Skew:                           0.059   Prob(JB):                     1.13e-61
Kurtosis:                       2.188   Cond. No.                     3.32e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.32e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
    Age        P    0.719    > .05
```

In [48]:
```
#calculations to reduce original model
df_encoded = data.copy()
del df_encoded['Area_Urban']
del df_encoded['Area_Suburban']
del df_encoded['Age']
independent_vars = sm.add_constant(df_encoded)
model = sm.OLS(df['MonthlyCharge'], independent_vars).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.554
Model:                            OLS   Adj. R-squared:                  0.554
Method:                 Least Squares   F-statistic:                     1129.
Date:                Sun, 14 Apr 2024   Prob (F-statistic):               0.00
Time:                        14:11:47   Log-Likelihood:                -47747.
No. Observations:               10000   AIC:                         9.552e+04
Df Residuals:                    9988   BIC:                         9.560e+04
Df Model:                          11
Covariance Type:            nonrobust
===============================================================================================
                                  coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------------
const                         125.3269      1.574     79.636      0.000     122.242     128.412
Income                       2.741e-06   1.02e-05      0.269      0.788   -1.72e-05    2.27e-05
Outage_sec_perweek              0.0900      0.096      0.933      0.351      -0.099       0.279
Gender_Male                     0.2571      0.581      0.442      0.658      -0.882       1.396
Gender_Nonbinary                0.7966      1.931      0.412      0.680      -2.989       4.582
InternetService_Fiber Optic    19.1935      0.652     29.456      0.000      17.916      20.471
InternetService_None          -13.9418      0.790    -17.643      0.000     -15.491     -12.393
Phone_Yes                      -1.3348      0.987     -1.353      0.176      -3.269       0.599
OnlineSecurity_Yes              2.7895      0.599      4.658      0.000       1.616       3.963
DeviceProtection_Yes           12.6775      0.579     21.899      0.000      11.543      13.812
StreamingMovies_Yes            51.8457      0.574     90.306      0.000      50.720      52.971
OnlineBackup_Yes               22.0941      0.577     38.302      0.000      20.963      23.225
==============================================================================
Omnibus:                      902.264   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              280.617
Skew:                           0.059   Prob(JB):                     1.16e-61
Kurtosis:                       2.188   Cond. No.                     3.30e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.3e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Outage_sec_perweek P 0.351 > .05

In [49]:

```python
#calculations to reduce original model
df_encoded = data.copy()
del df_encoded['Area_Urban']
del df_encoded['Area_Suburban']
del df_encoded['Age']
del df_encoded['Outage_sec_perweek']
```

```
independent_vars = sm.add_constant(df_encoded)
model = sm.OLS(df['MonthlyCharge'], independent_vars).fit()
print(model.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.554
Model:                            OLS   Adj. R-squared:                  0.554
Method:                 Least Squares   F-statistic:                     1242.
Date:                Sun, 14 Apr 2024   Prob (F-statistic):               0.00
Time:                        14:11:47   Log-Likelihood:                -47747.
No. Observations:               10000   AIC:                         9.552e+04
Df Residuals:                    9989   BIC:                         9.560e+04
Df Model:                          10                                         
Covariance Type:            nonrobust                                         
===============================================================================================
                                  coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------------
const                         126.2233      1.247    101.245      0.000     123.779     128.667
Income                       2.647e-06   1.02e-05      0.260      0.795   -1.73e-05    2.26e-05
Gender_Male                     0.2626      0.581      0.452      0.651      -0.876       1.402
Gender_Nonbinary                0.7967      1.931      0.413      0.680      -2.989       4.582
InternetService_Fiber Optic    19.1989      0.652     29.466      0.000      17.922      20.476
InternetService_None          -13.9337      0.790    -17.634      0.000     -15.483     -12.385
Phone_Yes                      -1.3437      0.987     -1.362      0.173      -3.278       0.591
OnlineSecurity_Yes              2.7878      0.599      4.656      0.000       1.614       3.962
DeviceProtection_Yes           12.6890      0.579     21.924      0.000      11.554      13.823
StreamingMovies_Yes            51.8551      0.574     90.337      0.000      50.730      52.980
OnlineBackup_Yes               22.0942      0.577     38.302      0.000      20.964      23.225
==============================================================================
Omnibus:                      902.691   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              280.571
Skew:                           0.059   Prob(JB):                     1.19e-61
Kurtosis:                       2.188   Cond. No.                     3.29e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.29e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Gender_Male P 0.651 > .05

In [50]:
```
#calculations to reduce original model
df_encoded = data.copy()
del df_encoded['Area_Urban']
del df_encoded['Area_Suburban']
```

