

PART I: RESEARCH QUESTION

A1. RESEARCH QUESTION

What factors contribute significantly to the variability in additional charges incurred by the patients?

A2. GOALS

The objective of this analysis is to improve patient financial planning. Patients benefit from knowing what factors contribute to additional charges. This can help them make informed decisions about their healthcare and plan for potential expenses. It enhances transparency and reduces financial surprises for patients.

PART II: METHOD JUSTIFICATION

B1. SUMMARY OF ASSUMPTIONS

There are several assumptions for multiple linear regression. These assumptions are needed for the model to be valid and for the statistical inferences to be accurate. These are the four key assumptions to keep in mind.

Firstly, the relationship between the independent and dependent variables is assumed to be linear. The changes in the independent variables are associated with the constant change in the dependent variable. Secondly, the residuals should be independent of each other. The residual value for one observation should not be related to the residual for further observation. Thirdly, the variance of the residuals should be constant across all levels of the independent variables. Lastly, residuals should have a normal distribution. This is especially essential for smaller sample sizes to ensure the validity of statistical tests and confidence intervals.

B2. TOOL BENEFITS

For this analysis, I used R. This language has several data-cleaning features and capabilities.

Firstly, R has a vast ecosystem of packages designed explicitly for data cleaning. In this assessment, **naniar**, **dplyr**, and **plyr** packages were used. Naniar was used for finding missing data. Dplyr was used for data manipulation and analysis. Plyr was used to convert and revalue variables. All these packages were essential to accomplish a clean dataset.

Lastly, R has easy-to-use data visualization capabilities. Visualization can aid in identifying outliers, missing values, and patterns between variables.

B3. APPROPRIATE BENEFIT

Multiple linear regression is an appropriate technique to find the factors that affect additional charges incurred by patients for numerous reasons.

Firstly, my research question involves understanding the impact of multiple factors on additional charges. Multiple linear regression allows the manipulation of more than one independent variable to capture the complex relationships among various factors. Moreover, multiple linear regression can help

identify which independent variables significantly contribute to the variability in additional charge. This is critical to explore the relative importance of different factors. This technique also allows for the assessment of variable importance. I can prioritize the most influential factors impacting additional charges by examining the coefficients and their significance.

PART III: DATA PREPARATION

C1. DATA CLEANING

Data cleaning is vital to data preparation. This ensures the quality, accuracy, and reliability of the data used for analysis. Firstly, find missing values. Ignoring missing data can lead to inaccurate conclusions and affect the study's trustworthiness. Then, find duplicates. Duplicates can introduce redundancy to the analysis. It can lead to overestimation of specific trends, which affects the reliability of insights. Lastly, count the outliers. Outliers can affect statistical measures. This leads to distorted results, affects the distribution of data, and leads to misleading conclusions.

To find the missing values, use the **naniar** package. **Naniar** provides valuable functions to visualize and handle missing data. Meanwhile, R makes it easier to find duplicates using **duplicated()**. This function identifies duplicate rows. Lastly, outliers can be identified using the interquartile range. Values beyond the lower and upper bound are considered outliers.

The code for detection is attached.

C2. SUMMARY STATISTICS

Below is a screenshot of the summary statistics of the medical_clean dataset.

```
> summary(dt)
  CaseOrder      Customer_id      Interaction      UID      City
Min.   : 1      Length:10000      Length:10000      Length:10000      Length:10000
1st Qu.:2501      Class :character      Class :character      Class :character      Class :character
Median :5000      Mode  :character      Mode  :character      Mode  :character      Mode  :character
Mean   :5000
3rd Qu.:7500
Max.   :10000

  State      County      Zip      Lat      Lng
Length:10000      Length:10000      Min.   : 610      Min.   :17.97      Min.   : -174.21
Class :character      Class :character      1st Qu.:27592      1st Qu.:35.26      1st Qu.: -97.35
Mode  :character      Mode  :character      Median :50207      Median :39.42      Median : -88.40
Mean   :50159      Mean   :38.75      Mean   : -91.24
3rd Qu.:72412      3rd Qu.:42.04      3rd Qu.: -80.44
Max.   :99929      Max.   :70.56      Max.   : -65.29

  Population      Area      TimeZone      Job      Children
Min.   : 0.0      Length:10000      Length:10000      Length:10000      Min.   : 0.000
1st Qu.: 694.8      Class :character      Class :character      Class :character      1st Qu.: 0.000
Median : 2769.0      Mode  :character      Mode  :character      Mode  :character      Median : 1.000
Mean   : 9965.2
3rd Qu.:13945.0
Max.   :122814.0

  Age      Income      Marital      Gender      ReAdmis
Min.   :18.00      Min.   : 154.1      Length:10000      Length:10000      Length:10000
1st Qu.:36.00      1st Qu.:19598.8      Class :character      Class :character      Class :character
Median :53.00      Median : 33768.4      Mode  :character      Mode  :character      Mode  :character
Mean   :53.51      Mean   : 40490.5
3rd Qu.:71.00      3rd Qu.: 54296.4
Max.   :89.00      Max.   :207249.1

  VitD_levels      Doc_visits      Full_meals_eaten      vitD_supp      Soft_drink
Min.   : 9.806      Min.   :1.000      Min.   :0.000      Min.   :0.0000      Length:10000
1st Qu.:16.626      1st Qu.:4.000      1st Qu.:0.000      1st Qu.:0.0000      Class :character
Median :17.951      Median :5.000      Median :1.000      Median :0.0000      Mode  :character
Mean   :17.964      Mean   :5.012      Mean   :1.001      Mean   :0.3989
3rd Qu.:19.348      3rd Qu.:6.000      3rd Qu.:2.000      3rd Qu.:1.0000
Max.   :26.394      Max.   :9.000      Max.   :7.000      Max.   :5.0000
```

```

Initial_admin      HighBlood      Stroke      Complication_risk  Overweight
Length:10000      Length:10000  Length:10000 Length:10000      Length:10000
Class :character   Class :character Class :character Class :character   Class :character
Mode :character    Mode :character Mode :character Mode :character    Mode :character

```

```

Arthritis      Diabetes      Hyperlipidemia  BackPain      Anxiety
Length:10000   Length:10000  Length:10000    Length:10000  Length:10000
Class :character Class :character Class :character Class :character Class :character
Mode :character Mode :character Mode :character Mode :character Mode :character

```

```

Allergic_rhinitis  Reflux_esophagitis  Asthma      Services      Initial_days
Length:10000       Length:10000        Length:10000 Length:10000    Min. : 1.002
Class :character   Class :character    Class :character Class :character 1st Qu.: 7.896
Mode :character    Mode :character     Mode :character Mode :character  Median :35.836
                                           Mean :34.455
                                           3rd Qu.:61.161
                                           Max. :71.981

```

```

TotalCharge  Additional_charges  Item1      Item2      Item3
Min. :1938   Min. : 3126        Min. :1.000 Min. :1.000 Min. :1.000
1st Qu.:3179 1st Qu.: 7986      1st Qu.:3.000 1st Qu.:3.000 1st Qu.:3.000
Median :5214 Median :11574       Median :4.000 Median :3.000 Median :4.000
Mean :5312 Mean :12935         Mean :3.519 Mean :3.507 Mean :3.511
3rd Qu.:7460 3rd Qu.:15626      3rd Qu.:4.000 3rd Qu.:4.000 3rd Qu.:4.000
Max. :9181 Max. :30566         Max. :8.000 Max. :7.000 Max. :8.000

Item4      Item5      Item6      Item7      Item8
Min. :1.000 Min. :1.000 Min. :1.000 Min. :1.000 Min. :1.000
1st Qu.:3.000 1st Qu.:3.000 1st Qu.:3.000 1st Qu.:3.000 1st Qu.:3.000
Median :4.000 Median :3.000 Median :4.000 Median :3.000 Median :3.000
Mean :3.515 Mean :3.497 Mean :3.522 Mean :3.494 Mean :3.51
3rd Qu.:4.000 3rd Qu.:4.000 3rd Qu.:4.000 3rd Qu.:4.000 3rd Qu.:4.000
Max. :7.000 Max. :7.000 Max. :7.000 Max. :7.000 Max. :7.000