```python
del df_encoded['Age']
del df_encoded['Outage_sec_perweek']
del df_encoded['Gender_Male']
independent_vars = sm.add_constant(df_encoded)
model = sm.OLS(df['MonthlyCharge'], independent_vars).fit()
print(model.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.554
Model:                            OLS   Adj. R-squared:                  0.554
Method:                 Least Squares   F-statistic:                     1380.
Date:                Sun, 14 Apr 2024   Prob (F-statistic):               0.00
Time:                        14:11:47   Log-Likelihood:                -47748.
No. Observations:               10000   AIC:                         9.552e+04
Df Residuals:                    9990   BIC:                         9.559e+04
Df Model:                           9                                         
Covariance Type:            nonrobust                                         
=================================================================================================
                                    coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------------
const                           126.3519      1.214    104.099      0.000     123.973     128.731
Income                         2.539e-06   1.02e-05      0.250      0.803   -1.74e-05    2.25e-05
Gender_Nonbinary                  0.6698      1.911      0.351      0.726      -3.075       4.415
InternetService_Fiber Optic      19.1957      0.652     29.464      0.000      17.919      20.473
InternetService_None            -13.9359      0.790    -17.638      0.000     -15.485     -12.387
Phone_Yes                        -1.3425      0.987     -1.361      0.174      -3.277       0.592
OnlineSecurity_Yes                2.7919      0.599      4.663      0.000       1.618       3.965
DeviceProtection_Yes             12.6933      0.579     21.936      0.000      11.559      13.828
StreamingMovies_Yes              51.8576      0.574     90.350      0.000      50.733      52.983
OnlineBackup_Yes                 22.0930      0.577     38.302      0.000      20.962      23.224
==============================================================================
Omnibus:                      903.348   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              280.679
Skew:                           0.059   Prob(JB):                     1.13e-61
Kurtosis:                       2.188   Cond. No.                     3.25e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 3.25e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Gender_Nonbinary P 0.726 > .05

In [51]:
```python
#calculations to reduce original model
df_encoded = data.copy()
```

```python
del df_encoded['Area_Urban']
del df_encoded['Area_Suburban']
del df_encoded['Age']
del df_encoded['Outage_sec_perweek']
del df_encoded['Gender_Male']
del df_encoded['Gender_Nonbinary']
independent_vars = sm.add_constant(df_encoded)
model = sm.OLS(df['MonthlyCharge'], independent_vars).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.554
Model:                            OLS   Adj. R-squared:                  0.554
Method:                 Least Squares   F-statistic:                     1553.
Date:                Sun, 14 Apr 2024   Prob (F-statistic):               0.00
Time:                        14:11:47   Log-Likelihood:                -47748.
No. Observations:               10000   AIC:                         9.551e+04
Df Residuals:                    9991   BIC:                         9.558e+04
Df Model:                           8
Covariance Type:            nonrobust
===============================================================================================
                                  coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------------
const                         126.3651      1.213    104.164      0.000     123.987     128.743
Income                       2.563e-06   1.02e-05      0.252      0.801   -1.74e-05    2.25e-05
InternetService_Fiber Optic    19.1958      0.651     29.465      0.000      17.919      20.473
InternetService_None          -13.9351      0.790    -17.638      0.000     -15.484     -12.386
Phone_Yes                      -1.3414      0.987     -1.360      0.174      -3.275       0.593
OnlineSecurity_Yes              2.7909      0.599      4.662      0.000       1.617       3.964
DeviceProtection_Yes           12.6899      0.579     21.934      0.000      11.556      13.824
StreamingMovies_Yes            51.8561      0.574     90.353      0.000      50.731      52.981
OnlineBackup_Yes               22.0989      0.577     38.331      0.000      20.969      23.229
==============================================================================
Omnibus:                      903.626   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              280.726
Skew:                           0.059   Prob(JB):                     1.10e-61
Kurtosis:                       2.188   Cond. No.                     2.54e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 2.54e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Phone_Yes   P 0.174   > .05

In [52]:
```
#calculations to reduce original model
df_encoded = data.copy()
del df_encoded['Area_Urban']
del df_encoded['Area_Suburban']
del df_encoded['Age']
del df_encoded['Outage_sec_perweek']
del df_encoded['Gender_Male']
del df_encoded['Gender_Nonbinary']
del df_encoded['Phone_Yes']
independent_vars = sm.add_constant(df_encoded)
model = sm.OLS(df['MonthlyCharge'], independent_vars).fit()
print(model.summary())
```