```

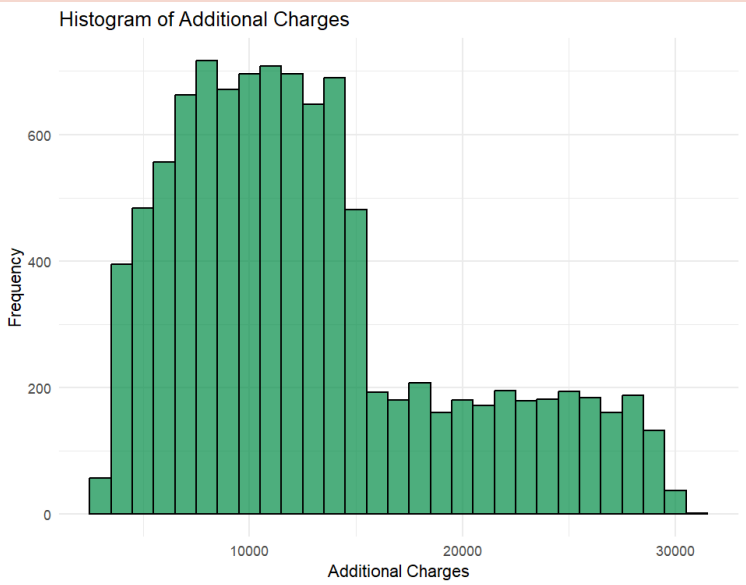
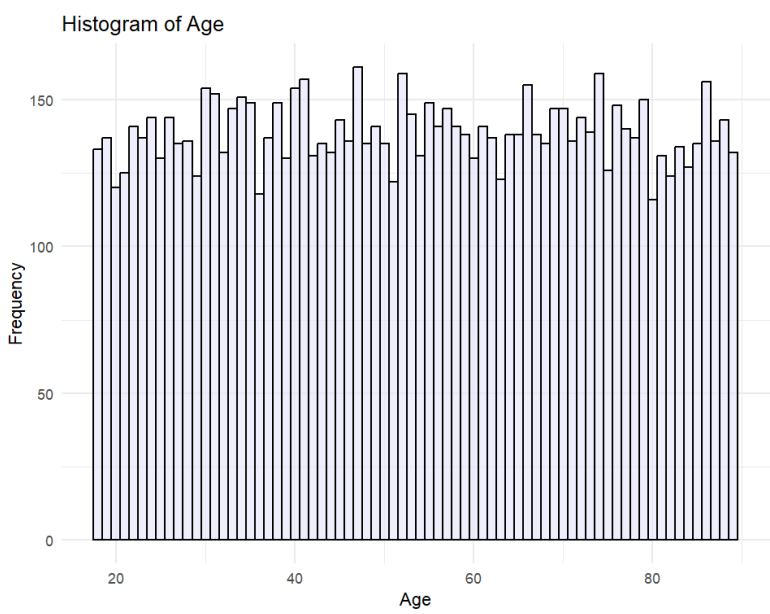
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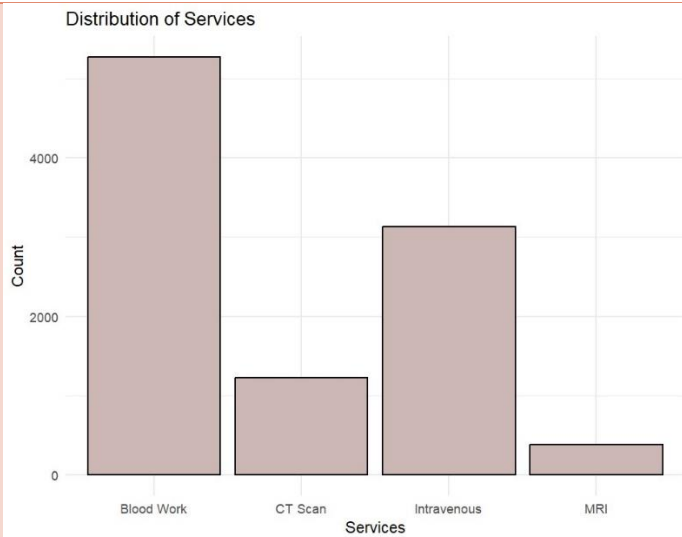
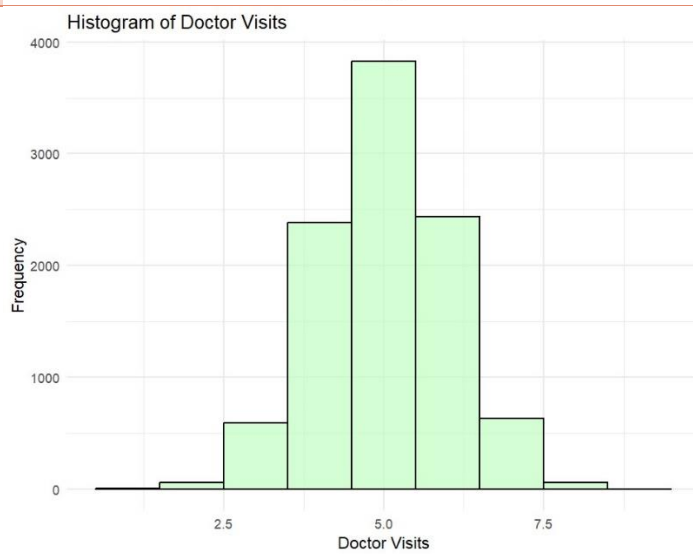
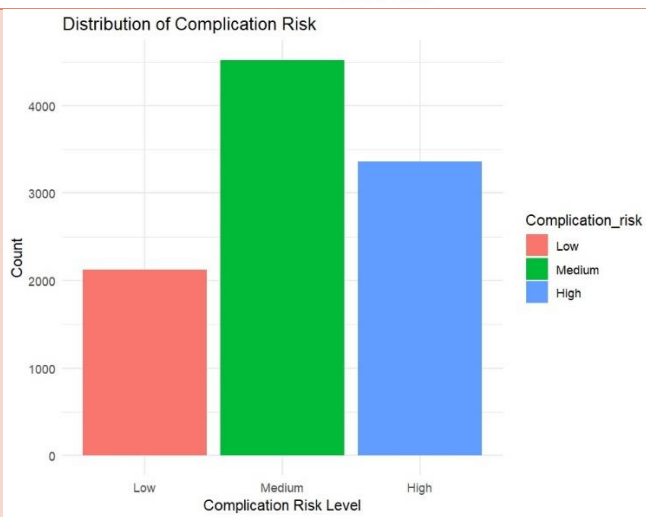
Variable	Data type	Variable type	Summary (for Categorical) *before data transformation
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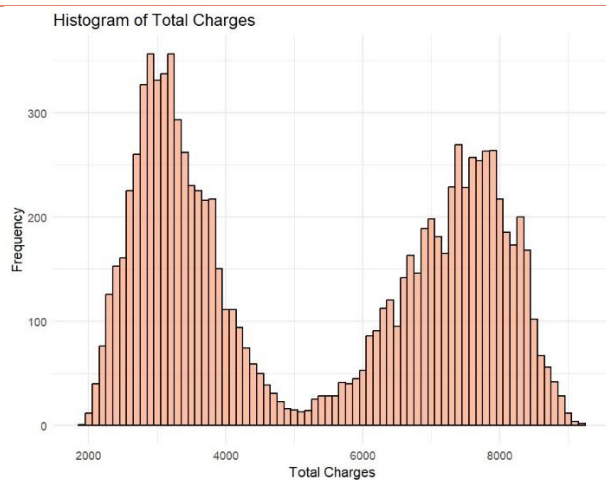
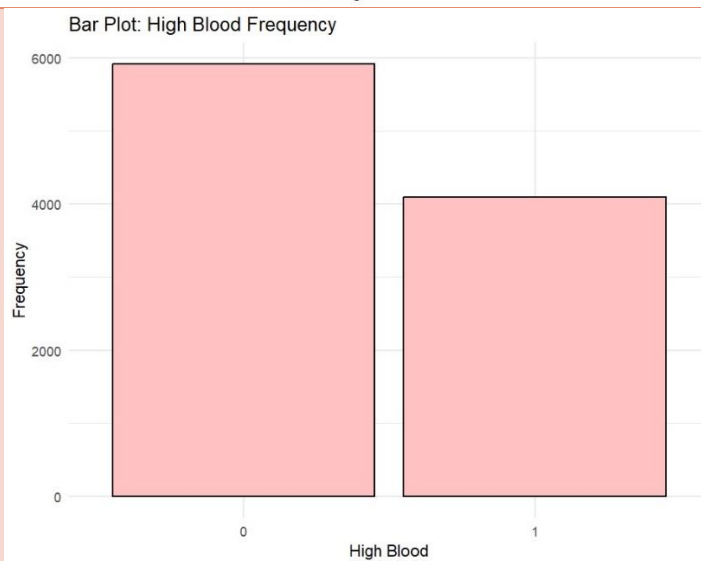
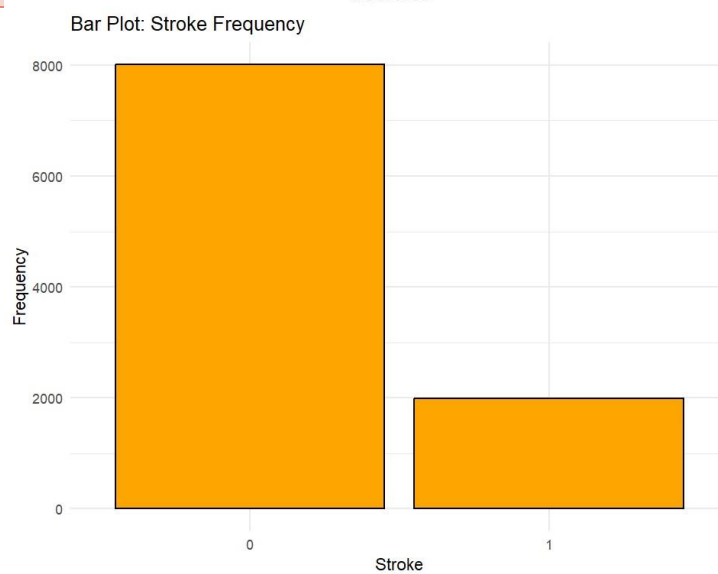
Dependent Variable: Additional Charges	Quantitative	Continuous	
Independent Variables:			
Age	Quantitative	Discrete	
Services	Qualitative	Categorical	<div> <div>Blood work</div> <div>5265</div> </div> <div> <div>CT Scan</div> <div>1225</div> </div> <div> <div>Intravenous</div> <div>3130</div> </div> <div> <div>MRI</div> <div>380</div> </div>
Doc visits	Quantitative	Discrete	
Complication risk	Qualitative	Categorical	<div> <div>High</div> <div>3358</div> </div> <div> <div>Low</div> <div>2125</div> </div> <div> <div>Medium</div> <div>4517</div> </div>
Total charges	Quantitative	Continuous	
High blood	Qualitative	Categorical	<div> <div>No</div> <div>5910</div> </div> <div> <div>Yes</div> <div>4090</div> </div>
Stroke	Qualitative	Categorical	<div> <div>No</div> <div>8007</div> </div> <div> <div>Yes</div> <div>1993</div> </div>

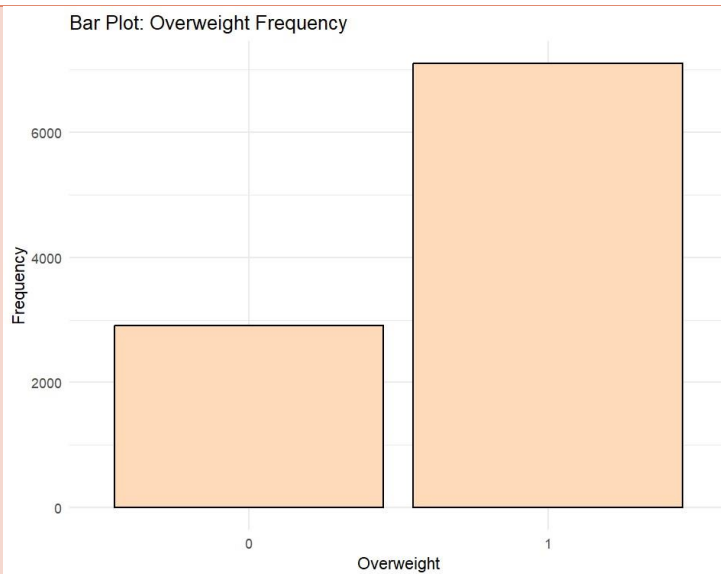
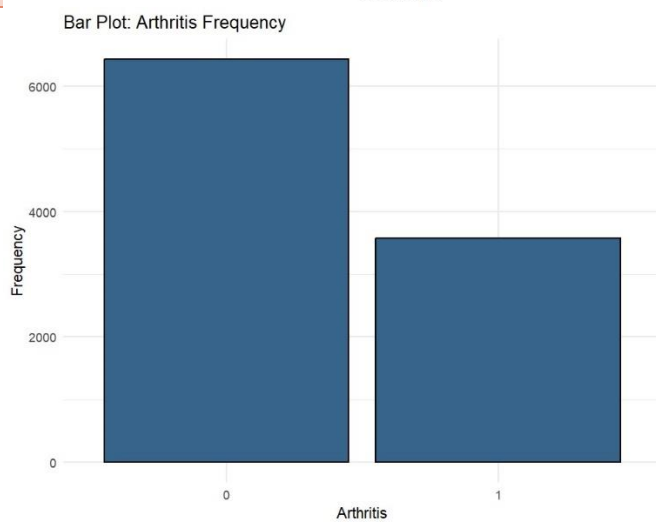
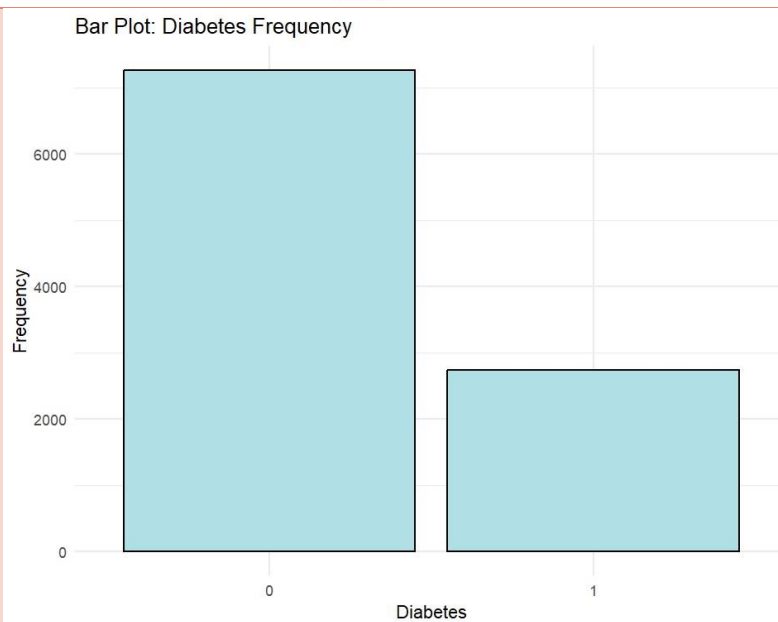
Overweight	Qualitative	Categorical	<div> <div>No</div> <div>Yes</div> <div>2906</div> <div>7094</div> </div>
Arthritis	Qualitative	Categorical	<div> <div>No</div> <div>Yes</div> <div>6426</div> <div>3574</div> </div>
Diabetes	Qualitative	Categorical	<div> <div>No</div> <div>Yes</div> <div>7262</div> <div>2738</div> </div>
Hyperlipidemia	Qualitative	Categorical	<div> <div>No</div> <div>Yes</div> <div>6628</div> <div>3372</div> </div>
Back pain	Qualitative	Categorical	<div> <div>No</div> <div>Yes</div> <div>5886</div> <div>4114</div> </div>
Anxiety	Qualitative	Categorical	<div> <div>No</div> <div>Yes</div> <div>6785</div> <div>3215</div> </div>
Allergic rhinitis	Qualitative	Categorical	<div> <div>No</div> <div>Yes</div> <div>6059</div> <div>3941</div> </div>
Reflux esophagitis	Qualitative	Categorical	<div> <div>No</div> <div>Yes</div> <div>5865</div> <div>4135</div> </div>
Asthma	Qualitative	Categorical	<div> <div>No</div> <div>Yes</div> <div>7107</div> <div>2893</div> </div>

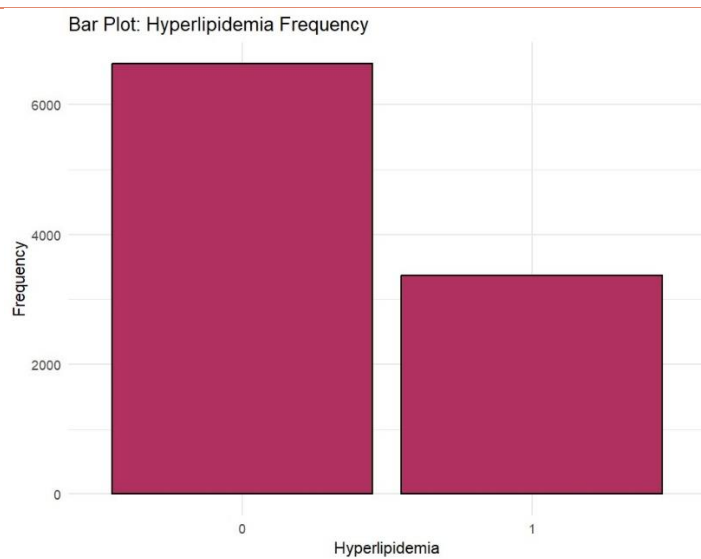
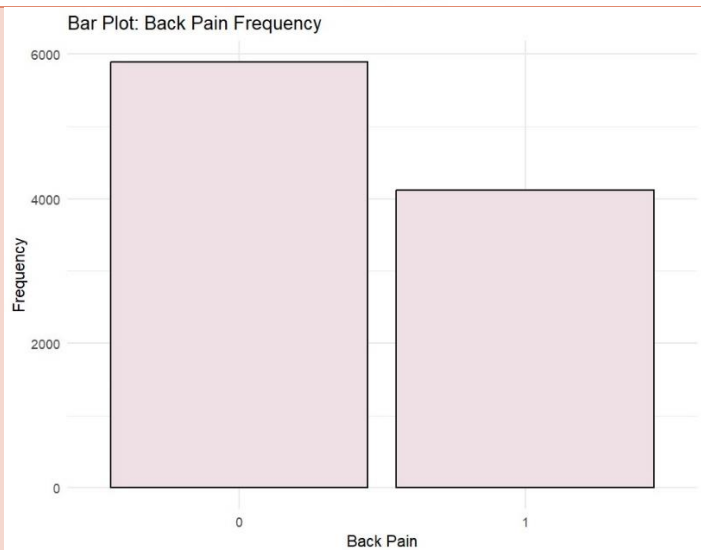
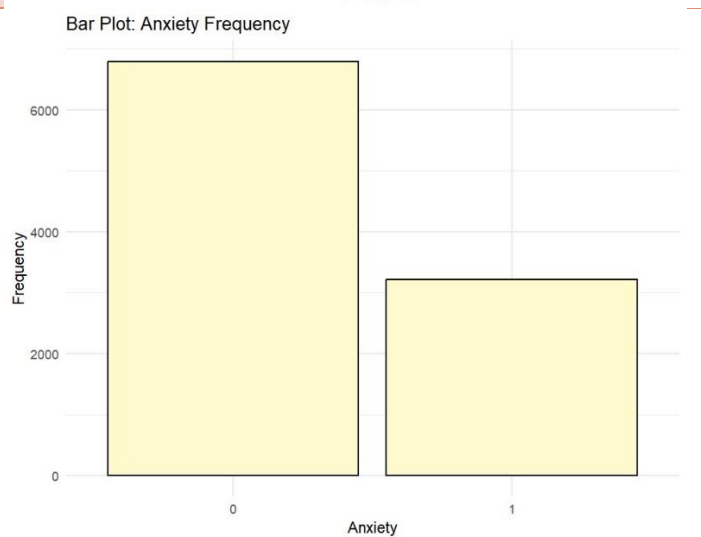
C3. VISUALIZATIONS