```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.554
Model:                            OLS   Adj. R-squared:                  0.554
Method:                 Least Squares   F-statistic:                     1774.
Date:                Sun, 14 Apr 2024   Prob (F-statistic):               0.00
Time:                        14:11:47   Log-Likelihood:                -47749.
No. Observations:               10000   AIC:                         9.551e+04
Df Residuals:                    9992   BIC:                         9.557e+04
Df Model:                           7                                         
Covariance Type:            nonrobust                                         
===============================================================================================
                                  coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------------
const                         125.1365      0.809    154.599      0.000     123.550     126.723
Income                       2.581e-06   1.02e-05      0.254      0.800   -1.74e-05    2.25e-05
InternetService_Fiber Optic    19.1992      0.651     29.469      0.000      17.922      20.476
InternetService_None          -13.9427      0.790    -17.647      0.000     -15.491     -12.394
OnlineSecurity_Yes              2.7894      0.599      4.659      0.000       1.616       3.963
DeviceProtection_Yes           12.7137      0.578     21.984      0.000      11.580      13.847
StreamingMovies_Yes            51.8576      0.574     90.353      0.000      50.733      52.983
OnlineBackup_Yes               22.1012      0.577     38.333      0.000      20.971      23.231
==============================================================================
Omnibus:                      905.412   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              281.021
Skew:                           0.059   Prob(JB):                     9.49e-62
Kurtosis:                       2.187   Cond. No.                     1.79e+05
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.79e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
    Income      P 0.800  > .05   final reduced model
```

In [53]:

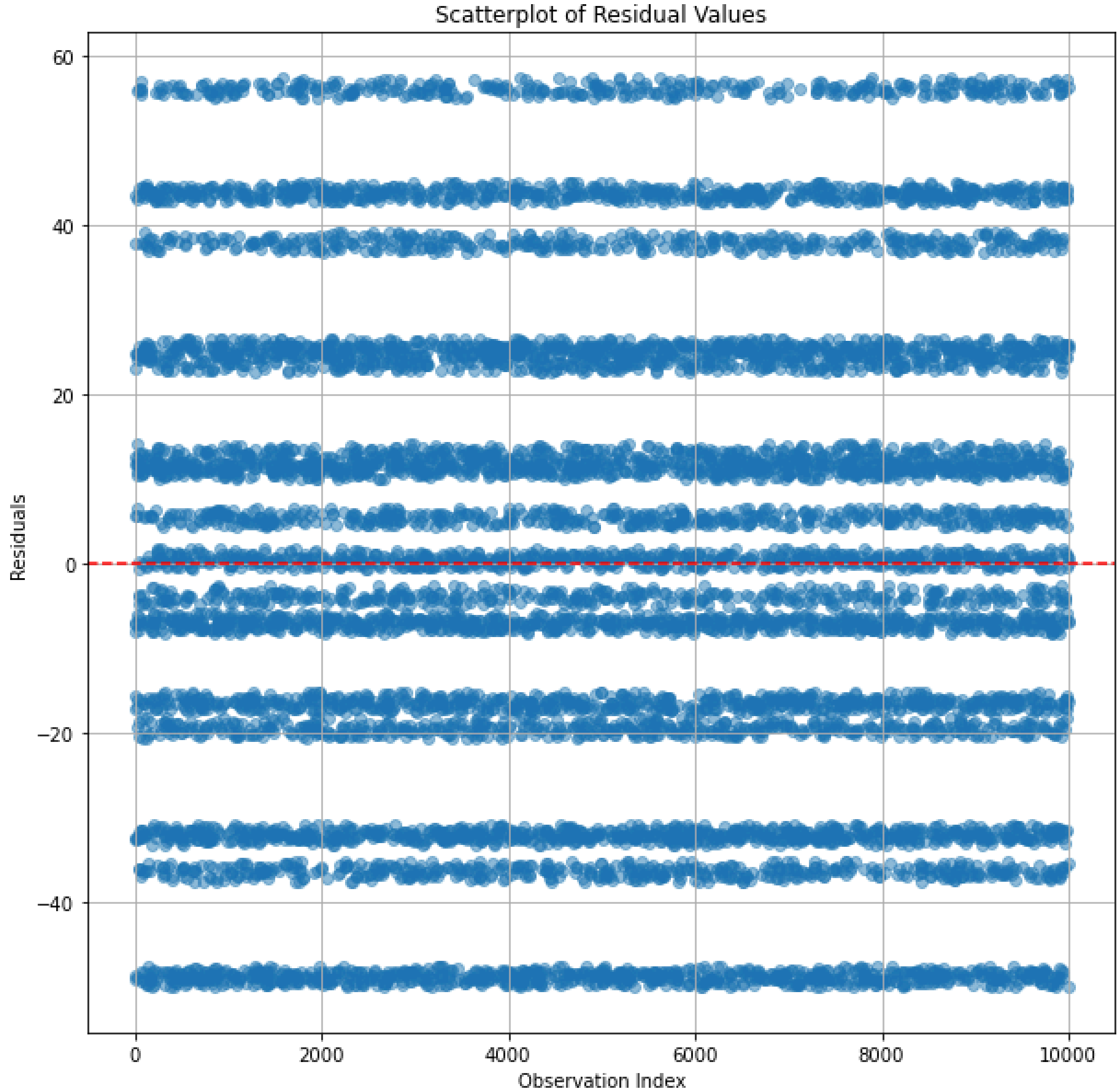
```python
df_encoded = data.copy()
del df_encoded['Area_Urban']
del df_encoded['Area_Suburban']
del df_encoded['Age']
del df_encoded['Outage_sec_perweek'] #final reduced model
del df_encoded['Gender_Male']
del df_encoded['Gender_Nonbinary']
del df_encoded['Phone_Yes']
del df_encoded['Income']
independent_vars = sm.add_constant(df_encoded)
model = sm.OLS(df['MonthlyCharge'], independent_vars).fit()
print(model.summary())
```

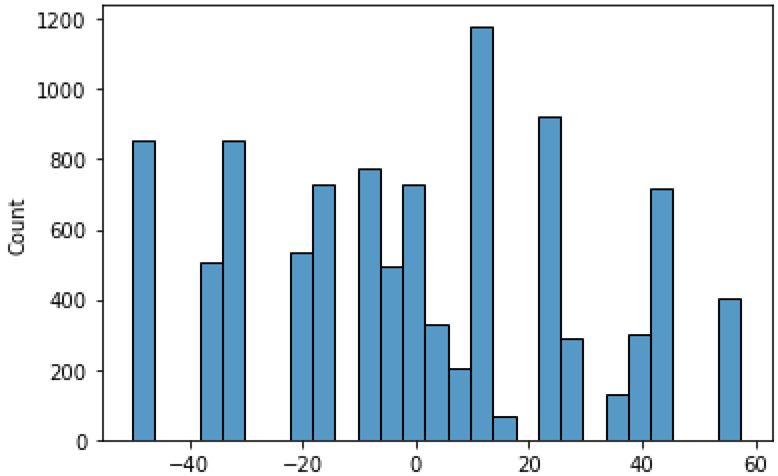
```
                            OLS Regression Results
==============================================================================