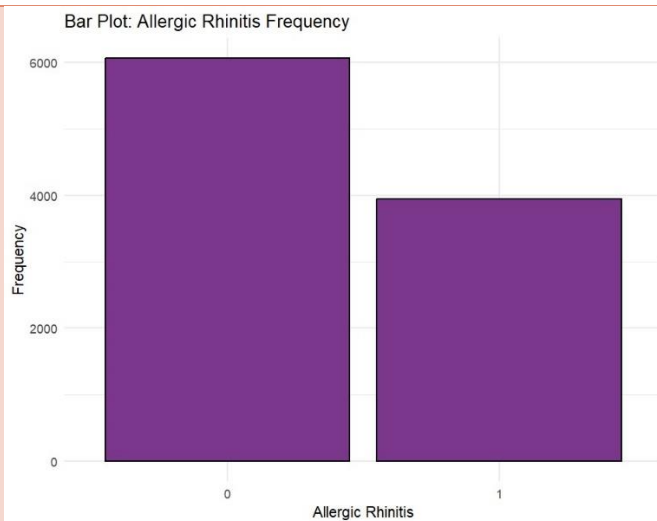
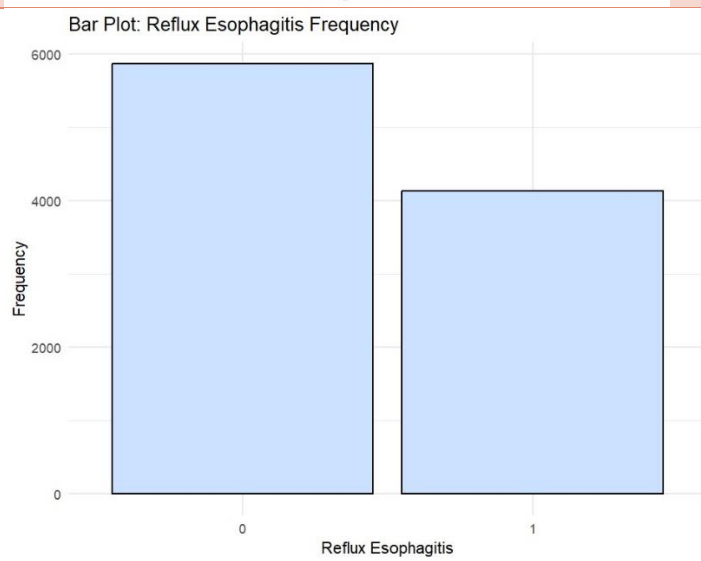
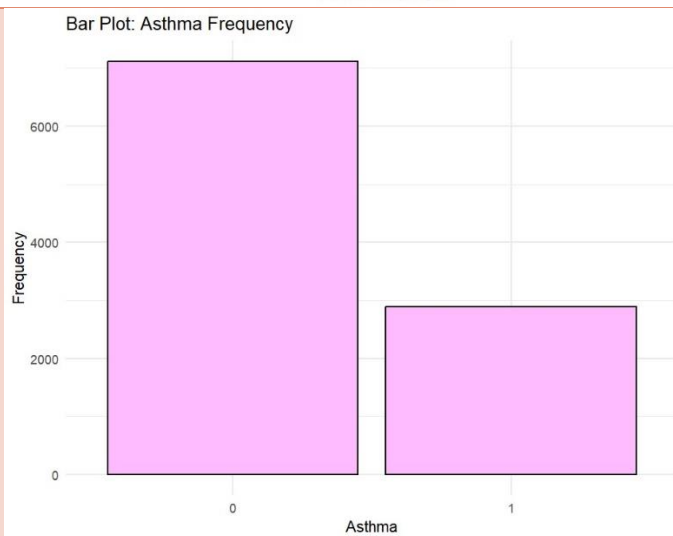
Variables	Univariate Visualizations	
Dependent Variable: Additional Charges	<div><div><div>Histogram of Additional Charges</div><p>A histogram showing the frequency distribution of 'Additional Charges'. The x-axis is labeled 'Additional Charges' and ranges from 0 to 30,000 with major ticks at 10,000, 20,000, and 30,000. The y-axis is labeled 'Frequency' and ranges from 0 to 600 with major ticks at 0, 200, 400, and 600. The bars are green. The distribution is unimodal and slightly right-skewed, with a peak frequency of approximately 700 occurring between 10,000 and 12,000. There is a long tail extending towards 30,000.</p></div></div>	
Age	<div><div><div>Histogram of Age</div><p>A histogram showing the frequency distribution of 'Age'. The x-axis is labeled 'Age' and ranges from 20 to 90 with major ticks at 20, 40, 60, and 80. The y-axis is labeled 'Frequency' and ranges from 0 to 150 with major ticks at 0, 50, 100, and 150. The bars are light blue. The distribution is roughly uniform, with frequencies fluctuating between approximately 120 and 160 across the entire age range from 20 to 90.</p></div></div>	

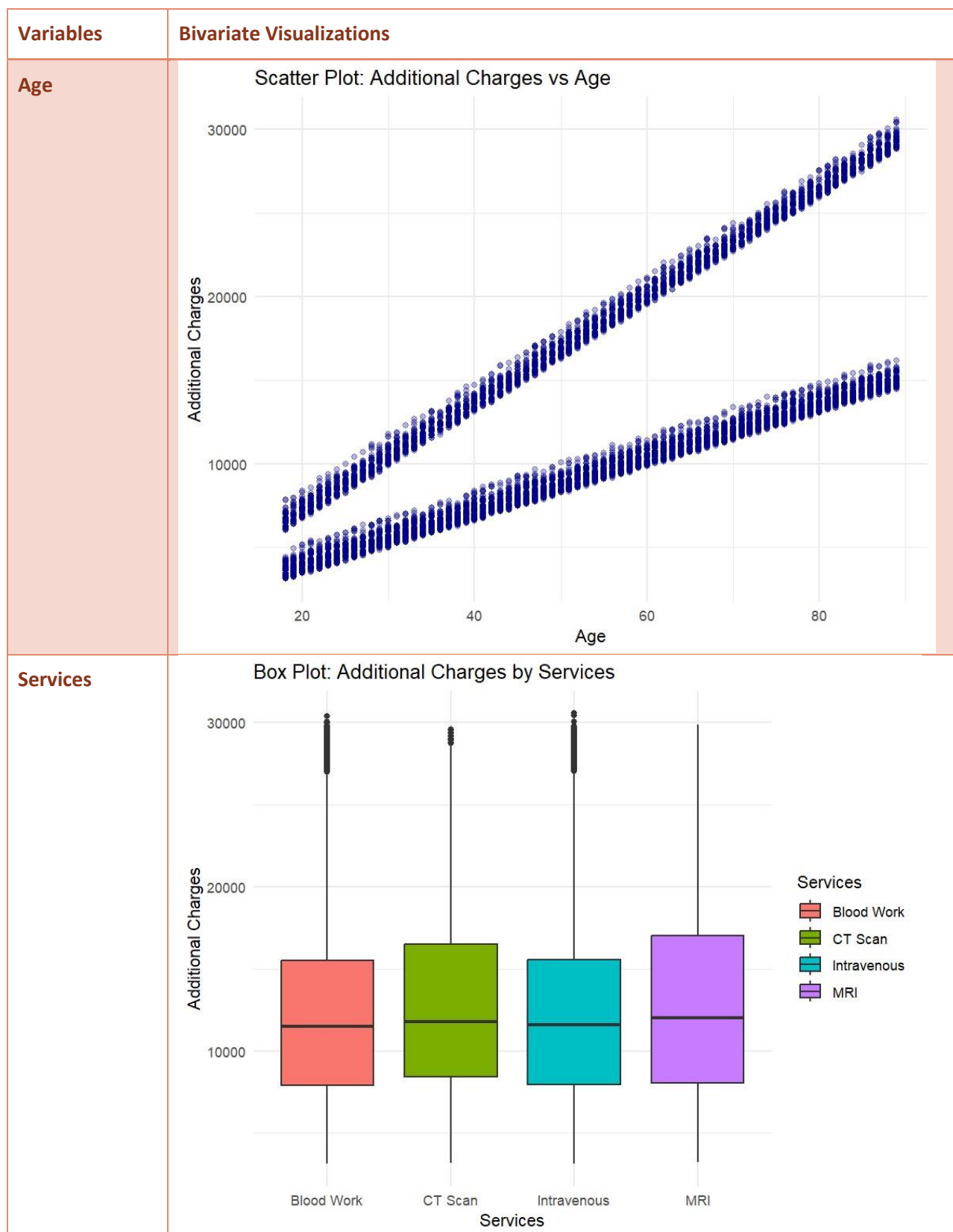
Services**Doc Visits****Complication Risk**

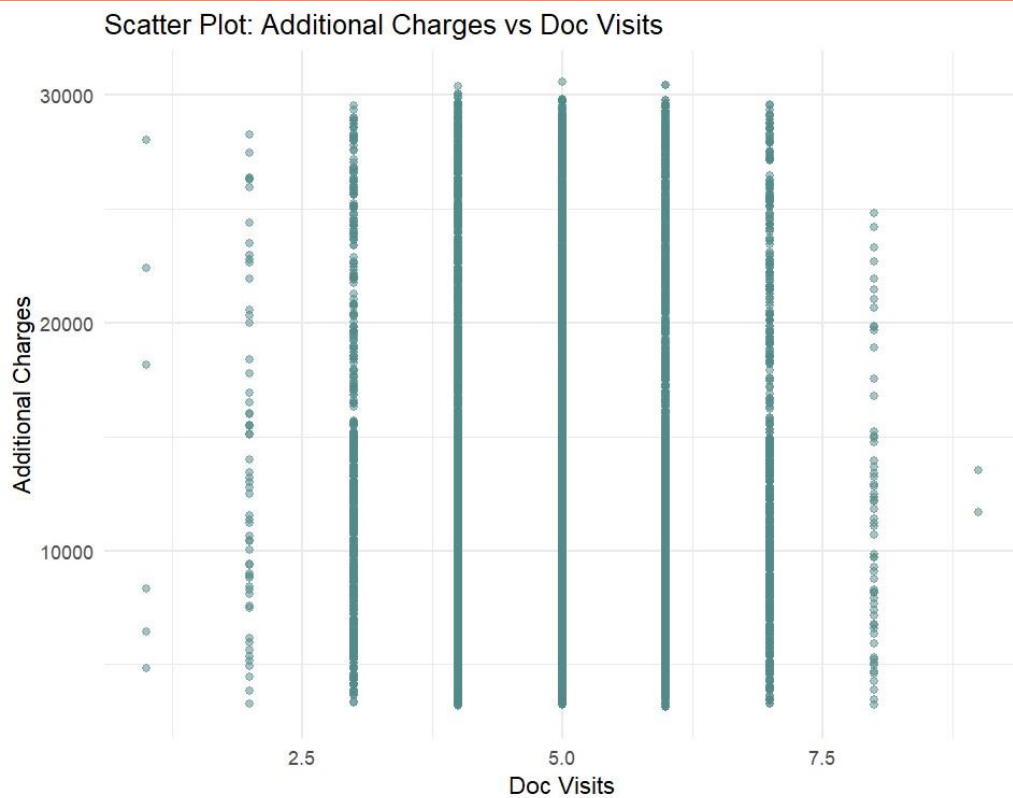
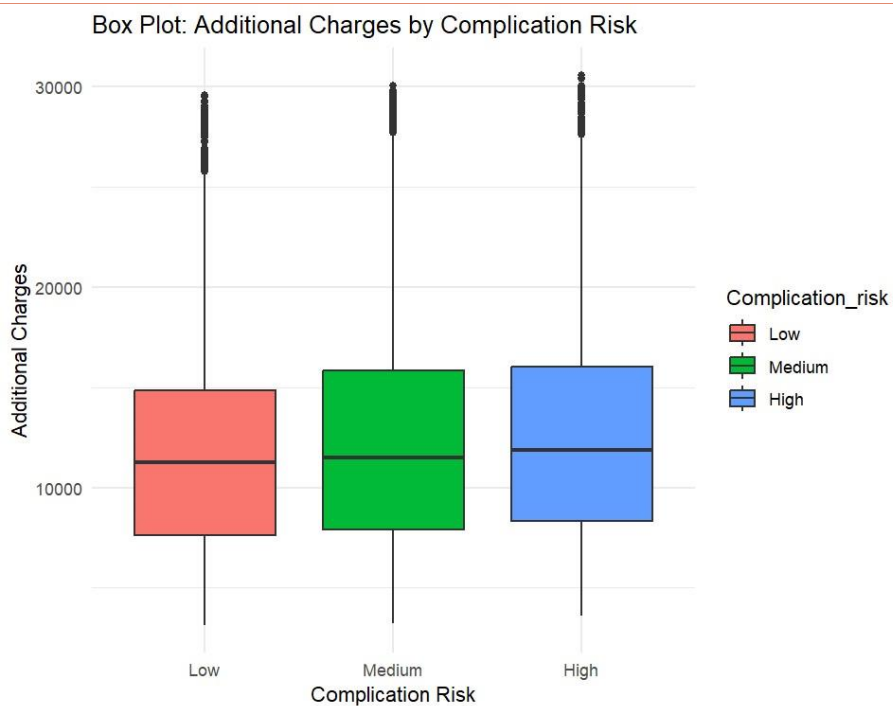
Total Charges**High Blood****Stroke**

Overweight**Arthritis****Diabetes**

Hyperlipidemia**Backpain****Anxiety**

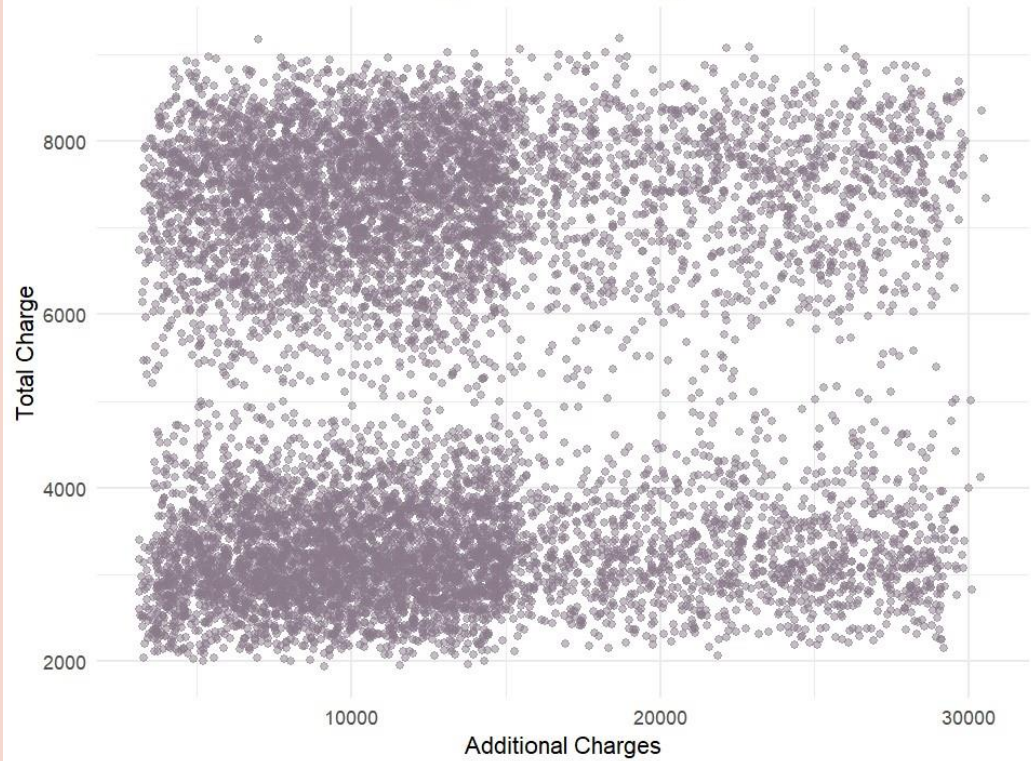
Allergic rhinitis**Reflux esophagitis****Asthma**