Dep. Variable:          MonthlyCharge   R-squared:                       0.554
Model:                            OLS   Adj. R-squared:                  0.554
Method:                 Least Squares   F-statistic:                     2070.
Date:                Sun, 14 Apr 2024   Prob (F-statistic):               0.00
Time:                        14:11:47   Log-Likelihood:                -47749.
No. Observations:               10000   AIC:                         9.551e+04
Df Residuals:                    9993   BIC:                         9.556e+04
Df Model:                           6
Covariance Type:            nonrobust
=================================================================================================
                                  coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------------
const                         125.2414      0.696    179.964      0.000     123.877     126.606
InternetService_Fiber Optic    19.1959      0.651     29.472      0.000      17.919      20.473
InternetService_None          -13.9448      0.790    -17.652      0.000     -15.493     -12.396
OnlineSecurity_Yes              2.7878      0.599      4.657      0.000       1.614       3.961
DeviceProtection_Yes           12.7159      0.578     21.991      0.000      11.582      13.849
StreamingMovies_Yes            51.8573      0.574     90.356      0.000      50.732      52.982
OnlineBackup_Yes               22.1003      0.577     38.334      0.000      20.970      23.230
==============================================================================
Omnibus:                      905.812   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              281.087
Skew:                           0.059   Prob(JB):                     9.18e-62
Kurtosis:                       2.187   Cond. No.                         5.17
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
```

residual plot

In [54]:
```
# Create a scatterplot of residual values
residuals = model.resid
plt.figure(figsize=(10, 10))
plt.scatter(range(len(residuals)), residuals, alpha=0.5)
plt.axhline(y=0, color='r', linestyle='--')  # Add a horizontal line at y=0
plt.title('Scatterplot of Residual Values')
plt.xlabel('Observation Index')
plt.ylabel('Residuals')
plt.grid(True)
plt.show()
# Create a histogram of residual values
sns.histplot(residuals);
```


Scatterplot of Residual Values
60
40
20
0
−20
−40
Residuals
0
2000
4000
6000
8000
10000
Observation Index



residual standard error

In [55]:
```
np.sqrt(np.sum(model.resid**2)/model.df_resid)
```

Out[55]: 28.68192657650494

3. code will be submitted with assignment.

F.

1. Discuss the results of your data analysis

regression equation :

Y = 125.2414 + 19.959(X) + -13.9448(X) + 2.7878(x) + 12.7159((x) + 51.8573(X) + 22.1003(X)

Interpretation of coefficients:

```
The coefficient itself is the magnitude which represents the strength of the relationship.

The sign tells us if the relationship is negative or positive to the value of the dependent variable.

all these coefficients have a p value of < .05 so they are statistically significant.

InternetService_Fiber Optic    19.1959   is the magnitude and it has a positive correlation with
'MonthlyCharge'.
```

```
InternetService_None          -13.9448   is the magnitude and it has a negative correlation with
'MonthlyCharge'.
OnlineSecurity_Yes              2.7878   is the magnitude and it has a positive correlation with
'MonthlyCharge'.
DeviceProtection_Yes           12.7159   is the magnitude and it has a positive correlation with
'MonthlyCharge'.
StreamingMovies_Yes            51.8573   is the magnitude and it has a positive correlation with
'MonthlyCharge'.
OnlineBackup_Yes               22.1003   is the magnitude and it has a positive correlation with
'MonthlyCharge'.
```

All other predictors must be constant for these rules to work.

For continuous predictors:

A one-unit increase in the predictor variable is associated with a change in the value of the dependent variable equal to the coefficient value, holding all other predictors constant.

For categorical predictors (dummy variables):

The coefficient represents the difference in the value of the dependent variable between the reference category (usually the category with the value of 0) and the category represented by the dummy variable.

```
    const is the y intercept.

A one unit increase in 'Income' will result in a change in the dependent variable equal to the
coefficient .6674.

Observing 'InternetService_Fiber_Optic' True will result in the difference of it's coefficient and
the reference category coefficient being applied to the dependent variable.

 Observing 'InternetService_None' True will result in the difference  of it's coefficient and the
reference category coefficient being applied to the the dependent variable.

Observing 'DeviceProtection_yes' True will result in the difference in it's coefficient and the
reference category coefficient being applied to the the dependent variable.

 Observing 'Streaming_Movies_Yes' True will result in the difference of it's coefficient and the
reference category coefficient being applied to the  the dependent variable.
```

```
 Observing 'Online_Backup_Yes' True will result in the difference of it's coefficient and the
reference category coefficient being applied to the dependent variable.

Observing 'Online_Security_Yes' True will result in the difference of it's coefficient and the
reference category coefficient being applied to the dependent variable.
```

significance

I think that the practical significance of this reduced model is moderate. That is because it basically shows us some common sense things that we could just guess. Such as if a person subscribes to more services the monthly charge would be greater.

The statistical significance here is moderate because the coefficients show what we could guess with common sense. So the coefficients provide valuable information. The measure of statistical signifance that I used was adjusted R squared. At .554 this shows that the statistical signifance of the reduced model could be much better. This lower adjusted R squared metric shows that there is variance in the dependent variable that is not explained in the independent variables. This is also evident by looking at the plots of residual standard error.

Limitations.

Some of the limitations of this analysis are that the model works better with normally distributed variables that have a linear correlation with the outcome variable. Another limitation is that the standard error can be pretty large. A third limitation is that the adjusted r squared value is low.

2.

My recommendations based on this analysis are that the organization should allocate resources to the sales team to upsell more services to increase the 'MonthlyCharge' for each customer. We could have guessed that maybe, but the data is here to confirm that and remove any doubt.

Citations

Assumptions of multiple linear regression (2024) Statistics Solutions. Available at: https://www.statisticssolutions.com/free-resources/directory-of-statistical-analyses/assumptions-of-multiple-linear-regression/ (Accessed: 11 April 2024).

Dansbecker (2018) Using categorical data with one hot encoding, Kaggle. Available at: https://www.kaggle.com/code/dansbecker/using-categorical-data-with-one-hot-encoding (Accessed: 11 April 2024).

How to replace column values in a pandas DataFrame (2023) Saturn Cloud Blog. Available at: https://saturncloud.io/blog/how-to-replace-column-values-in-a-pandas-dataframe/ (Accessed: 06 April 2024).

In [56]:

```
import sys
print(sys.version)
```

```
3.10.12 (main, Nov 20 2023, 15:14:05) [GCC 11.4.0]
```

In [ ]:

```
```