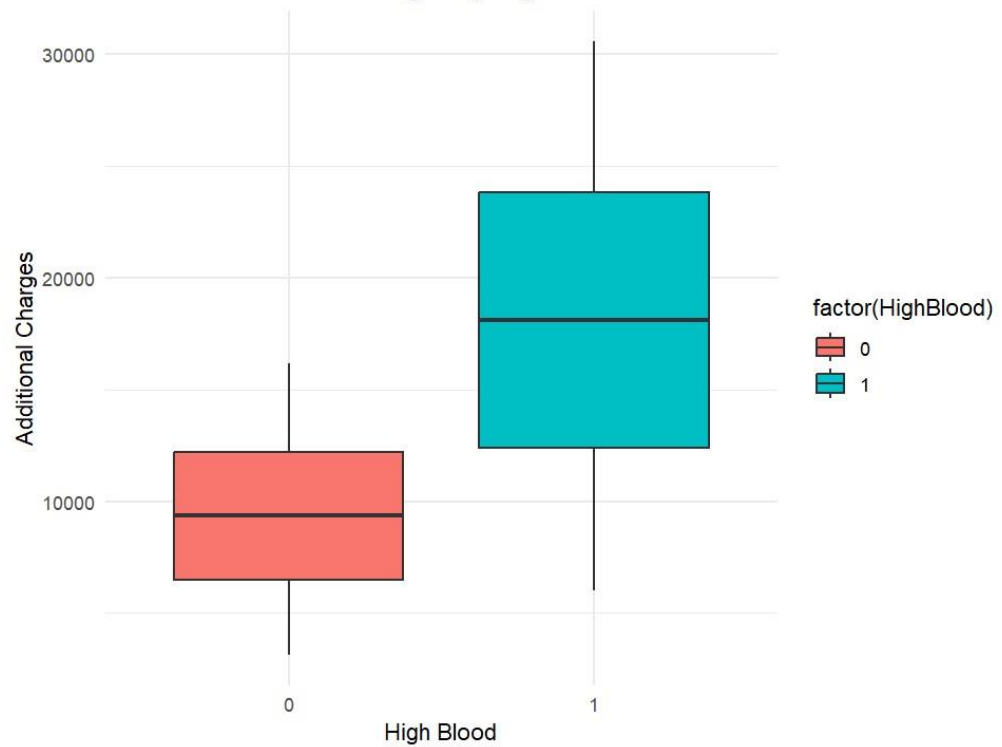
Doc Visits**Complication Risk**

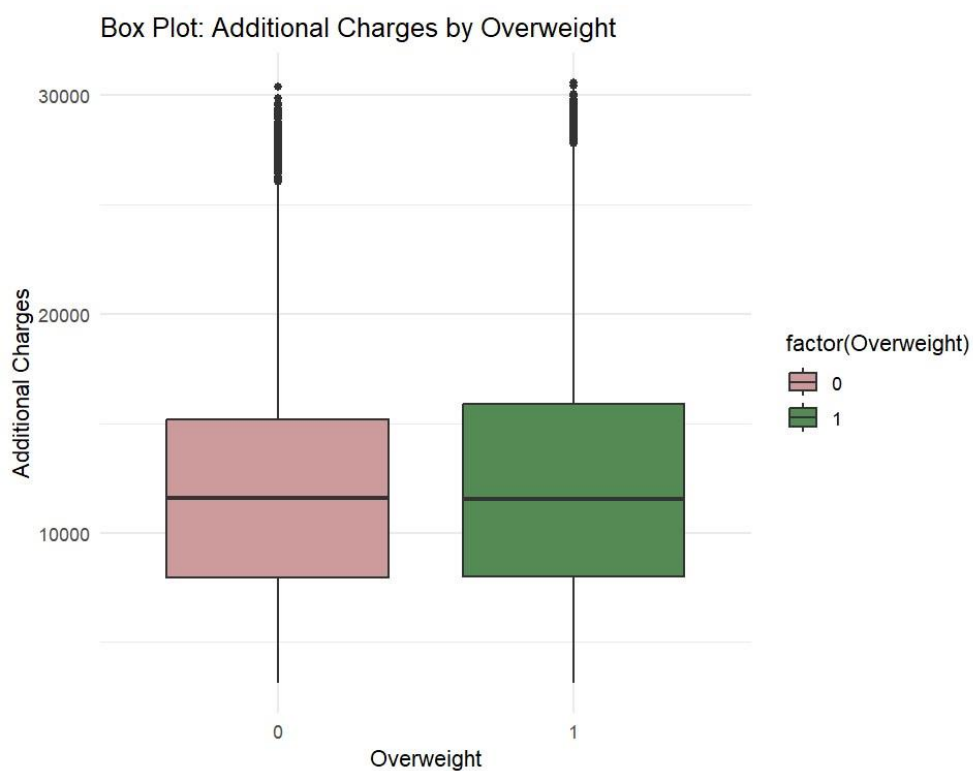
Total Charges

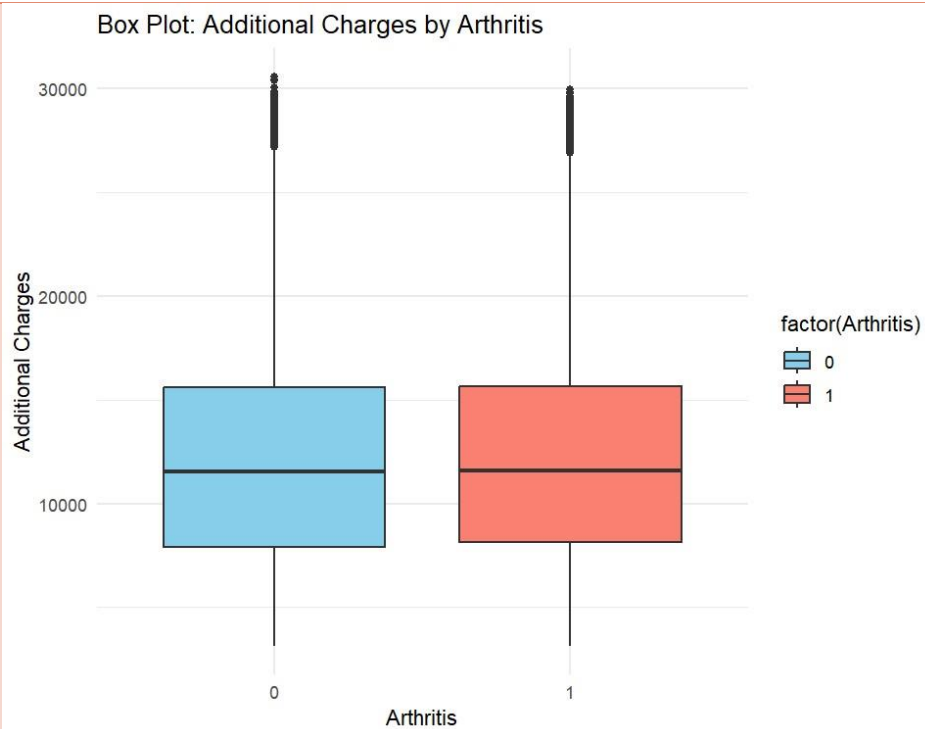
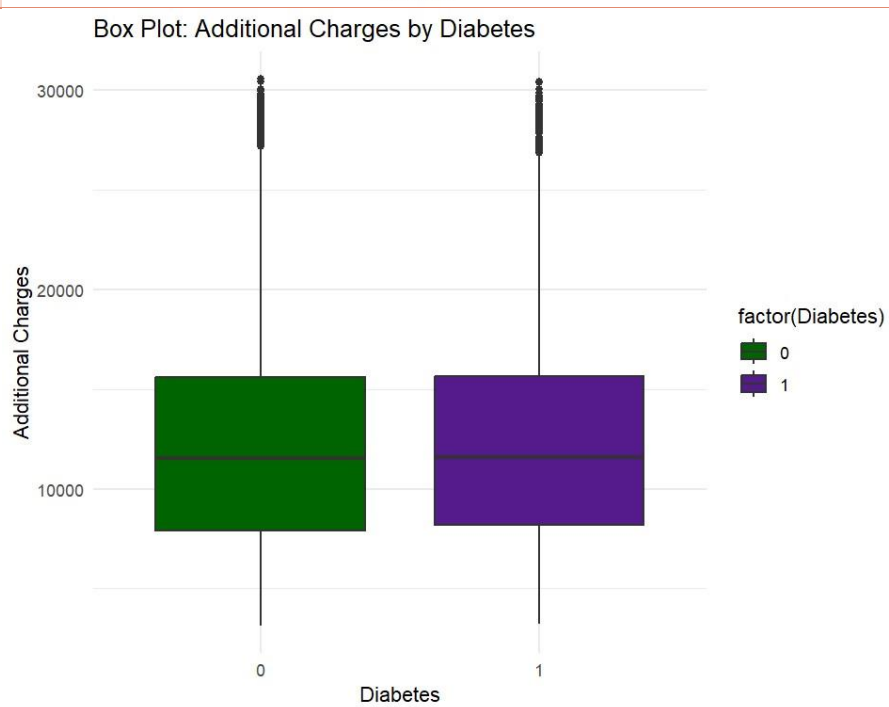
Scatter Plot: Additional Charges vs Total Charge

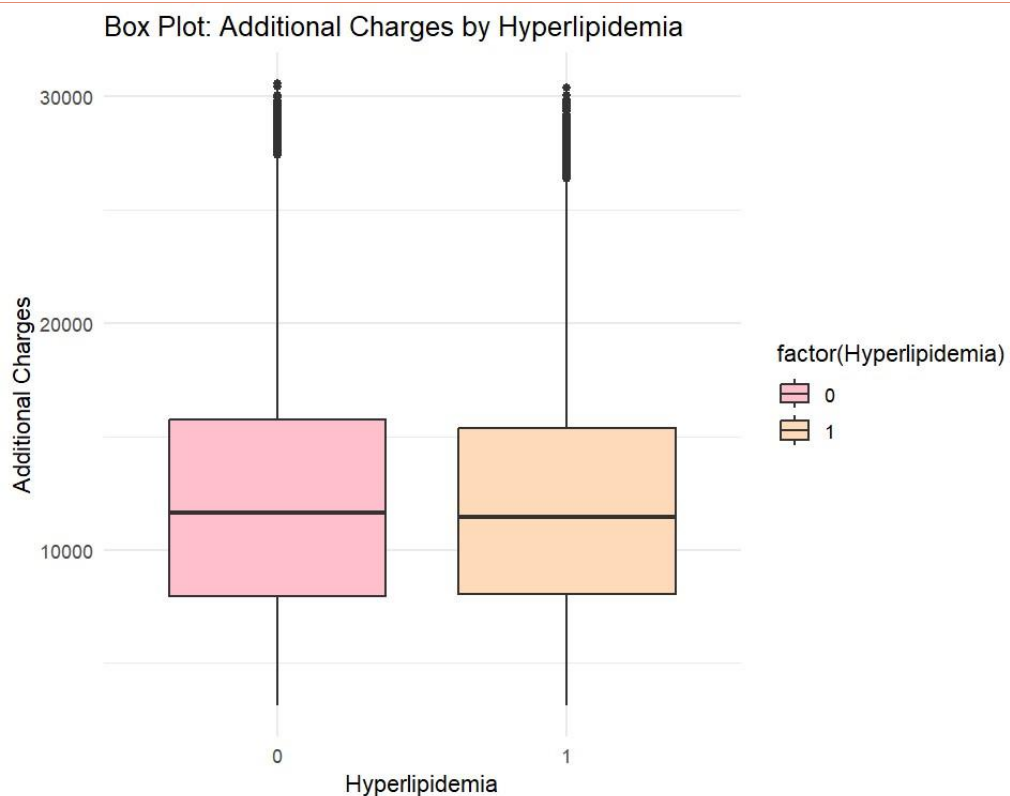
**High Blood**

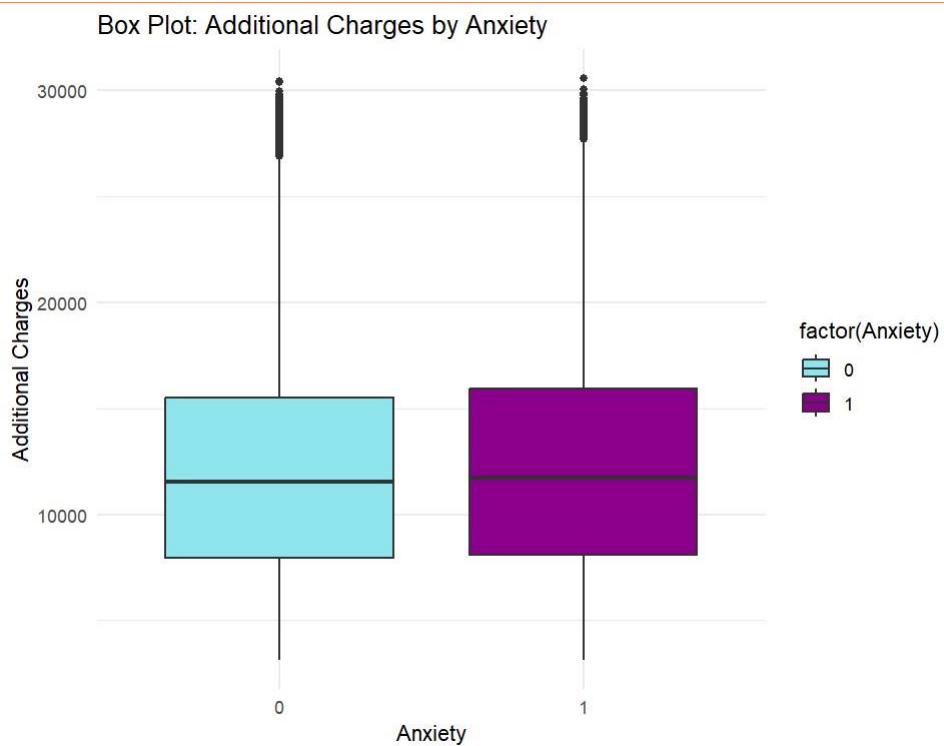
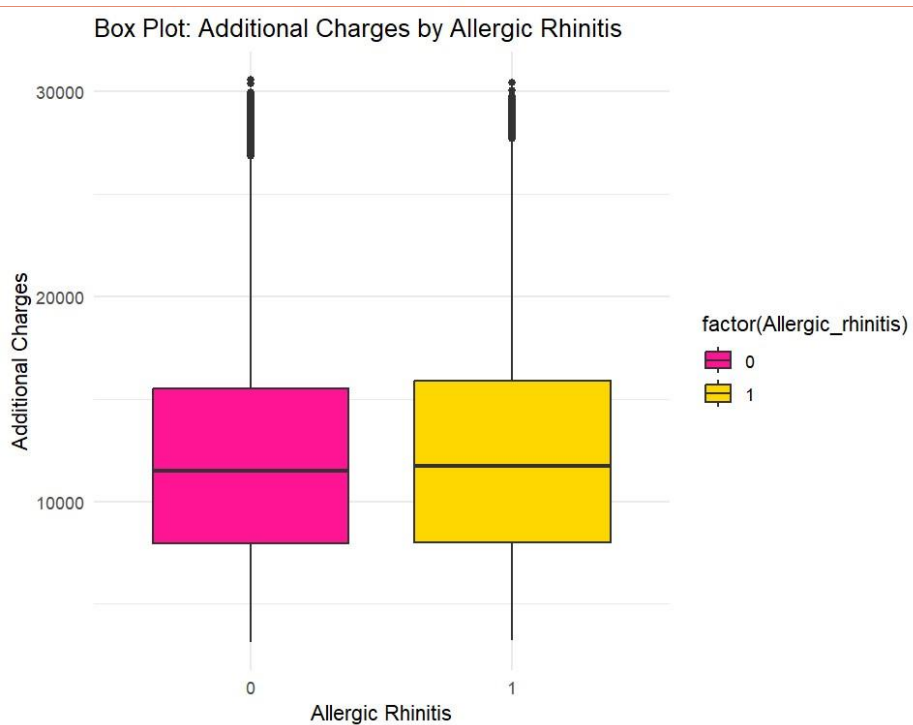
Box Plot: Additional Charges by High Blood

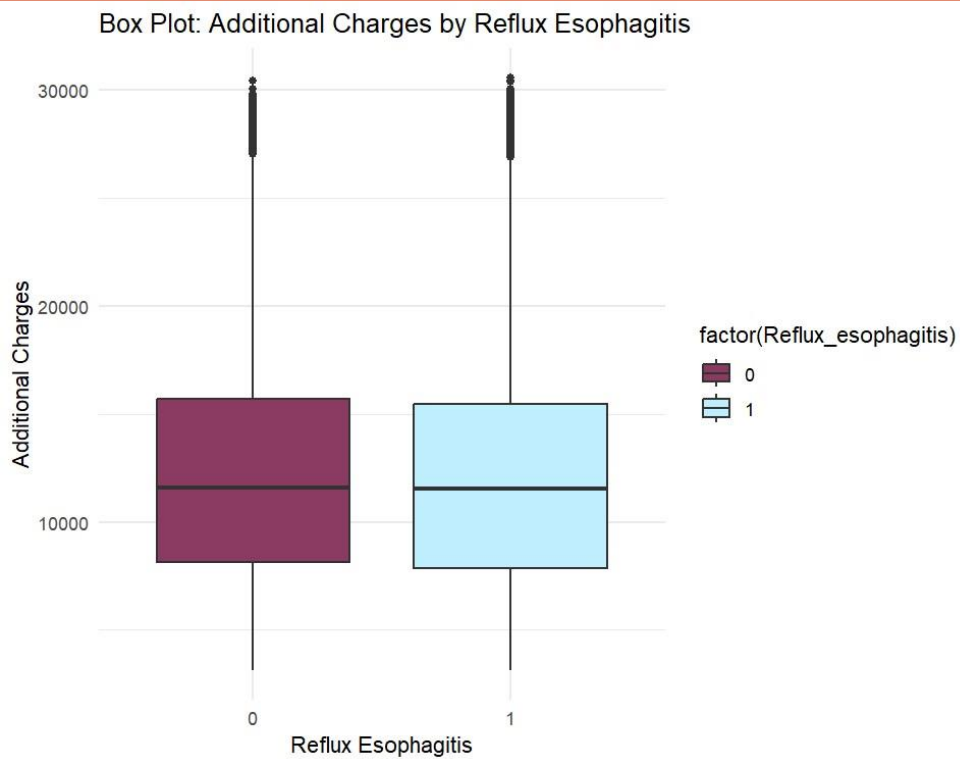
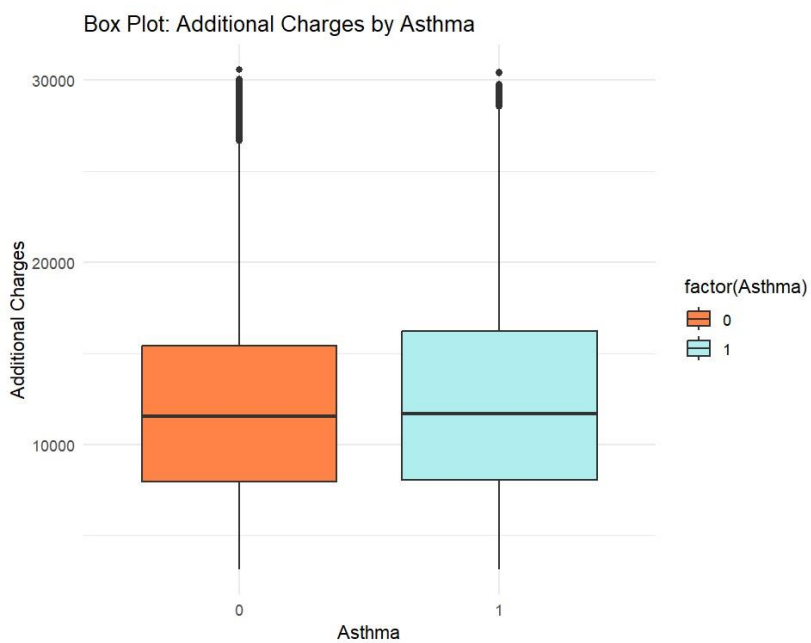


Stroke**Overweight**

Arthritis**Diabetes**

Hyperlipidemia**Backpain**

Anxiety**Allergic rhinitis**

**Reflux
esophagitis****Asthma**

C4. DATA TRANSFORMATION

The data wrangling activities performed on the dataset are converting categorical variables to numeric and factor-level adjustments.

Several categorical variables, such as high blood, stroke, overweight, arthritis, diabetes, hyperlipidemia, back pain, anxiety, allergic rhinitis, reflux esophagitis, and asthma, were converted into numeric factors. This conversion was achieved using the `plyr` package with the `revalue` function. The conversion turned Yes to 1, No to 0, and NA to NA. The variable complication risk was adjusted to Low, Medium, and High levels. This was done with `factor()`.

Performing the conversion and adjustment is essential to answer my research question. Firstly, this ensures consistency in data types and makes it easier to work with the dataset. Numeric representation of categorical variables helps maintain uniformity across the data set. Furthermore, adjusting factor levels is essential for ensuring that categorical variables are treated correctly in statistical models. Overall, data wrangling activities contribute to data quality. Uniform and well-structured data are necessary for obtaining reliable and meaningful insights from analysis.

Code for wrangling is attached

C5. PREPARED DATA SET

.csv attached

PART IV: MODEL COMPARISON & ANALYSIS

D1. INITIAL MODEL

```
Call:
lm(formula = Additional_charges ~ Age + Services + Doc_visits +
  Complication_risk + TotalCharge + HighBlood + Stroke + Overweight +
  Arthritis + Diabetes + Hyperlipidemia + BackPain + Anxiety +
  Allergic_rhinitis + Reflux_esophagitis + Asthma, data = df)

Residuals:
    Min       1Q   Median       3Q      Max
-3912.6 -1308.5   17.4  1328.1  3925.9

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.963e+03  1.138e+02 -26.045 < 2e-16 ***
Age          2.257e+02  7.978e-01  282.848 < 2e-16 ***
ServicesCT Scan -2.497e+01  5.222e+01 -0.478  0.63250
ServicesIntravenous 2.779e+01  3.715e+01  0.748  0.45437
ServicesMRI       1.230e+02  8.742e+01  1.406  0.15961
Doc_visits      -1.801e+01  1.575e+01 -1.143  0.25286
Complication_riskMedium 1.201e+02  4.332e+01  2.773  0.00556 **
Complication_riskHigh  5.077e+02  4.570e+01  11.109 < 2e-16 ***
TotalCharge     6.267e-03  7.596e-03  0.825  0.40935
HighBlood      8.631e+03  3.350e+01  257.642 < 2e-16 ***
Stroke         3.549e+02  4.121e+01  8.612 < 2e-16 ***
Overweight     2.976e+01  3.626e+01  0.820  0.41195
Arthritis      -5.704e+01  3.438e+01 -1.659  0.09711 .
Diabetes       5.264e+01  3.692e+01  1.426  0.15397
Hyperlipidemia  1.943e+01  3.483e+01  0.558  0.57697
BackPain       -3.506e+01  3.349e+01 -1.047  0.29519
Anxiety        3.239e+01  3.526e+01  0.919  0.35827
Allergic_rhinitis -5.137e-01  3.368e+01 -0.015  0.98783
Reflux_esophagitis 2.431e+01  3.344e+01  0.727  0.46736
Asthma         5.360e+01  3.631e+01  1.476  0.13995
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1645 on 9980 degrees of freedom
Multiple R-squared:  0.9369,    Adjusted R-squared:  0.9368
F-statistic: 7801 on 19 and 9980 DF, p-value: < 2.2e-16
```

D2. JUSTIFICATION OF MODEL REDUCTION

For this model, I used the backward stepwise elimination. Firstly, construct the initial regression model with all the predictor variables in your dataset. Then, the **step()** function does all the work. It utilizes multiple iterations that evaluate the contribution of each predictor variable. Every predictor variable that has the highest p-value and thus contributes the least to the model is removed. The function stops when the iteration with the lowest AIC is obtained.

The backward stepwise elimination method is vital to my research question since it enables me to select the variables that are statistically significant. These variables are considered the most important contributors to the increase in additional charges.

D3. REDUCED LINEAR REGRESSION MODEL

```
> summary(reduced_model)
```

Call:

```
lm(formula = Additional_charges ~ Age + Complication_risk + HighBlood +  
    Stroke + Arthritis + Diabetes + Asthma, data = df)
```

Residuals:

```
      Min       1Q   Median       3Q      Max  
-3911.5 -1313.2   14.7  1323.2  3967.2
```

Coefficients:

```
              Estimate Std. Error t value Pr(>|t|)  
(Intercept)   -2976.5087    60.4656  -49.226 < 2e-16 ***  
Age             225.6459     0.7971  283.098 < 2e-16 ***  
Complication_riskMedium 120.7432    43.2788   2.790 0.00528 **  
Complication_riskHigh  508.9442    45.6075  11.159 < 2e-16 ***  
HighBlood      8631.2481    33.4679  257.896 < 2e-16 ***  
Stroke         352.7240    41.1815   8.565 < 2e-16 ***  
Arthritis      -54.9452    34.3354  -1.600 0.10957  
Diabetes        53.4839    36.8914   1.450 0.14716  
Asthma         53.2815    36.2801   1.469 0.14197  
---
```

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1645 on 9991 degrees of freedom

Multiple R-squared: 0.9369, Adjusted R-squared: 0.9368

F-statistic: 1.853e+04 on 8 and 9991 DF, p-value: < 2.2e-16

E1. MODEL COMPARISON

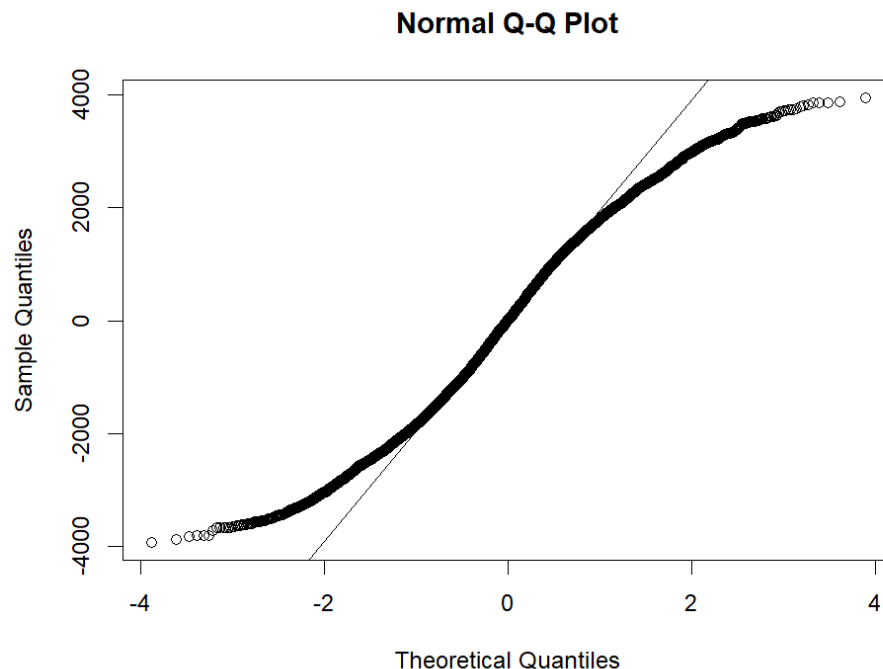
Metrics	Initial Model	Reduced Model
Residual Standard Error (RSE)	1645 on 9980 degrees of freedom	1645 on 9991 degrees of freedom
R-squared	0.9369	0.9369
Adjusted R-squared	0.9368	0.9368
F-statistic	7801 on 19 and 9980 degrees of freedom	1.853e+04 on 8 and 9991 degrees of freedom
p-value	p-value < 2.2e-16	p-value < 2.2e-16

The residual standard error is similar in both models. This indicates a similar goodness of fit regarding the spread of residuals. R-squared values are identical in both models. This demonstrates that models have similar variability in the response variable. The p-values are both extremely low, which indicates that both models have strong evidence against the null hypothesis. The F-statistic is much higher in the final model. This change suggests that the reduced model is a more statistically significant improvement over the initial model.

The F-statistic is vital to choosing my model since this metric measures the overall model significance. In this analysis, the F-statistic increased substantially in the reduced model. This indicates that the reduced model should be chosen over the initial model.

E2. OUTPUT & CALCULATIONS

RESIDUAL PLOT OF THE REDUCED MODEL



RESIDUAL STANDARD ERROR FOR THE REDUCED MODEL

Residual standard error: 1645 on 9991 degrees of freedom
 Multiple R-squared: 0.9369, Adjusted R-squared: 0.9368
 F-statistic: 1.853e+04 on 8 and 9991 DF, p-value: < 2.2e-16

E3. CODE

See .R code attached

PART V: DATA SUMMARY & IMPLICATIONS

F1. RESULTS

REGRESSION EQUATION

Additional_charges

$$= \beta_0 + \beta_1 \times \text{Age} + \beta_2 \times \text{Complication_riskMedium} \\ + \beta_3 \times \text{Complication_riskHigh} + \beta_4 \times \text{HighBlood} + \beta_5 \times \text{Stroke} + \epsilon$$

INTERPRETATION

Additional_charges

$$= -2966.5087 + 225.6459 \times \text{Age} + 120.7432 \times \text{Complication_riskMedium} \\ + 508.9442 \times \text{Complication_riskHigh} + 8631.2481 \times \text{HighBlood} \\ + 352.7240 \times \text{Stroke} + \epsilon$$

β_0 with the value of -2966.5087 is the intercept. This represents the estimated additional charges when all predictor variables are zero. β_1 with the value of 225.6459 means that for every one unit increase in age, the additional charges increase by 225.6459 , holding other variables constant. If the complication risk is medium, additional charges will increase by β_2 , which is 120.7432 , holding other variables constant. If the complication risk is high, additional charges will increase by β_3 , which is 508.9442 , holding other variables constant. If a patient has high blood, additional charges will increase by β_4 which is 8631.2481 , holding other variables constant. If a patient has experienced a stroke, additional charges will increase by β_5 , which is 354.7240 , holding other variables constant.

STATISTICAL SIGNIFICANCE

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	-2976.5087	60.4656	-49.226	< 2e-16	***
Age	225.6459	0.7971	283.098	< 2e-16	***
Complication_riskMedium	120.7432	43.2788	2.790	0.00528	**
Complication_riskHigh	508.9442	45.6075	11.159	< 2e-16	***
HighBlood	8631.2481	33.4679	257.896	< 2e-16	***
Stroke	352.7240	41.1815	8.565	< 2e-16	***
Arthritis	-54.9452	34.3354	-1.600	0.10957	
Diabetes	53.4839	36.8914	1.450	0.14716	
Asthma	53.2815	36.2801	1.469	0.14197	

Residual standard error: 1645 on 9980 degrees of freedom

Multiple R-squared: 0.9369. Adjusted R-squared: 0.9368

F-statistic: 7801 on 19 and 9980 DF, p-value: < 2.2e-16

The p-values of the reduced model and the F-statistic are essential to assessing the statistical significance. The p-values should be very small to indicate that the variable is statistically significant in predicting additional charges. All the corresponding variables chosen are below the significance level (0.05). Also, the overall reduced model's F-statistic has a very low p-value. This suggests that at least one predictor variable contributes significantly to the variability.

Since both metrics are statistically significant, this implies that the observed relationships are unlikely to have occurred by chance alone. The results are more likely due to the relationships between variables. This strengthens the validity and reliability of the model.

PRACTICAL SIGNIFICANCE

It is crucial to find the practical significance of the model to focus on the relevance of the results. The model suggests that age, complication risk, high blood, and stroke are significant factors that influence additional charges. Older patients should expect higher charges in their hospital bills. Moreover, patients with medium and high complication risk levels should expect higher additional charges. Patients with the medical condition of high blood and stroke should be wary of the additional financial impact on their hospital bills.

The model's practical significance is its ability to identify specific patient characteristics directly impacting healthcare costs. Practical significance is found in understanding these variables' effects on patients and healthcare professionals. It can help with resource allocation, budgeting, and patient care planning.

LIMITATIONS OF THE ANALYSIS

It is vital to be aware of the limitations of the analysis. The transformation of categorical variables in regression analysis is one of the potential limitations. Firstly, the dataset may lose some information inherent in the categories. In this analysis, this transformation is evident for variables like high blood and stroke, and potential complication risk. Moreover, recoding categorical variables into numerical values might lead to a loss of meaningful information. Assigning 1 to Yes and 0 to No may not capture the nuances of each category. This can lead to a risk of misinterpretation. Users of the model may interpret the binary if not adequately communicated.

Furthermore, the linear regression model assumes a linear relationship between predictors and the response variable. If the true relationship is non-linear, the model may not capture the complexity of the data. It is also important to note causation and correlation. The analysis identifies an association between predictor values and additional charges but does not establish causation. Lastly, the final reduced model simplifies the true underlying relationships. While this simplification aids interpretation, it may overlook nuanced interactions present in the data.

F2. RECOMMENDATIONS

Based on the regression analysis where I identified the significant predictors for additional charges on the hospital bill, I have several recommendations for the organization.

It is crucial to integrate regression findings into clinical decision support systems. Ensure that healthcare professionals are aware of the significant predictors. Training can support a more informed approach to patient care. Also, consider allocating resources based on identified risk factors. The organization should prioritize resources and preventive measures for patients with a patient with higher complication risk and those with a history of high blood and stroke.

It is widely known that prevention is better than cure. The organization should implement strategies to engage patients. Actively involve patients in their care plans, especially those with identified risk

factors. Patient engagement can contribute to better health outcomes. Also, there is a need to develop patient education programs. Teach patients about the importance of preventive measures. It should be highly emphasized that this initiative is all for the sake of patients. This not only reduces their hospital bills but improves their overall quality of life.

These recommendations gained from the analysis are to enhance the effectiveness of healthcare and improve patient outcomes. It is vital that the organization implement these recommendations with a focus on continuous improvement and further development in alignment with its mission and values.